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Evaluating the impact of the Ebola epidemic on aid allocation across sectors in Sierra Leone: an interrupted time series analysis

Mark Jaeger

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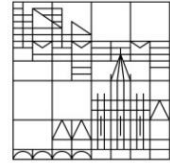
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Mark JAEGER

EVALUATING THE IMPACT OF THE EBOLA EPIDEMIC ON AID ALLOCATION ACROSS SECTORS IN SIERRA LEONE

An Interrupted Time Series Analysis

Academic Year 2020-2021

Master's Thesis

Under the direction of Sabine SAURUGGER and Anja OSEI

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List of Abbreviations

Abbr.	Abbreviations
AfDB	African Development Bank
AIC	Akaike Information Criterion
AIMS	Aid Information Management System
ARIMA	AutoRegressive Integrated Moving Average
CDC	Center for Disease Control and Prevention
CRED	Centre for Research on the Epidemiology of Disasters
CRS	Credit Report System
DAC	Development Assistance Committee
DAD	Development Assistance Database
EDA	Education for All
EU	European Union
EVD	Ebola Virus Disease
GDP	Gross Domestic Product
GoSL	Government of Sierra Leone
ITS	Interrupted Time Series
MDGs	Millennium Development Goals
ODA	Official Development Assistance
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PVAR	Panel Vector Autoregression
SDGs	Sustainable Development Goals
UK	United Kingdom
UN	United Nations
UNDP	United Nations Development Programme
UNMEER	United Nations Mission for Ebola Emergency Response
UNSC	United Nations Security Council
US	United States
USD	United States Dollar
WHO	World Health Organization

Abstract

Epidemics, like natural disasters in general, are highly disruptive events that can drastically shift circumstances and priorities in affected countries. In already vulnerable developing and aid-dependent countries, any reprioritization and reallocation considerations are not nationally limited, but are likely to also extend to international donors. Applying sectoral aid allocation theory to the context of the 2014-2016 Ebola crisis, this study examines how the Ebola epidemic impacted donor aid allocation across sectors. This gap in research is approached quantitatively through an interrupted time series analysis of aid flows across sectors between 2005 and 2019 in Sierra Leone. Although mixed and partly inconclusive, the results suggest that the epidemic induced immediate and sustained changes in aid flows to given sectors, both during as well as in the aftermath of the crisis. Significant differences are observed between effects on bilateral and multilateral aid. While multilateral aid shows to react with increases in aid to non-health sectors (i.e., infrastructure, education and non-health aid in general), this is not observed for bilateral aid. When looking at the largest donors individually, strong support is found that the United States responded to the crisis with cross-sectoral reallocation of aid from other sectors towards the health sector. On a general level, the results also suggest that the Ebola epidemic led to a sustained decline in infrastructure aid in the years following the epidemic. Despite their preliminary nature, these findings can provide important implications for affected recipient governments to anticipate and respond to accordingly.

Keywords: sectoral aid allocation, post-disaster aid, health crisis, epidemics, Ebola, Sierra Leone, interrupted time series analysis, cross-sector, sectoral reallocation, development aid, health aid, education aid, infrastructure aid

1 Introduction

The disruptive effect health crises can have on nearly every aspect of daily life is surely no longer a secret, as has been exemplified in all its facets by the ongoing COVID-19 pandemic. What the COVID-19 pandemic has effectuated in the past two years on a global level, West-African countries have already experienced to a – in several aspects – comparable extent during the 2014-2016 Ebola epidemic. Beyond the direct health impact of the Ebola virus (i.e., over 28,000 infections and 11,000 deaths reported, see Center for Disease Control and Prevention [CDC], 2020), the epidemic heavily strained the already vulnerable health-care system and, inter alia, led to a shutdown of economic activity, interruption of infrastructure projects, closing of schools and enforcement of mobility and trade restrictions (see Government of Sierra Leone [GoSL], 2015; Stephens, 2017; Smith et al., 2019; Kum, Olayiwola & Aloysius, 2019). The three countries hit hardest by the Ebola epidemic – Guinea, Liberia, and Sierra Leone – had already been burdened before the epidemic with high levels of poverty, weak institutions, and were in the process of recovery from a history of political instability and/or civil war. These pre-existing challenges thus further exacerbated the adverse multisectoral impacts of the epidemic.

Given the drastic shift in circumstances and urgencies by the rapid spread of the virus, government response through adaptation, reprioritization or budgetary reallocation of resources is indispensable (see e.g., Benson & Clay, 2004; Kum et al., 2019; World Bank, 2014, p. 1). As, however, the three affected countries already exhibited a high reliance on foreign aid prior to the epidemic and were also highly dependent on international support to contain and manage the crisis (Kargbo, 2012; Mobula et al., 2018), these reallocation considerations are likely to also extend to international donors. Given the finite nature of donor resources, cross-sector reallocation of aid can be a useful tool to redirect limited resources to sectors where the need is most urgent (Benson & Clay, 2004, p. 35). However, donors do not necessarily allocate aid along needs-based criteria but are, inter alia, also driven by strategic, visibility, or risk pooling considerations (Pietschmann, 2014). In other words: the epidemic and shift in circumstances could possibly also affect donors' strategic or interest considerations, potentially resulting in new priorities in donors' respective aid portfolios. As the drainage of resources from certain sectors can have adverse effects on the economic development of the affected country (Benson & Clay, 2004, p. 35), understanding the impact of aid allocation mechanisms in the context of epidemics is of critical importance.

Prior scholarly literature on the impact of natural disasters – which also include epidemics (Centre for Research on the Epidemiology of Disasters [CREED], 2009) – on aid flows has largely concentrated on patterns and determinants of post-disaster aid allocation at the country level (see e.g., Strömberg, 2007; David, 2011; Becerra, Cavallo & Noy, 2014). Only few studies (see Benson & Clay, 2004; Becerra, Cavallo & Noy, 2015) counter this aggregation bias by also examining the impact of natural disasters on the sectoral allocation of aid within the affected countries. Conducting the so far only systematic quantitative analysis of cross-sector aid allocation (and reallocation) mechanisms following natural disaster shocks, Becerra et al. (2015) find some tentative evidence for cross-sector reallocation. They, however, do not distinguish by the type of natural disaster in their analysis and no epidemics are included in their sample. Keeping in mind the nature of the 2014-2016 Ebola crisis, epidemics, however, can show features that decisively distinguish them from other natural disasters: They are generally likely to last over a comparatively longer period of time than other types of more “instant” natural disasters (e.g., earthquakes or hurricanes) and may require active human efforts to contain the spread (like lockdowns and large-scale mobility and trade restrictions), while most other natural disasters pass naturally. Given this distinguished nature and the dynamics this could unfold, there is need to study aid (re-)allocation in the context of epidemics, specifically and separately.

Considering the scarcity of both theoretical and empirical literature on the matter, still relatively little is known about the relationship between epidemics and sectoral aid allocation. To address this gap in research, this study devotes itself to the following research question: *How did the Ebola epidemic in West-Africa impact donor aid allocation across sectors?*

The research question is approached by means of single-case quantitative interrupted time series (ITS) analysis. Focusing on a single country allows for more detail and accuracy to be devoted towards developing hypotheses that take into account both the epidemic shock and aid allocation in their unique country-specific context. Of the three countries hardest hit by the Ebola epidemic, Sierra Leone was estimated to have experienced the highest economic damage (World Bank, 2016, 2021a). This makes Sierra Leone a particularly relevant case to study as the strong multi-sectoral impacts of the crisis could make cross-sector reallocation particularly necessary but at the same time could also induce a double jeopardy on certain sectors. ITS analyses are considered the strongest quasi-experimental designs to assess how an intervention (here: the Ebola epidemic) changed an outcome of interest (i.e., aid allocated to a given sector), either immediately and/or over time (Wagner, Soumerai, Zhang & Ross-Degnan, 2002, p. 299).

Segmented regression models are thus estimated using longitudinal time series data on monthly aid flows across sectors between 2005 and 2019 in Sierra Leone, which are interrupted by the 22-months long epidemic. To ensure a higher validity of results, a series of control models and robustness checks are included in the analysis.

Presenting the first quantitative study on the impact of epidemics on sectoral aid allocation and the first ITS analysis in the context of post-disaster aid allocation¹, this paper seeks to extend the scope of this understudied field and provide an initial contribution for a better understanding of the matter. Considering that developing – and in many cases, aid-dependent – countries are expected to experience the highest economic consequences from the ongoing COVID-19 pandemic (Djankov & Panizza, 2020; Noy et al., 2020), gaining a better understanding of the impact of prior health crises on aid allocation mechanisms in aid-receiving countries, thus has become as relevant as ever.

This paper is structured as follows: First, prior scholarly literature on aid allocation in the context of natural disasters is reviewed, revealing the gap in research and relevance of the studied research question. Second, contextual background on the Sierra Leone case is provided. The subsequent section introduces the theoretical framework and a set of derived hypotheses. Next, the pursued methodological strategy is outlined, explaining the used data, model specification and accounting for potential methodological issues. After providing some foundational descriptive statistics, the results of the ITS analyses are presented. This is followed by a discussion of the results and some limitations of the study. The final section summarizes and concludes.

2 Literature Review and Research Gap

2.1 Natural Disasters and Foreign Aid

While there has been extensive research on the impact of aid on natural disaster response and recovery (see e.g., Masyrafah & McKeon, 2008; Nunnenkamp & Öhler, 2010; Peiffer & Boussalis, 2010; Raschky & Schwindt, 2009; Wood & Wright, 2016), only a handful of studies examine how the occurrence of a natural disaster impacts aid flows into countries already receiving support (or aid-dependent):

¹ To the author's best knowledge.

Through examining the impact of hurricanes on aid flows to developing countries through means of a constructed time-varying storm index, Yang (2008) found that hurricanes were generally followed by large surges in foreign aid to affected countries. However, using a Panel Vector Autoregression (PVAR) model, Raddatz (2007) did not find any significant evidence in his sample of developing countries, that aid flows fluctuate substantially in response to a natural disaster. Similarly, David (2011) shows that while aid flows increase slightly after geological disaster shocks, no statistically significant effects are observed for climatological crises nor for disaster shocks in general. The results of his analysis can be distinguished further when differentiating by income group, as increases in foreign aid, in response to geological shocks, are more significant in low-income countries (David, 2011). These varying results and inconsistent patterns and magnitudes of aid flows in the aftermath of natural disasters, strongly depend on the type of disaster, sample selection, and method used.

Alongside the literature on post-disaster aid surges, determinants and motivations for donors to commit disaster relief aid have been scrutinized: Strömberg (2007) finds support for needs-based allocation motives, with the amount of humanitarian aid increasing with the severity of the disaster (i.e., number of casualties) and also increasing in lower-income countries. However, aid allocation also appears to be determined by other factors beyond humanitarian considerations alone. Strömberg (2007) also shows that significantly higher amounts of aid flow to affected countries that donors share a well-founded connection with (through geographic proximity, common language or colonial ties). Media coverage of the disaster is also found to influence relief aid, although, this might indeed likely correlate with the severity of the disaster and proximity of the relations between donor and affected country. Beyond confirming similar patterns regarding geographic proximity and colonial ties, Fink & Raedelli (2011) find evidence of underlying geostrategic interests driving the allocation of humanitarian aid: Specifically, their analysis shows that oil exporting countries (posited as due to their increased economic and strategic relevance) and politically less aligned countries (posited as a way of improving bilateral relations) are favored by donors in humanitarian aid allocation. Building on these findings, Raschky & Schwindt (2012) tested needs-based opposed to strategic post-disaster aid allocation decisions by examining the channel (bilateral/multilateral) and type (cash/in-kind) of post-disaster aid deployment.

Given the divergences in results, Becerra et al. (2014) revisit questions of post-disaster aid surges and determinants by analyzing a comprehensive sample of Official Development Assistance (ODA) flows in the wake of 98 large natural disasters from 1970 to 2010. In contrast

to the prior literature, they employ an event study approach, allowing to accurately measure changes in post-disaster aid based on trends in aid flows to the affected country in the years preceding the disaster (Becerra et al., 2014, p. 447). While the severity of the disaster (measured through damage caused) and income per capita are confirmed as determinants of post-disaster aid surges, no evidence of political or strategic considerations is found. Further, they find that on average disasters lead to a surge in ODA of 18%, which however only covers around 3% of the damage caused (Becerra et al., 2014, p. 446). If the provision of additional funds is limited, the consequential question to be asked is, what other channels and mechanisms could be pursued by donors to respond to disaster shocks? A possible explanation is that donors reallocate funds across countries or sectors. This would be in line with Benson & Clay (2004), who find anecdotal case study evidence that the absence of post-disaster aid surges could be traced back to sectoral reallocation and advance commitment of funds, which are employed as disaster management. Thus, to gain a more nuanced understanding of aid flows in the context of natural disasters, an analysis disaggregated by sector is needed.

2.2 Disaggregating Aid at the Sector Level

The bulk of literature on development aid allocation focuses on aid flows in the aggregate. However, as Peiffer & Boussalis (2015, p. 45) point out, this implies the homogeneity of aid and indirectly also the uniformity of motivations forming aid allocation decisions. Inter alia, Mavrotas and Nunnenkamp (2007), Thiele, Nunnenkamp & Dreher (2007), and Peiffer & Boussalis (2015), draw attention to this “aggregation bias” and associated faulty assumptions, underlining the importance for a sector-based analysis of aid allocation determinants, effects and dynamics. Sector-based studies confirm this by showing that aid allocation along needs-based considerations (Eger, Öhler & Rudolph, 2018), political favoritism (Öhler & Nunnenkamp, 2014), and Millennium Development Goals (MDGs) (Thiele et al. 2007) varies strongly across sectors. Furthermore, donors alter their sectoral composition according to changes in need or strategic interests (Bermeo, 2017). As Peiffer & Boussalis (2015, p. 46) pointedly put it, “only by disaggregating aid and testing motivational hypotheses at the sectoral level, can we gain a richer understanding of the overall decision-making motivations of a given donor.”

Post-Disaster Aid Allocation Across Sectors

This aggregation bias is also apparent in the literature on post-disaster aid allocation, with the large majority of studies lacking differentiation by sector. Becerra et al. (2015) present a rare

and much needed exception: As a follow-up to their earlier study (see Becerra et al., 2014), they conduct a large-N quantitative analysis across large donors, employing a PVAR model to systematically test sectoral reallocation mechanisms following natural disasters. They use detailed ODA data, disaggregated by sector, for each large donor, available through the Credit Report System (CRS) of the Organisation for Economic Co-operation and Development's (OECD) Development Assistance Committee (DAC). While finding no signs of cross-country reallocation, they do find some evidence that donors engage in post-disaster substitution of aid across sectors by increasing humanitarian aid, while reducing aid flows to the same recipient in other sectors.

Presenting the first (and so far, only) systematic quantitative analysis of cross-sector aid allocation (and reallocation) mechanisms following natural disaster shocks, the study by Becerra et al. (2015) presents a critical contribution to the scholarly understanding of the matter. Nevertheless, attention needs to be drawn towards a few critical shortcomings in their analysis. As they themselves admit, their data are fairly noisy, with reallocation effects only statistically distinguishable in the United States (US) data (Becerra et al., 2015, p. 583). This is potentially related to how they aggregate their data in the context of 19 disasters first to the country-year level and then by donor. This highly aggregated data has the caveat of individual reallocation effects in recipient countries potentially getting lost or being canceled out through aggregation. Furthermore, there arguably is a selection bias present in their sample: Having selected the 19 largest disasters in their observation period, no natural disasters in Sub-Saharan Africa are included in their sample. Lastly, while Becerra et al. (2015) differentiate between donors and low-, mid-, and high-income recipient countries, no distinction between different *types* of natural disasters is made, which would be critical given their unbalanced sample selection. Depending on the type and magnitude of a disaster, it is likely for different dynamics to unfold (see e.g., Drury, Olson & Van Belle, 2005). For example, an epidemic outbreak, like experienced in West-African countries with Ebola in 2014-2016, is likely to have very different consequences on the development of a country than, e.g., storms or landslides that only affect certain regions/cities and generally do not lead to lockdowns and large-scale shut down of economic activity. Making this differentiation could be critical, as aid receiving countries experiencing a natural disaster that also has far-reaching economic consequences, could suffer a double jeopardy if aid is also diverted from sectors meant to drive the economic development of the country.

2.3 Aid Allocation in the Wake of Epidemics

Aid allocation and reallocation in aid-receiving countries in the aftermath of an epidemic/pandemic thus presents a unique case worth studying that has not received much scholarly attention so far. The COVID-19 pandemic – referred to in recent literature as a “reallocation shock” (Barrero, Bloom & Davis, 2020) – has drawn new attention towards the issue. Based on anecdotal evidence and tendencies, Brown (2021) expects the COVID-19 pandemic to cause a shift in donor priorities characterized by increased attention on health and urgent welfare needs instead of long-term infrastructure projects, as well as an increased focus on self-interest when justifying aid. However, with the COVID-19 pandemic still unfolding, scholarly work has not been able to go beyond discussing preliminary trends and potential scenarios, making it premature to empirically analyze shifts in aid allocation in the wake of the pandemic. With developing – and in many cases – aid-dependent countries expected to experience the highest economic consequences from COVID-19 (Djankov & Panizza, 2020; Noy et al. 2020), examining the impact of *prior* pandemics/epidemics, such as the 2014-2016 Ebola crisis, on aid allocation mechanisms in aid-receiving countries, thus has become as relevant as ever.

Foreign Aid and the 2014-2016 Ebola Epidemic

As there have been no prior studies on the impact of the 2014-2016 Ebola epidemic on development aid allocation patterns, the literature on foreign aid in the wake of the Ebola outbreak is discussed more broadly, covering contributions from a variety of different angles:

Leach (2015) argues that the Ebola crisis was also the outcome of a “structural violence”, in terms of interlocking institutions having created a chain of inequalities, dependencies, and insecurities that has left the affected countries extremely vulnerable and contributed to the Ebola outbreak becoming an Ebola crisis. As one of the key drivers of this structural violence, she identifies the global aid industry’s discourses and practices surrounding health issues. A history of aid conditionality and vertical targeting of globally “attractive” health priorities² has worked against establishing a resilient and accessible network of health services (Leach, 2015, p. 823). It is argued that the failure to do so has fed a variety of narratives, skepticisms and distrust that further undermined a quick and effective response to the initial outbreak (Leach, 2015).

² MDG targets and surrounding high profile discourse and associated recognition has framed HIV/AIDS, malaria and mother-child health as global health priorities (Leach, 2015, p. 823).

When looking at the international response *during* the outbreak, there is a scholarly consensus that the affected countries were highly dependent on international support in their efforts to contain the virus (see e.g., Kum et al., 2019; Mobula et al., 2018). Nevertheless, the literature scrutinizing the international response during the epidemic also finds a number of critique points: Grépin (2015) underlines the slow reaction of the donor community to the outbreak, while Moon et al. (2017) point out the insufficient coordination between international donors. Southall, DeYoung & Harris (2017) argue that lacking local focus and cultural competency in the international response at times even exacerbated the spread of the virus rather than helping contain it. Quirk, Gheorghe & Hauck (2021) highlight the significant discrepancies in the amount of international Ebola aid pledged and that actually disbursed. Stephens (2017) argues that donors in their response aid neglected the severe socio-economic consequences of the epidemic, while Smith et al. (2019) draw attention to the multi-sectoral impacts of the crisis.

Highlighting that the Ebola epidemic was not only a global health issue but also a global political event, Roemer-Mahler & Rushton (2016) discuss determinants and motivations of the international reaction through the lens of International Relations theory. They cover issues of responsibility, securitization, power inequalities and Western economic interests. Building on this, Abeysinghe (2016) explains how Western media focused on domestic consequences of the outbreak and framed the epidemic as a problem for the West rather than for West Africa, which in turn is reflected in the crisis-management focus of the international response. This is also in line with Nunes (2016) who holds that security concerns and crisis narratives resulted in a quick-fix approach, neglecting substantive lasting solutions and much-needed structural overthink. Going beyond the “Western” response, Huang (2017), discusses the dimensions, underlying motivation, and implications of the Chinese Ebola response: While China was one of the first international responders, making substantial contributions to containment efforts, the strict domestic prevention and surveillance measures demonstrated how also here the primary focus was to prevent a spill-over of the disease into China.

Returning to natural disasters as disruptive events in aid allocation patterns – and as already mentioned above – the scholarly literature provides little to no discussion of this in the context of Ebola. There have been a few studies on the impact of Ebola on government capital expenditure during the outbreak (see Kum et al., 2019; Fu & Chang, 2021). Kum et al. (2019) find a diversion of human capital investment and infrastructural funds towards disease control and a concomitant decline in economic development and growth. They highlight how expenditure decisions regarding the containment of the disease stand in conflict to reducing the

chances of future outbreaks, which would entail prioritization of human capital investments, i.e., universal education, water and sanitation, a settings approach to health etc. (Kum et al., 2019, p. 87). With regard to the affected country's dependence on foreign aid, they draw attention towards the consequences of similar reallocation mechanisms in aid allocation, underlining it as an avenue for future research.

Considering the disclosed vulnerabilities and multi-sectoral impacts of the epidemic (see e.g., Smith et al., 2019), various papers refer to the epidemic as a potential wake-up call and opportunity for a reprioritization in international health aid and development approaches more generally (see e.g., Leach, 2015; Southall et al., 2017; Moon et al., 2017; van de Pas & van Belle, 2015, p. 98). Examining if and how a shift and reprioritization reflect themselves in aid allocation decisions in the aftermath of the epidemic, thus presents the consequential next step. Also methodologically, given that the literature on the nexus of Ebola and foreign aid so far largely relies on qualitative or testimonial analysis, a systematic and rigorous evaluation of cross-sectoral aid allocation data in this context is needed.

This paper therefore aims to address this research gap through a quantitative analysis of the impact of the 2014-2016 Ebola epidemic on donor development aid (re)allocation across sectors in Sierra Leone.

3 The Case of Sierra Leone: Contextual Background

Post-Conflict Recovery

The 2014-2016 Ebola outbreak in and foreign aid to Sierra Leone both need to be examined in the country's post-conflict context. Emerging in 2002 from a decade-long civil war, characterized by destruction, displacement, and absence of rule of law, Sierra Leone faced significant gaps in infrastructure and social indicators and urgent needs for recovery and reconstruction: Wartime destruction inter alia left 91% of the population without electricity access, only 13% of classrooms in a useable condition, 76% of health care infrastructure in need of rehabilitation or reconstruction, many roads unpassable, and water facilities largely unusable (GoSL, 2002). During the conflict-decade Sierra Leone consistently ranked among the lowest countries (often also last) in poverty, child and maternal mortality and human development (Foday, Addison & Petrie, 2010, p. 2; Poate et al, 2008, p. 7). As a consequence of these

immense cross-sectoral needs, Sierra Leone experienced a significant surge in foreign aid in the post-war period (Foday, Addison & Petrie, 2010, p. 2; Kargbo, 2012, p. 22)

The post-war, pre-Ebola donor landscape in Sierra Leone was defined by a large number of bilateral donors but few with significant commitments (Poate et al, 2008, p. 8). Given the United Kingdom's (UK) colonial ties to the country, the UK has maintained its status as the country's largest bilateral donor throughout the post-war period, accounting for 15-20% of ODA receipts (Poate et al., 2008, p. 8). In the immediate aftermath of the conflict, the sectoral composition of aid flows set a strong focus on establishing and strengthening core government functions³ (31% in 2003), which then, as the security and political situation stabilized, lost some of its relevance to social sectors and long-term infrastructure (United Nations Development Programme [UNDP], 2019, p. 197). For a detailed breakdown of aid flows across sectors and donors, consult the descriptive statistics in Section 6.1.

In the decade following the end of the conflict and preceding the Ebola outbreak, Sierra Leone made rapid progress, establishing democratic institutions, restoring basic services and rebuilding key infrastructure (African Development Bank [AfDB], 2015, p. 21). Poverty had dropped significantly in the years following the end of the civil war, from 73% of the population living below \$1.90 per day in 2003 to 54% in 2011 (World Bank, 2021b). As Kargbo (2012) finds, foreign aid has contributed significantly to economic growth in Sierra Leone, which grew steadily in the post-conflict years. In the years directly preceding the 2014 Ebola outbreak, growth in gross domestic product (GDP) amounted to remarkable 15.2% in 2012 and 20.7% in 2013 (World Bank, 2021a). Despite these notable improvements, Sierra Leone still faced a number of challenges: infrastructure coverage still was limited, provision of social services lagged behind targets, and agricultural productivity remained low (AfDB, 2015, p. 21). Sierra Leone stayed among the poorest countries globally and was still highly dependent on foreign development assistance (Kargbo, 2012, p. 2).

The 2014-2016 Ebola Outbreak

Still recovering from the civil war, Sierra Leone thus found itself in a highly vulnerable position, when Ebola broke out in West-Africa. After initial cases in neighboring Guinea and Liberia were confirmed in March 2014, the first Ebola cases in Sierra Leone were reported on May 27th, 2014 (CDC, 2016, p. 59). Poor health infrastructure and unfamiliarity with the disease

³ Core government functions include executive coordination, public revenue and expenditure management, public administration, local governance, security, and aid management (UNDP, 2019, pp. 10-11).

and its containment impeded a quick detection and effective response to the rapidly spreading outbreak (CDC, 2016, p. 7). High mobility of intermixing populations, densely populated urban areas, overcrowded hospitals, and distrust of government authorities contributed to widespread transmission and steady increase in cases (CDC, 2016, p. 4, 7).

Ebola had severe impacts on the already vulnerable health system in Sierra Leone. Already prior to the epidemic outbreak, the ratio of 17.2 skilled health care workers per 10.000 citizens was below the suggested minimum of 25 per 10.000 (GoSL, 2015, p. 6). The infection and death of medical staff drastically reduced the already low level to mere 3.4 personnel per 10.000 people, significantly straining national health care capacities (GoSL, 2015, p. 6). On top of Ebola inflicted deaths, Ebola also crowded out the treatment of other basic health needs and widespread illnesses like Malaria, further adding to the death toll (GoSL, p. 6; Elston et al., 2017).

Beyond severe health impacts, the epidemic and consequential nation-wide lockdown also had comprehensive socio-economic and multisectoral impacts, including a cease in economic activity, reduced agricultural production, sharp decrease in investment, interruption of infrastructure projects, loss of employment and increase in poverty levels as well as the closing of schools for over 9 months (see GoSL, 2015; Stephens, 2017; Smith et al., 2019; Kum et al., 2019). In consequence, the economy contracted by 20.6% in 2015 (World Bank, 2021a).

Given the inadequate surveillance systems and lack in expertise, resources and general health infrastructure, Sierra Leone was highly dependent on international support (Mobula et al., 2018). Initial international response, however, was slow: Despite first cases being confirmed in neighboring Guinea and Liberia already in March 2014, the World Health Organization (WHO) only declared the Ebola outbreak a Public Health Emergency of International Concern on August 8, 2014 (WHO, 2014) and it took until end of September 2014 for the United Nations (UN) Mission for Ebola Emergency Response (UNMEER) to be established (United Nations Security Council [UNSC], 2014). In the meantime, transmission in Sierra Leone continued to increase rapidly, reaching its peak in October 2014 with 3317 new monthly cases⁴ (CDC, 2019). Once international support picked up, establishing rigorous infection control, contact tracing mechanisms and widespread Ebola treatment units, Sierra Leone was able to bend the curve and drastically drive down cases by beginning of 2015 (CDC, 2016). However, as discussed in Section 2.3, the international response also faced a number of criticisms regarding insufficient

⁴ Due to initially inadequate surveillance and contact tracing mechanisms, significant underreporting of cases is suspected, especially in the first months of the outbreak (CDC, 2016, p. 41).

coordination, lacking cultural competency, or neglect of the severe socio-economic consequences of the epidemic.

When Sierra Leone was officially declared Ebola free in March 2016, a total of 14,124 cases and 3,956 deaths had been confirmed (CDC, 2020). While quick reopening and normalization of activity was visible across sectors once cases dropped and restrictions were lifted (Himelein et al., 2015), the GoSL (2015) and UNDP (2015) reported urgent need for recovery policies, rebuilding, and financial support and investment across sectors. Apart from the remaining damages to health care and wider health consequences following the end of the epidemic (see Elston et al., 2017), lasting effects were also especially visible in the education sector: The loss of 780 learning hours led to a significant learning gap as well as a large increase in school dropouts in the post-Ebola period (Smith, 2021). The impact of Ebola is thus not limited to the crisis period, but also has a long-term legacy.

4 Theoretical Mechanism

Keeping the outlined contextual background in mind, this section discusses theoretical mechanisms that could potentially explain and hypothesize the impact of the 2014-2016 Ebola outbreak on cross-sectoral aid allocation in Sierra Leone.

Approaching post-disaster aid allocation on the macro-level, Becerra et al. (2015) suggest that the response from a donor in response to a catastrophic event in a recipient country must take one of the following three possible mechanisms: (1) Official Development Assistance (ODA) to the affected recipient increase, while the donor's overall ODA commitments stay the same (suggesting cross-recipient reallocation); (2) ODA to the affected recipient increases while also the overall ODA from that donor increases in the same amount (implying no reallocation), and (3) no increase of total ODA flows nor of aid flows directed to the affected recipient country. This third possibility is explained by cross-sector reallocation.

One scenario that, however, falls short in this framework is a mixed model, combining elements of both scenarios (2) and (3), i.e., there is an increase in ODA to the affected recipient country as well as significant levels of cross-sector reallocation. Disaster shocks are unexpected budget stressors and require immediate (humanitarian) support in the affected country, resulting on average in an 18% increase in foreign aid (Becerra et al., 2014, p. 449). However, in comparison to the direct damages and consequences of natural disasters, the surges in aid tend to be

comparatively small (Becerra et al., 2014, p. 446). Given the shifted priorities in a post-disaster context, it can be expected that donors are likely to not only respond with an increase in aid but also assume a reprioritization in fund allocation across sectors (Benson & Clay, 2004, p. 36).

It thus must be understood how a natural disaster (i.e., an epidemic) could influence or shift the underlying factors that shape donor aid allocation across sectors (see Pietschmann, 2014, pp. 83-84). Drawing from sectoral aid allocation literature, the potentially interruptive impact of epidemics on (1) sector needs, (2) visibility concerns, and (3) strategic interests is discussed in terms of sectoral prioritization, reallocation, degradation and compensation. These provide the basis for the derivation of a set of hypotheses respectively on the impact of the 2014-2016 Ebola outbreak on sectoral aid allocation in Sierra Leone.

4.1 Determinants of Sectoral Aid Allocation and Prioritization

4.1.1 Needs-Based Considerations

A needs-based approach to aid allocation implies that development aid is most effective when directed towards ‘areas’ where recipient needs are the greatest (Pietschmann, 2014, p. 18). What these needs are and how they are measured, however, can depend on a wide variety of criteria: Need could for example be measured in terms of economic, education or health indicators, which then again could differ depending on whether aggregated country needs, the number or density of people in need, or countries facing exceptional circumstances due to exogenous shocks are examined (Pietschmann, 2014, pp 18-20). Some studies partly address this ambiguity by comparing needs across countries for certain sectors individually by referring to MDG targets (Thiele et al., 2007) or sector-specific need indicators as proxies (Nielsen, 2010). Comparing the needs across sectors *within* a recipient country, however, has only received very limited scholarly attention. As Pietschmann (2014, p. 69) rightly remarks, comparing the level of need in sectors that may be inherently different from each other is both conceptually and methodologically challenging, which is also reflected in the existing studies that investigate this issue: Kasuga (2008) uses the World Bank’s World Development Indicators to rank recipient need in each sector in comparison to other recipients. In a second step the placement of each sector in the inter-recipient comparison is then in turn used to create an inter-sector priority ranking to identify needs relative to other sectors within the same recipient country. Eger, Öhler & Rudolph (2018) operationalize the same research interest differently: While using similar need indicators, they do not create a recipient internal prioritization of sector needs but claim that the use of sector aid shares (rather than absolute amounts) is already sufficient to ensure an exclusive focus on donors’ sectoral aid allocation decisions *within* recipient countries

individually. Given the differences in operationalization but also the potential validity issues in their choice in proxies, it is no surprise that the outcomes of the two studies are also inherently different: Kasuga's (2008) results show that often sectoral aid allocation does not reflect the recipient's relative needs across different sectors. Eger, Öhler & Rudolph (2018), on the other hand, do find patterns of needs-orientation in the sectoral aid composition within a recipient country. Acknowledging the difficulty in measuring and comparing needs across sectors, Pietschmann (2014, p. 70) argues that the most promising basis to identify a recipient's sector-specific needs and their relative priority towards each other, is to refer to national development strategy papers (see also Harrison, Klugman & Swanson, 2005, p. 2). In line with the two key aid effectiveness principles of ownership and alignment (OECD, 2008), benchmarking needs-oriented aid allocation based on the sectoral need priorities that recipient countries define themselves, allows for a more accurate and nuanced prioritization of needs in a country than distant and standardized proxy indicators (Pietschmann, 2014, pp. 69-73).

Thus, while the empirical evidence on sectoral needs-based allocation is inconclusive, there is a strong theoretical argument that at least to some extent needs-based considerations do play a role in sectoral aid allocation, as it is to these national development strategy documents that donors commit to base their aid allocation on (Pietschmann, 2014, p. 73).

Returning to the context of the 2014-2016 Ebola outbreak in Sierra Leone, how are sectoral needs affected by an epidemic outbreak? The Ebola outbreak had a comprehensive cross-sectoral impact, dramatically increasing needs across multiple/all sectors (GoSL, 2015, pp. 14-30; Smith et al., 2019). Given the finite nature of donor resources (GoSL, 2015, p. 32), a needs-based aid allocation, however, would imply a surge in aid to those sectors where the increase in need is the largest or the most evident⁵. As argued above, the post-Ebola need priorities across sectors in Sierra Leone can be drawn from the National Ebola Recovery Strategy for Sierra Leone (GoSL, 2015). For the immediate post-epidemic period, objectives and strategies to mitigate, manage and learn from the epidemic's impact on social sectors, economic growth and governance are discussed in detail. This includes multiple sectors: health care, water and sanitation, education, social protection, labor, agriculture, trade, transport, tourism, infrastructure, mining, governance, justice, and security. There is, however, a notable difference in the type and priority of objectives between sectors: While objectives in non-health sectors are generally set on 'relaunching', 'restarting', 'recovering', 'reopening' and 'restoring' services and activities (GoSL, 2015, pp. 36-41), the identified needs in the health sector go

⁵ See Section 4.1.2 for further elaboration on the role of visibility on sectoral aid allocation.

beyond simply reinstalling the pre-Ebola status quo. The Recovery Strategy defines the following priority objectives for health care in the aftermath of the epidemic:

(1) To build a sustainable national health system that delivers safe, efficient and quality health care services that are accessible, equitable and affordable for all Sierra Leoneans. (2) To build a resilient national health system that can respond robustly to possible recurrence of EVD [Ebola Virus Disease] and outbreaks of any other deadly diseases. (GoSL, 2015, p. 36)

The focus in the objectives put forth is clearly set on strengthening and investing in the health care system, indicating an increased priority in comparison to before the epidemic. This aligns with the scholarly literature, which repeatedly underlines how Ebola not only weakened the national health system but also exposed its vulnerabilities and urgent need for increased investment (see e.g., Koltun, McNena & Shibli, 2015; van de Pas & van Belle, 2015, p. 97). Hence, a needs-based approach would thus not only predict a surge in health aid during the epidemic outbreak but also increased amounts of aid being directed towards the health sector in the years following the end of the outbreak.

Given the inconclusiveness of empiric results (see above) and the number of alternative factors that can explain donor sectoral priorities (discussed extensively in Pietschmann, 2014, pp 83-91), it is unlikely that needs-based considerations alone will be sufficient to explain a continued prioritization of the health sector. Further incentives potentially shaping donor preferences in aid allocation must therefore be considered as well.

4.1.2 Visibility Concerns

Like with almost every aspect of aid delivery, when examining the dynamics of cross-sectoral aid allocation the point of departure is a principal-agent problem: With donors (agents) being accountable to domestic taxpayers (principals), who however generally are not in the position to accurately assess aid effectiveness (information asymmetry), donors are incentivized to focus on projects and sectors with a high visibility to ensure their continued relevance and secure future funding (Vollmer, 2012; Nunnenkamp, Öhler & Thiele, 2013, p. 558). Sectoral preferences in aid allocation thus also depend on their appeal to public opinion in donor countries (Schulz, 2007, p. 6).

Agyepong et al. (2021), applying these visibility considerations to the Ebola context, note that while both the national governments of the affected countries as well as active foreign

governments (donors) need to demonstrate their efforts in response to the epidemic outbreak visibly to their constituents, the underlying dynamics differ significantly: Assuming that governments aim to stay in power through reelection, government actors in the affected countries need to show results with day-to-day value and improvement to the citizens living in the epidemic context. In consequence, given the comprehensive and far-reaching impact of the crisis and variety of struggles faced by their constituents, government efforts are likely to follow a “multi-agenda, multi-sectoral and synergistic” approach (Agyepong et al., 2021, p. 12). Foreign governments and their respective development agencies, in contrast, need to present results of their efforts in the countries they are supporting to their own citizens, who are distant from the realities of the affected countries. Donor governments are thus incentivized to selectively demonstrate dramatic improvements in measurable terms as (visible) proof that taxpayer money is spent ‘effectively’ (Agyepong et al., 2021, p. 12). In the context of a health crisis, most visible efforts are naturally those directed towards the containment of the outbreak – rather than for example addressing the more complex socio-economic consequences of the crisis (see Stephens, 2017). Containment efforts pursue a clearly identifiable, realistically achievable, and measurable target of ‘getting to zero’ (Nuriddin et al., 2018, p. 2), making the health sector thus a visible and attractive focal point for donors in their aid allocation considerations.

These considerations gain further weight in light of the media attention the outbreak attracts. In the context of health emergencies, media and newspaper coverage play a critical role in shaping public debate and opinion, and consequently also government response (Leach & Dry, 2010; Pieri, 2019, p. 76). The West-African Ebola outbreak received “an unprecedented level of international, public, and media attention” (Leach, 2015, p. 816). Although a variety of narratives circled in the media and public debate (see e.g., Chaumont, 2017; Leach, 2015; Pieri, 2019), given the underlying epidemiological nature of the crisis, the discourse put a new spotlight on health issues in the international and public eye (Heymann et al., 2015; Kolie et al., 2019). This often overshadowed other issues, like the severe socioeconomic and multi-sectoral consequences of the epidemic (Stephens, 2017). Recalling the role of visibility in aid allocation decisions (see Vollmer, 2012; Nunnenkamp, Öhler & Thiele, 2013, p. 558), one could thus expect the surge in visibility of health issues to incentivize donors to prioritize the health sector even after the end of the outbreak.

One could argue that the mutually reinforcing needs-based and visibility concerns are further amplified by so-called herding effects (see e.g., Frot & Santiso, 2011; Pietschmann, 2014, pp.

42-43, 90-91). Herding implies that donor aid allocation decisions are also influenced by the allocations of other donors (Pietschmann, 2014, p. 42). As Shiffman (2006, p. 412) explains, risk-pooling considerations and fears of being left behind, prompt donors to follow other actors in the donor community and crowd in the same sectors. It thus could be expected that increased need and newly won visibility of the health sector unleashes such herding effects, further reinforcing the sector's priority status in the post-epidemic phase.

The literature on needs-based principles and on visibility concerns make strong cases for donors to prioritize health in their aid allocation – both during and after an epidemic. The two explanations could even be considered mutually reinforcing: An epidemic crisis leads to greater need in the health sector. At the same time, the magnitude of that greater need is even more pronounced due to the extra visibility the crisis draws to the sector. With the two strands of literature arguing in the same direction, hypothesis H1a therefore predicts:

***H1a:** The Ebola epidemic triggers an abrupt increase in health aid during the crisis-period and is the cause for a substantial portion of this increase to be sustained in the post-Ebola period.*

4.1.3 Strategic Considerations and Securitization Theory

Beyond needs-based and visibility concerns, also donors' strategic interests must be considered, which in turn could predict an alternative course for health aid allocation.

Bermeo (2017) argues, that the provision of development aid to certain recipient countries can follow a strategic interest, with the purpose of countering spillover effects (e.g., environmental pollution, political instability, disease transmission, etc.) from recipient to donor. As Pietschmann (2014, p. 86) notes, this argument can easily also be transferred from the country to the sector level, explaining why donors prioritize certain sectors. This is especially visible in the health sector, where donors are likely to provide aid as disease control in response to their concerns of the cross-border spread of a contagious disease (Esser, 2009). This would be in line with Shiffman's (2006) "provider interest framework", suggesting that donor aid allocation decisions in response to communicable diseases are a reflection of the economic and political interests of its constituencies. For example, the Clinton administration intensively engaged in combatting HIV/AIDS in developing countries, classifying the epidemic's global spread as a potential source of instability and a threat to national security (Shiffman, 2006, p. 412). MacKellar (2005) and Feldbaum & Michaud (2010) argue that there is also a prioritization within the health sector, with donors devoting special attention to contagious diseases that pose

a greater perceived threat to spreading to donor countries. A highly infectious disease like Ebola could inspire such self-protection considerations.

These aid allocation considerations are thus directly linked to the broader issue of ‘health security’ – a derivation from securitization theory (see Buzan, Wæver & de Wilde, 1998) – which has received considerable scholarly attention over the past two decades (see e.g., Aldis 2008; Enemark, 2009; McInnes & Lee, 2006; Rushton, 2011). As Feldbaum and Lee (2004, p. 22-24) spell out, the health security argument is based on two key considerations: (1) the contagious nature of infectious diseases and the concomitant potential of rapid spreading in a globalized world can pose a health threat to individuals far beyond the national borders of initial epicenters; (2) the depopulating and socially restricting effects of disease outbreaks can undermine state capacities economically, militarily, and politically and thus are a potential source of national, regional, or even global instability. The elevation of health as a security concern originally became apparent in the debate surrounding HIV/AIDS: The adoption of Resolution 1308 of the UNSC was the first time a health issue was officially declared as a concern of international security (UNSC, 2000; Elbe, 2005; McInnes, 2006). Since then, health threats, in particular pandemic influenza, have featured regularly in domestic security policy considerations (Rushton, 2011, p. 782). The securitization of health has had considerable consequences for global health and disease management: On the one hand, the framing of health as a security issue has increased global attention towards infectious diseases and boosted political motivation to allocate resources accordingly (Enemark, 2009, p. 195; Rushton, 2011, p. 779). This has especially been visible in the context of HIV/AIDS, where the change in framing has propelled the issue on the global agenda, unleashing critical resources and increasing global cooperation (Elbe, 2006). Rushton (2011) explains that the banner of ‘health security’ has also contributed – at least to some extent – to uniting the capacities of both health and security communities in cause. On the other hand, the concept of health security promotes a focus on those health issues endemic in the Global South that are deemed a threat by ‘the West’, reinforcing a prioritization according to domestic interests rather than long-term global health needs (Labonté & Gagnon, 2010, p. 5; Rushton, 2011). This carries the risk of the emergence of a culture of responding to global health issues through short-sighted, ineffective and counterproductive crisis-management approaches (Enemark, 2009, p. 209).

Applying health securitization theory to the 2014-2016 Ebola outbreak, Roemer-Mahler & Rushton (2016) argue that the threat of a spread of the disease sparked substantive international efforts and resources to help contain the crisis, but at the same time also led to a security-driven

emergency focused response from the international donor community. As also discussed by Abeysinghe (2016), the representation of Ebola in Western media harnessed public fears, with domestic issues, border control and security concerns taking precedence over underlying problems and consequences of the epidemic for the affected West-African countries, which ultimately also reflected itself in the West's short-sighted crisis-management response to the outbreak (see Nunes, 2016).

Following a health security argument, one would expect aid allocation patterns to reflect a focus on quick containment of the outbreak rather than a long-term preventive strengthening of the health system. Health security theory would therefore predict the following impact of the Ebola epidemic on foreign aid flows assigned to the health sector:

***H1b:** The Ebola epidemic triggers an abrupt increase in health aid during the crisis-period. The end of the crisis causes health aid to return to levels in line with the pre-epidemic trend.*

4.2 Reallocation Mechanisms

As previous literature shows, disasters tend to often have little impact on total aid flows (Benson & Clay, 2004; Raddatz, 2007; David, 2011) and in average surges in overall aid immediately following a disaster last only for a short time period (Becerra et al., 2015). As disasters, however, place increased demands on finite aid resources (MacKellar, Freeman & Ermolieva, 1999), funds are likely to be diverted from other sectors through cross-sectoral reallocation to address those demands (Benson & Clay, 2004). Reallocations can be a useful tool to temporarily prioritize urgencies, limit overall expenditures of finite aid resources, but also to reduce the administrative burden, allowing aid funds to be allocated more quickly without having to negotiate new commitments; on the other hand, the drainage of resources from certain sectors, which are usually not compensated for after the crisis, is likely to have adverse effects on economic development (Benson & Clay, 2004, p. 35). Some reallocations might also be a natural consequence of operations of certain projects and sectors being disrupted due to the impediments and restrictions induced by the crisis (Benson & Clay, 2004, p. 36).

Brown (2021, p. 46) argues that health disasters increase aid flows towards the health sector, which in turn induce cuts in other non-health aid sectors, both for ongoing and planned projects. In the context of the Ebola epidemic reallocation mechanisms have only received scholarly attention with regard to government expenditure. Kum et al. (2019) link a decline in capital

expenditure to a diversion of funds towards health priorities during the Ebola outbreak in Sierra Leone. They note that given the country's dependence on foreign aid, a similar shift in sectoral priorities can also be expected in aid allocation (Kum et al., 2019, p. 86).

Despite scarce prior literature, there is a straightforward case to be made for why post-disaster aid reallocation considerations (as discussed in Benson & Clay, 2004) also apply to the 2014-2016 Ebola outbreak in Sierra Leone: Containing the outbreak and addressing the severe needs in the health sector were more 'urgent' than needs in other sectors, which only were of second-tier importance (GoSL, 2015, p. 7). The Ebola-induced lockdown and restricted mobility naturally also disrupted and stalled aid projects across nearly all sectors, with special mention of agriculture, education, energy, gender & youth, infrastructure, and water & sanitation (GoSL, 2015, pp. 7, 15, 17, 18, 40). The cross-sectoral reallocation of funds thus on the one hand was a donor reaction to the needs-based, visibility-related or strategic prioritization of the health sector (as discussed in Section 4.1), but also functioned as a practical expedient due to the forced shutdown of activity in other sectors (Benson & Clay, 2004, p. 36).

If surges in overall aid are limited and hypothesis H1a and H1b assume an increased level in health-related aid, reallocation theory would consequently expect aid flows in other development sectors to decrease. A decline in non-health aid would be expected to be especially evident if hypothesis H1a is confirmed, which predicts a sustained prioritization of health aid. Given the finite nature of aid resources, and the general purpose of reallocation to limit expenditure, one would generally not expect the induced level change in total non-health aid as a whole to be compensated for after the end of the crisis. Therefore, based on the reallocation literature the following hypothesis H2 is derived:

***H2:** The Ebola epidemic causes an abrupt drop in aid flows to non-health sectors, which does not recover in the post-epidemic period.*

4.3 Degradation of Sectors

Apart from examining overall trends of non-health related aid, it should also be differentiated between individual sectors, as it is unlikely for all sectors to be affected by reallocations in the same fashion (Peiffer & Boussalis, 2015). A comprehensive crisis, like an epidemic, is likely to cause a shift in sectoral prioritization (Tandon, Fleisher, Li & Yap, 2014, p. 6; Benson & Clay, 2004, p. 36). Just like donors tend to prioritize sectors that present a particular salience in terms of visibility concerns or strategic interests, donors are likely to neglect sectors that are

unattractive with regard to these factors (Pietschmann, 2014, p. 83-84). With an increase in importance and aid flows to the health sector, one could assume other sectors to be degraded in prioritization, losing their visibility, strategic importance, or potentially becoming comparatively less relevant from a needs-based perspective.

As donors will be reluctant to draw back from sectors that are highly visible (Knack & Rahman, 2008), it reversely would then be expected that sectors that are already less attractive to donors and not a priority for post-crisis recovery, would be prone for further reduction in aid flows. At a global level, Frot & Santiso (2010) find that while donors herd in social sectors, other sectors, such as infrastructure, agriculture and energy, tend to generally be less of a priority for donors. This is associated with the hurdle of high fixed costs induced by infrastructure projects in the productive sector (Frot & Santiso, 2010, p. 24) as well as their typically slower implementation that makes projects less attributable and visible (Pietschmann, 2014, p. 84). A crisis is likely to intensify these considerations on donor side: If the crisis induces a drastic increase in need for resources in other sectors, lower-priority projects and sectors are the natural target for reallocations (see Benson & Clay, 2004, p. 36). Funding for less pressing and less attractive productive infrastructure projects could consequently be expected to decrease.

Also in the case of pre-Ebola Sierra Leone, addressing challenges in productive infrastructure tend to have been neglected due to donors focusing their attention to more “attractive” social sectors (Pushak & Foster, 2011). In the wake of the Ebola epidemic and the accompanying increase in urgent needs in social sectors (such as health, education, livelihoods etc.), the less visible and cost-intensive infrastructure sector is likely to become even less of a priority for donors. This also reflects itself in the National Ebola Recovery Strategy, where it is repeatedly stressed that scarce government and donor resources need to be directed towards the “highest priorities”, which do not include the productive infrastructure sector (GoSL, 2015, p. 32). Finite donor resources and the need for donors to prioritize, thus manifest the sector’s status as an underaided sector. While already started infrastructure projects will likely to be continued/completed, the reprioritization can be expected to reflect itself in a cutback in new infrastructure commitments in the aftermath of the crisis. Hypothesis H3 therefore predicts:

***H3:** The Ebola epidemic causes a decline in infrastructure aid in the post-Ebola period (slope change).*

4.4 Compensation in High Priority Sectors

While some sectors might experience a degradation in importance in the post-crisis period, according to Knack & Rahman (2008), donors will be reluctant to draw back in sectors that are very visible. In the past decades social sectors, especially education, have enjoyed a high visibility, with a high appeal for public opinion in donor countries (Driscoll & Evans, 2005; Frot & Santiso, 2010; Knack & Rahman 2008). This is in line with the priorities set by the international community, which has “placed education [...] at the top of the international development agenda” (Nishimuko, 2009, p. 18). Novelli & Smith (2011, pp. 11-12) argue that in the early 2000s the creation of the MDGs and the Education for All (EFA) movement spurred the realization that a large portion out-of-school children were in conflict-affected countries, implying that in consequence achieving educational MDGs meant addressing educational access and quality in these (post-)conflict contexts. Sierra Leone’s emergence from a long civil conflict at a time that coincided with the adoption of the MDGs and EFA goals thus put a spotlight on the country and its significant deficits in education: During the decade-long civil war it is estimated that about 70% of school-aged children were out of school, resulting in a surge in international advocacy and aid for education in Sierra Leone (Novelli & Smith (2011, p. 12; Women’s Commission for Refugee Women and Children, 2004, p. 62). In consequence, education aid in Sierra Leone is marked by a strong focus on EFA- and MDG-related objectives (Nishimuko, 2009, pp. 21-22), which in turn also has made the sector extremely visible.

The Ebola epidemic in Sierra Leone had a severe impact on the education system, forcing a closure of primary and secondary schools from July 2014 to April 2015 and reversing progress towards achieving EFA and educational MDGs (GoSL, 2015, p. 26; UN, World Bank, European Union [EU] & AfDB, 2017, p. 10). While the closure of schools surely also led to disruption of education aid programs, it also incentivized funding for promoting potential solutions and programs for remote/alternative learning (UN, 2015). One could thus expect the fall away of regular education projects and newly committed funds to enable remote learning to level each other out during the crisis period. In the direct aftermath of the pandemic, both nationally (GoSL, 2015, p. 26, 32, 37) and internationally (UN et al., 2017, p. 32) the strengthening of the education system is established as a key priority in Ebola recovery plans. Given the sectors high visibility both on a global and national level, it can be expected for donors to – at least partially – compensate for the Ebola-induced challenges the education sector faced through an increase in education aid in the wake of the epidemic. Given this, Hypothesis H4 suggests:

H4: The Ebola epidemic is the cause for a temporary increase in education aid in the post-Ebola period (level change).

5 Methodology

This section outlines the methodology of the empirical analysis: First, the case selection is briefly explained. Second, the data and operationalization of dependent and independent variables are elaborated. This is followed by a presentation of the method and model specification. Lastly, potential methodological issues and robustness checks are discussed.

5.1 Case Selection

This study has opted to examine a single case, which is held to provide more detail and accuracy and thus better captures the underlying mechanism and interruptive effect of the epidemic shock in its unique context (Yin, 1998, p. 98). Of the three countries at the epicenter of the 2014-2016 Ebola epidemic (Guinea, Liberia, and Sierra Leone), Sierra Leone was estimated to have experienced the highest economic damage amounting to around \$ 1.9 billion, with the real GDP in 2015 contracting by -20.6% (World Bank, 2016, 2021a). This presents a particularly interesting case, as sectoral reallocation of aid or an excess focus on the health sector could possibly have led to neglecting the general economic development of the country. Considering the multiple critiques arguing that the foreign aid response to the Ebola Epidemic was inadequate (Grépin, 2015; Stephens, 2017; Quaglio et al., 2016), especially also regarding mitigating the economic impacts of the crisis, the case is thus particularly relevant.

5.2 Data and Operationalization

To investigate the impact of the Ebola epidemic on allocated aid by sector, monthly time series data on aid allocations in respective sectors is examined, which is acquired from the Sierra Leone Development Assistance Database (DAD, 2021). The DAD is Sierra Leone's national aid information management system (AIMS), providing a comprehensive account of foreign aid flows to Sierra Leone on the project level for 1,787 recorded development projects between 2005 and present day (2021). The database includes, inter alia, data on project start and end date, committed and disbursed aid, respective sector, funding source (donor), and donor type. General advantages of using AIMS data (which also apply to the DAD) in comparison to OECD CRS data are its in-country reporting, up-to-dateness as well as the inclusion of non-DAC donors – all of which falls short in CRS data (Petras, 2009; Park, 2017). Furthermore, the DAD

includes information on donor type (bilateral/multilateral), a key control variable in this analysis (see Section 5.5).

The observation period for the analysis is set from January 2005 to December 2019. It was decided to stop the observation period at the end of 2019 for two reasons: (1) Any potential confounding through the COVID-19 pandemic can be excluded (see Section 5.5); (2) it prevents projects being added while the analysis is conducted – projects are likely to be added to the database with a slight delay. After removing missing values, the final sample thus records 1470 projects, which are then aggregated at the monthly level (as explained below).

5.2.1 Dependent Variables

As determined in hypotheses H1-H4, aid flows are examined across four defined sectors: (1) Health Aid, (2) Non-Health Aid, (3) Infrastructure Aid, and (4) Education Aid. As the DAD differentiates between over 30 sectors, overlap is likely which requires some recoding.

The “Health Aid” variable is thus coded to include the DAD sector classifications ‘Health’, ‘HIV/AIDS’, as well as ‘Ebola Response’. However, ‘Ebola Response’ aid is likely to also include measures that go beyond the health sector, targeting issues like food security, socio-economic recovery, or gender-implications. All ‘Ebola Response’ projects are therefore recoded based on the sectoral focus described in the respective project descriptions included in the online DAD. While project descriptions in some cases still might be vague, it nevertheless allows for identification and recoding of ‘Ebola Response’ projects that evidently do not have a health focus and thus also ensures increased validity.

For the “Non-Health Aid” variable, consequently, projects from all sectors *not* represented in the “Health Aid” variable are included. The variable “Infrastructure Aid” is coded to include the DAD sector classifications ‘Infrastructure’, ‘Roads’, ‘Water & Sanitation’, and ‘Energy’ (as defined in Pietschmann, 2014, p. 79; and Tierney et al., 2011, p. 1901). The “Education Aid” variable corresponds with the sector classification in the DAD.

To analyze over-time variation, the data needs to be recoded from the project-level to have ‘sector-month’ as the unit of analysis. The DAD provides data on the start and end date of a project as well as the overall amount of aid allocated. As projects naturally run over multiple months/years, the overall amount of aid allocated to a project needs to be disaggregated. Assigning the entire amount to a certain month would significantly distort the data, as projects can vary significantly in length (see Section 6.1). It is thus opted to equally spread the amount of aid

allocated to a project across the months of its activity. The overall amount of aid allocated to a project is divided by the project duration (number of months); this calculated monthly average is then assigned to each month within the start and end date of the respective project. For each of the four sector variables, the amount of aid allocated is then aggregated for each month.

5.2.2 Independent Variables

Time-series studies focus on the passing of time (months) between start and end of the observation period (i.e., January 2005 to December 2019), a total of 180 months / time points in this case. The intervention variable(s) describe(s) the occurrence of an intervention – in this case the prevalence of Ebola in Sierra Leone – causing an interruption in the time variable. As the Ebola epidemic in Sierra Leone lasted for 22 months and cannot be fixed to a single date, it is differentiated between a pre-intervention, during intervention, and post-intervention period. The Ebola period can be defined as the period from the first confirmed case until the timepoint the country was declared “Ebola-free”, i.e., from May 27th, 2014 to March 17th, 2016 (CDC, 2016, p. 59). At the monthly level this is from beginning of June 2014 to end of March 2016. Given this, there are two separate intervention variables: the outbreak of Ebola (start of the intervention) and the end of the epidemic (withdrawal of the intervention). Broken down, this corresponds to 113 months in the ‘pre-Ebola’ period, 22 months in the ‘during Ebola’ period, and 45 months in the ‘post-Ebola’ period.

5.3 Method

The derived hypotheses will be tested by means of an Interrupted Time Series (ITS) analysis. ITS analysis is a quasi-experimental design that can be used to evaluate the impact of an intervention. It uses time series data of a certain outcome of interest to create an underlying trend, which is discontinued by the intervention event at a determined point in time (Bernal, Cummins, & Gasparini, 2017, p. 349). To evaluate the impact of the intervention, any occurring change in the outcome variable in the post-intervention period is examined in comparison to *what would have happened* if the intervention had not occurred, i.e., the counterfactual (Cook, Campbell & Shadish, 2002, p. 5). The hypothetical scenario described by the counterfactual in this case refers to the expected trend without the intervention, based on the pre-existing trend (Bernal et al., 2017, p. 349).

The appropriateness of an ITS design further depends on the nature of both intervention and outcome variables: (1) It requires intervention variables that can be clearly located in time, allowing for a clear differentiation between pre- and post- intervention period; and (2) the

outcome variable should be expected to react to the intervention relatively quickly or after a distinctly definable lag (Bernal et al., 2017, p. 350).

The method has been applied in various research areas to evaluate the impact of policies, changes in law, major events, medical treatment, etc. on a particular outcome variable. There have also been some prior studies employing an ITS approach to evaluate the impact of the Ebola epidemic as the intervention event on different outcomes, such as on indicators of child and maternal healthcare services in Guinea (Delamou et al., 2017), emergency department visits in Dallas where the first Ebola case in the US was reported (Molinari, LeBlanc & Stephens, 2018), or the tuberculosis notification rate in Guinea (Magassouba et al., 2020).

Given the nature of the data available for single countries on cross-sectoral aid allocations in the context of the Ebola ‘intervention shock’ and the absence of a respective control group, an ITS design provides a suitable methodological approach to address the research question at hand. Both intervention and outcome variable meet the key prerequisite assumptions for an ITS analysis: (1) The prevalence (and absence) of Ebola cases in the country offers a clearly identifiable distinction of the intervention period; (2) considering the crisis-character of the epidemic and the aid-dependency of Sierra Leone, it can be expected for aid flows to show a prompt response to the intervention.

5.4 Model Specification

Given the nature of the variables described above, a standard ITS segmented regression model is applied, fitting an Ordinary Least Squares (OLS) regression and separate line segment to each time interval of the independent variable, time (Wagner et al., 2002 p. 301). Following Wagner et al. (2002, p. 302) and Bernal et al., 2017 (p. 351), the following model is specified, summarizing the effects of changes in level and slope at two intervention time points on the outcome variable Y at timepoint t :

$$Y_t = \beta_0 + \beta_1 \text{time} + \beta_2 \text{intervention}1_t + \beta_3 \text{time after intervention}1_t + \beta_4 \text{intervention}2_t + \beta_5 \text{time after intervention}2_t$$

The outcome variable, in terms of the amount of aid disbursements made to the sector of interest at timepoint t , is represented by Y_t . The *time* variable represents the months passed since the start of the observation period. The dummy variable *intervention* 1_t codes all months that lie within the intervention phase of the 2014-2016 Ebola outbreak in Sierra Leone as ‘1’. A continuous variable, *time after intervention* 1_t , indicates the time passed during the epidemic (all

time points before and after the intervention period are coded as ‘0’). A second dummy variable $intervention2_t$ captures the introduction of an additional phase (in this case the post-Ebola period), coded as ‘1’ for all months after the end of Ebola. The $time\ after\ intervention2_t$ counts the number of months in the post-Ebola period.

The Y-intercept β_0 is interpreted as the baseline level at timepoint $t = 0$. β_1 represents the change in aid flows associated with an increase in time unit (month), expressing the underlying pre-Ebola trend. The level effect β_2 , indicating the change in level, captures the effect of the Ebola intervention immediately after its introduction. The slope effect β_3 describes the change in slope during the Ebola outbreak period, i.e., between start and end of the epidemic. This is then mirrored for the post-Ebola phase, with β_4 displaying the level effect after the end of the Ebola outbreak and β_5 representing the continuing effect over the entire post-Ebola time period (slope change).

This model applies for all hypotheses H1 to H4, with only the outcome variable (Health Aid, Non-Health Aid, Infrastructure Aid, and Education Aid) changing accordingly.

5.5 Addressing Potential Methodological Issues

The basic segmented regression model introduced above, describes a general potential association between the intervention and outcome variable. However, there are several methodical issues that are distinct to time series data and need to be accounted for accordingly to increase the robustness of the analysis (Bernal et al., 2017, p. 352).

Time-varying Confounders and History Bias

One of the strengths of ITS designs – given their single-case and over-time nature – is that all common confounding variables that remain constant or only change slowly over time (and are thus captured in the underlying trend) do not affect the intervention impact estimation (Bernal et al., 2017, p. 353). This is also the case for many of the factors identified in the literature that potentially shapes aid allocation, including the recipient’s geographical location, colonial past, language, regime type, oil export, population size, human rights, political rights or onset of war (as discussed in Section 2 and see specifically Fink & Raedelli 2011; Nielsen, 2010, p. 14). Due to the constant or slow-changing nature of these variables they can be excluded from the analysis.

More rapidly changing, time-varying confounders, however, may affect the ITS analysis and need to be controlled for (Bernal et al., 2017, p. 353). A potential source of such confounding

in ITS are events that occur at a similar time as the intervention, potentially effecting the outcome variable, referred to as a *history bias* (Bernal, Cummins & Gasparrini, 2018, p. 2084). Given the aggregate (donor-indistinct) form of the outcome variable, it thus must first be considered what global events concurrent to the 2014-2016 Ebola outbreak could potentially affect sectoral aid allocation in Sierra Leone in general:

The adoption of the Sustainable Development Goals (SDGs) in September 2015, designed to provide a global blueprint for sustainable development, overlaps with the Ebola epidemic in Sierra Leone. As Rudolph (2017) shows, to provide development aid that reflects the SDGs and works towards achieving the 2030 Agenda, donors would need to comprehensively adjust their aid allocation decisions with regard to country, channel, sector, and instrument. The adoption of the Sustainable Development Agenda thus could potentially shape and shift donor aid allocation decisions and priorities across sectors globally. In comparison to the MDGs' narrow focus on poverty reduction, the SDGs expand the scope towards embedding economic development, social inclusivity and environmental sustainability together (Halisçelik & Soytas, 2018, p. 546). To what extent donors align their development aid portfolios to global development agendas, however, is under-researched. Thiele et al. (2007) is one of the few studies testing this systematically, finding a substantial gap between MDG rhetoric and sectoral aid allocation. Nevertheless, the coinciding adoption of the SDGs is a potentially confounding intervention that needs to be controlled for.

Other major shocks that could have significantly impacted aid allocation globally are the 2007-2008 global financial crisis (Dang, Knack & Rogers, 2013) or the recent COVID-19 outbreak, which has been referred to as a "reallocation shock" (Barrero et al., 2020). Both events, however, lie in significant temporal distance (over / close to 50 time points) to the intervention variables (start and end of Ebola). Any potential fluctuations in aid allocations caused by the 2009 financial crisis will thus be captured and accounted for in the underlying long-term pre-intervention trend (Bernal et al, 2017, p. 353). To ensure that the COVID-19 pandemic does not intervene with the post-Ebola trend, the period of observation is deliberately cut-off at the end of 2019.

Therefore, while the global financial crisis and the COVID-19 pandemic can be excluded as potential confounders, the adoption of the SDGs in 2015 remains a possible source of history bias. An effective way to control for history bias is by including a control series of the outcome variable in a population that was subject to the same time-varying confounders, but where the intervention under investigation did not occur (Bernal, Cummins & Gasparrini, 2018, p. 2083).

An absence (or lack) of effect in a well-selected control series implies that any co-interventions that would affect both populations can be excluded and thus provides further support for a causal relationship between intervention and outcome variable (Bernal, Cummins & Gasparrini, 2018, p. 2083). However, prerequisite for a control series in natural experiments is available data for a natural control population, that – apart from the offset of the intervention variable – has balanced covariates. Therefore, in practice, only very few ITS studies include a control in their design (Hategeka, Ruton, Karamouzian, Lynd & Law, 2020, p. 6). Given the complexity of aid allocation determinants and recipient-specific factors, balancing covariates is difficult and error-prone, which is further impeded by data unavailability. Thus, no control series can be included in this case. If certain co-interventions cannot be ruled-out (in this case the adoption of the SDGs), interpretation of causality needs to be done with caution and considered accordingly when discussing results (Bernal et al., 2017, p. 354). This is one of the major shortcomings of ITS designs and also one of the limitations of this study (see Section 8).

Subgroups: Donor and Donor Type

In ITS analysis, outcome data is commonly aggregated for the entire study population, which, however, would assume a uniform trend, intervention effect, and confounding events within the study population (Bernal, Cummins & Gasparrini, 2018, p. 2085; Bernal, Soumerai & Gasparrini, 2018, p. 84). As this, however, is likely to vary across certain subgroups, differentiating between these subgroups increases validity of results. In the case of aid allocation to Sierra Leone, the intervention effect and potential confounding events may vary depending on donor and donor type. The scholarly literature argues aid allocation motivations and patterns differ between bilateral and multilateral donors: Multilateral donors are generally sought to be more impartial and bound by institutional rules in their aid allocation, while bilateral donors are considered to be freer to allocate based on strategic or political considerations (Burnside & Dollar, 2000; Christensen, Homer & Nielson, 2011; Raschky & Schwindt, 2012; Rodrik, 1995). To account for this, models differentiating between bilateral and multilateral aid are run for each of the four hypotheses. Furthermore, beyond the bilateral/multilateral distinction, individual donors' altruistic, strategic or other interests could lead to significant differences in their aid allocation behavior (see e.g., Berthélemy, 2006). The results are therefore further differentiated by running separate models for each of the largest bilateral (i.e., UK and US) and multilateral donors (i.e., EU, UN, and World Bank) in Sierra

Leone for hypotheses H1 and H2.⁶ When examining donor-specific aid allocations, it needs to be checked if there are any donor-specific confounding events that coincide with the intervention. As Schneider & Tobin (2016, p. 651) argue, shifts in the constellation of domestic government, may result in significant changes in development aid portfolios of a donor country. While both the UK and US have held national elections during or shortly after the Ebola epidemic, only in the US did those result in a change in leading government party. This co-intervention must thus be considered when interpreting the impact of Ebola on US aid.

Seasonality

Another common issue in time series data that needs to be controlled for are seasonal fluctuations. Cyclical patterns caused by seasonal variation in the outcome variable could intervene with the intervention effect or could lead to high correlation of outcomes for the same months each year – both potentially biasing results and need to be accounted for (Wagner et al., 2002, p. 305). In the context of development aid allocation, seasonality could possibly occur in periodic donor reporting of aid flows (Development Initiatives, 2020, p. 6) or a potential preference of donors to start projects in the dry season due to limited access and impeded implementation of aid projects during months with heavy rainfall (Sammeth, Michel, Hites & Paloma, 2010, p. 9). To detect potential seasonality, it is examined whether the plotted data shows cyclical patterns or if error terms 12 months apart correlate (Wagner et al., 2002, p. 305). If seasonality exists, it can be corrected for by fitting an AutoRegressive Integrated Moving Average (ARIMA) model (see Schaffer, Dobbins & Pearson, 2021, explained in more detail below).

Non-Stationarity

A further key methodological consideration that requires checking is (non-)stationarity of the data. However, as the systematic methodological reviews by Hudson, Fielding & Ramsay (2019) and Hategeka et al. (2020) show, this is often ignored in ITS studies. Stationarity can be tested using an Augmented Dickey-Fuller Test (Dickey & Fuller, 1979). If the outcome variable is non-stationary – meaning that there is an underlying positive or negative trend irrespective of an intervention – it needs to be stationarized accordingly (Hategeka et al., 2020, p. 3). Depending on the source of non-stationarity, this is done by either applying a log transformation or by differencing the data, which can be also done within an ARIMA function (Schaffer et al.,

⁶ For infrastructure (H3) and education aid (H4), no separate models on the individual donor level are included, given the low number of projects and flat distributions for single donors in these sectors (see Section 6.1.2).

2021, p. 2). Ignoring non-stationarity of time series data can lead to under- or overestimation of the underlying effect (Hudson et al., 2019, p. 6).

Autocorrelation

As with any standard regression model, a key assumption is that residuals are independent. In time series data this assumption often does not hold, as observations next to each other are likely to be more similar than observations further apart in time, implying serial autocorrelation (Bernal et al., 2017, p. 353). Often non-stationarity or seasonality can be the cause for autocorrelation and accounting for these thus may already be sufficient (Bernal et al., 2017, p. 353). Nevertheless, it is critical to assess if autocorrelation persists, which is done by running a Breusch-Godfrey test (as suggested in Bernal et al., 2017, p. 354). Possibilities to adjust for autocorrelation include ARIMA modeling (see below).

5.6 Robustness Checks: ARIMA Modeling

Autocorrelation, non-stationarity and seasonality are all sources of distortion and potential overestimation of statistical significance that can be accounted for through ARIMA modeling. ARIMA models are a combination of an autoregressive (AR) model, differencing/integration (I) and a moving average model (MA) (Schaffer et al, 2021): The AR model predicts the outcome variable Y_t through a number of lagged values of Y_t . Differencing (i.e., taking the difference between consecutive observations) induces stationarity in the time series. The MA model uses lags of the error to predict the outcome and is usually needed when there is negative autocorrelation. An ARIMA model is thus described using a (p, d, q) notation, where p represents the order of the AR component, d the degree of differencing, and q the MA-order of the model (Schaffer et al, 2021, p. 3). If seasonality is present in the data⁷, also seasonal AR, I, and MA terms are included. When using ARIMA modeling in the context of an ITS design, the same time, level (i.e., *step*), and slope (i.e., *ramp*) variables are used as in the segmented regression model described in Section 5.4 (Schaffer et al., 2021, pp. 3-4).

Determining which p , d , and q ARIMA model terms are the best fit for the underlying Y_t data is facilitated through an automated algorithm (in *R* the *auto.arima* function). Searching over a series of potential ARIMA models, guided by a number of tests for potential stationarity, autocorrelation and seasonality, the terms with the lowest Akaike Information Criterion (AIC) value (i.e., lowest prediction error) are selected (Schaffer et al., p. 9). If terms of the ARIMA

⁷ Seasonality is tested for in the automated algorithm through a Seasonal and Trend decomposition using Loess (STL decomposition).

model can already be determined in advance, it helps to already pre-specify these. This is usually the case if the data is non-stationary, implying the need for differencing of the outcome variable, which can be done by setting $d = 1$ (as done in Schaffer et al., p. 9).

Despite its modeling flexibility and usefulness to account for biases, only few studies have used ARIMA modeling in ITS analysis (Hudson et al., 2019, p. 5; Hategeka et al., 2020 p. 7). This can be partly explained by the complex and unintuitive interpretation of coefficients due to multiple transformations in the data as well as the threat of potential overfitting of models (Bottomley, Scott & Isham, 2019, p. 3; Schaffer et al., 2021, p. 10). It is therefore opted to run segmented regression models first (following Bernal et al, 2017 and as described in Section 5.4) and then use respective ARIMA modeling as robustness checks to account for potential autocorrelation, non-stationarity and seasonality issues (following Schaffer et al., 2021). For each of the segmented regression models thus also a respective ‘best-fit’ ARIMA model is run. A Ljung-Box test allows to check whether the respective ARIMA modeling presents a good model fit or if autocorrelation persists (Schaffer et al., 2021, p. 9).

6 Empirical Analysis

6.1 Descriptive Statistics

Before moving on to the ITS analysis, a sound understanding of the data is key, which provides support for the associated methodological decisions put forth in Section 5. This Section discusses the data used in their raw (Section 6.1.1) and aggregated forms (Section 6.1.2).

6.1.1 Project-Level Data

Within the period of observation from January 2005 to end of December 2019, the DAD provides comprehensive data for 1,460 projects and a total of USD 6,29 billion in aid flows. This implies that of the 1,632 projects recorded within the observation period, 172 are dropped due to missing values in either project duration (i.e., start and end date) or in the amount of overall aid disbursed for a given project.

The summary statistics for the project level data are visible in Table 1. Unsurprisingly, the amount of aid allocated to a project can vary strongly. While for some projects the amount of overall aid disbursed lies below USD 10,000, the highest recorded project reports an overall amount of over USD 182 million. The middle 50% of projects lie between USD 0.15 million

and USD 2.45 million. Examining the outliers within the upper and lower quartiles, the significant differences can be traced back to a combination of factors: Firstly, depending on the immediate or long-term nature of projects, the project duration ranges from 1 month to 180 months (i.e., 15 years). When examining the amount per month, the interquartile range shrinks to USD 7,921 and USD 86,254. Nevertheless, significant differences in minimum and maximum remain. Given the crisis context, this, however, seems plausible as large amounts of aid could be required for immediate / short-term projects. Furthermore, depending on the respective sector of a project, aid disbursements will vary significantly (see Appendix A, Table A.1). Lastly, remaining outliers are likely to be linked to differences in donors and donor reporting (see Appendix A, Table A.2, as discussed below). A closer look at individual data points at both ends of the distribution affirms that the strong variance in disbursed aid can be explained by the nature of project-level data, excluding potential measurement/coding errors. The wide range in disbursed aid thus also confirms the operationalization decision to aggregate and spread the project-level data across months, accounting for project duration.

Table 1
Aid Projects in Sierra Leone 2005-2019 in USD

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Project Duration	1,460	34	28	1	12	48	180
Disbursed Aid	1,460	4,311,573	11,713,414	2,500	152,321.8	2,498,393.0	182,867,356
Committed Aid	1,460	4,561,099	12,155,562	2,500	175,563	2,727,690.0	182,867,355
Aid Disbursed per Month	1,460	179,554	954,824	227	7,921	86,254	28,405,582
Aid Committed per Month	1,460	188,156	969,588	227	9,074	94,323	28,405,582

N = Number of projects

As expected, the levels of committed and disbursed aid differ (see Table 1), confirming the operationalization decision to use actual disbursed aid. The two, however, are still fairly similar, showing for the same minimum and maximum values and a divergence of 5.5% between their respective mean values.

Grouped by Sector

Given the cross-sector focus of the study, variation in the project-level aid data across sector is described next. As shown in Table A.1 in Appendix A⁸, levels of disbursed aid differ

⁸ Table A.1 in Appendix A provides a comprehensive overview of project-level aid, grouped by sector.

significantly across sectors, ranging from a total of USD 18.49 million in gender aid to USD 1.84 billion in health aid. The particularly high amount in health aid is possibly related to the increased and urgent health needs in the context of the Ebola epidemic. When examining the average amount of aid disbursed to a project per sector, the range lies between USD 1.47 million and USD 7.85 million, with gender (USD 0.54 million per project) and macroeconomy (USD 16.96 million per project) sectors as outliers⁹. As one would expect, the infrastructure¹⁰ sector is more resource intensive, while good governance and social sectors, such as gender, youth, and social welfare are of low-cost nature (see Pietschmann, 2014, p. 84). Regarding the sectors of interest for this analysis, there are 370 health projects and 1,090 non-health projects, which include 165 infrastructure and 81 education projects. Table A.1 also draws attention to one of the caveats in the data, a total of 84 projects and USD 576.98 million are coded as ‘multi-sector’, likely capturing overlap between sectors of interest (see also Section 8).

Grouped by Donor

Also, across donors the number of projects and amount of total disbursed aid vary significantly (see Appendix A, Table A.2). While India records a single project of USD 0.15 million, the UK for USD 1.73 billion spread across 130 projects. The UK, US, EU, World Bank, and UN are the five largest donors, accounting together for approximately 73% of total aid, which explains their selection as donor-specific controls (see Section 5.5). Table A.2 also illustrates the significant difference in how donors structure or report their aid: The UK and World Bank both have noticeably high amounts of total aid disbursed, which, however, is spread over comparatively few projects, resulting in averages of USD 11.79 million and USD 11.47 million per project respectively. The UN on the other hand records only a quarter/half of these amounts, however, spreads them over 327 individual projects (i.e., USD 1.08 million per project). The EU and US lie somewhere in between, with an average of USD million 3.16 and USD 4.14 million respectively. The variation, which appears to be independent of the donor type (bilateral/multilateral), confirms the need to also control for the largest donors separately.

Just like when grouping the data by sector, also here the data shows some ambiguity, with a total of 32 projects and over 557.32 USD million being recorded as ‘multi-donor’ aid. A look into the raw data shows that especially small donors are involved in these projects (thus possibly

⁹ This can be explained through the typically low-cost nature of gender projects, while macroeconomy projects have a focus on large-scale economic stabilization/diversification or budget support.

¹⁰ To recall the coding decision in Section 5.2.1, infrastructure aid here also includes road, energy and water and sanitation projects.

leading to an underestimation of their respective aid disbursed displayed in Table A2). This limitation is discussed in more detail in Section 8.

6.1.2 Aggregated Monthly-Level Data

Dependent Variables

While it is important to understand the raw project-level data, as part of the ITS analysis the data is transformed to the monthly level. Thus, the distribution of monthly aid data for our dependent variables of interest within the period of observation needs to be examined next. Table 2 shows the summary statistics for overall aid as well as the four sector-specific dependent variables. The interquartile range lies between USD 23.49 million and USD 40.94 million. While monthly infrastructure and education aid have a range of USD 10.29 million and USD 2.86 million respectively, the minimum (USD 0.56 million) and maximum (USD 74.35 million) for monthly health aid are wide apart. It is noticeable, that maximum value for monthly health aid exceeds the highest recorded of all non-health aid, which lies at USD 63.66 million.

Table 2
Monthly Aid in Sierra Leone 2005-2019 (in Million USD)

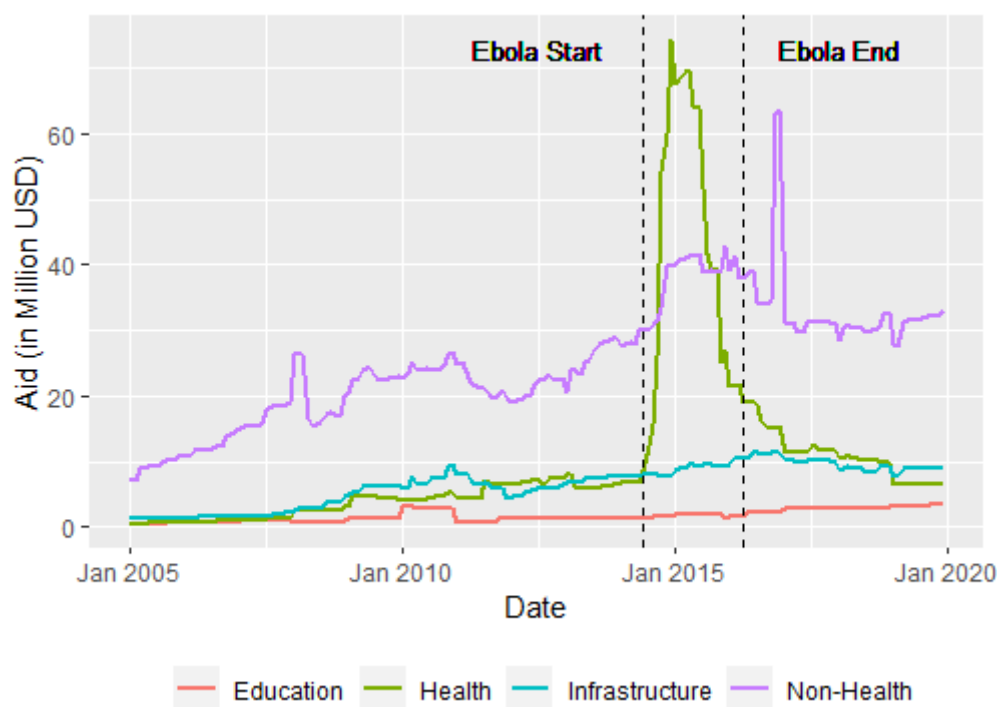
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Overall Aid	180	35.75	22.20	7.81	23.49	40.94	114.16
Health Aid	180	10.41	14.85	0.56	2.64	10.39	74.35
Non-Health Aid	180	25.34	9.50	7.25	19.24	31.21	63.66
Infrastructure Aid	180	6.47	3.09	1.26	3.71	8.97	11.55
Education Aid	180	1.70	0.87	0.54	1.01	2.81	3.40

N = Number of months

Intervention Variable

Next, the distribution is viewed in the context of the intervention variables, which divide the data into three segments (pre-, during, and post-Ebola). Before looking at the dependent variables, Figure B.1 (see Appendix B) provides an understanding of how overall aid flows trend over time and across the different intervention periods. It is visible that there is a significant increase in overall aid during the Ebola outbreak. In the post-Ebola period overall aid flows fall rapidly and seem to balance in line with the pre-epidemic trend, suspecting potential sectoral reallocation to cater to shifted needs and priorities.

Figure 1
Plotted Trend of Dependent Variables (2005-2019)



Tables A.3, A.4, and A.5 (see Appendix A) break down the distribution of the four dependent variables¹¹ in the pre-, during, and post-Ebola period respectively, presenting the following key takeaways: The means of all four variables of interest are higher in the post-Ebola than in the pre-Ebola phase. While health aid reaches its maximum during the Ebola epidemic, non-health aid, infrastructure aid, and education aid both peak in the post-epidemic period. At the same time, all four of the dependent variables exhibit minimum values for the post-Ebola period that lie below their respective maximum values in pre-Ebola phase. For infrastructure and education aid, even the mean of pre-Ebola period lies below the respective pre-epidemic peak values. Thus, while these summary statistics provide important information about differences in distribution, they cannot provide robust evidence for the impact of the intervention on the outcome variable. Same applies also when plotting the distributions over time (see Figure 1): For health aid, the drastic change in trend during the Ebola period is visually evident, hinting towards a possible relation; however, visual interpretation of time trends is far less straightforward, especially for the other three outcomes of interest. Visual trends can be deceptive, and a seemingly clear temporal overlap with the intervention is insufficient to

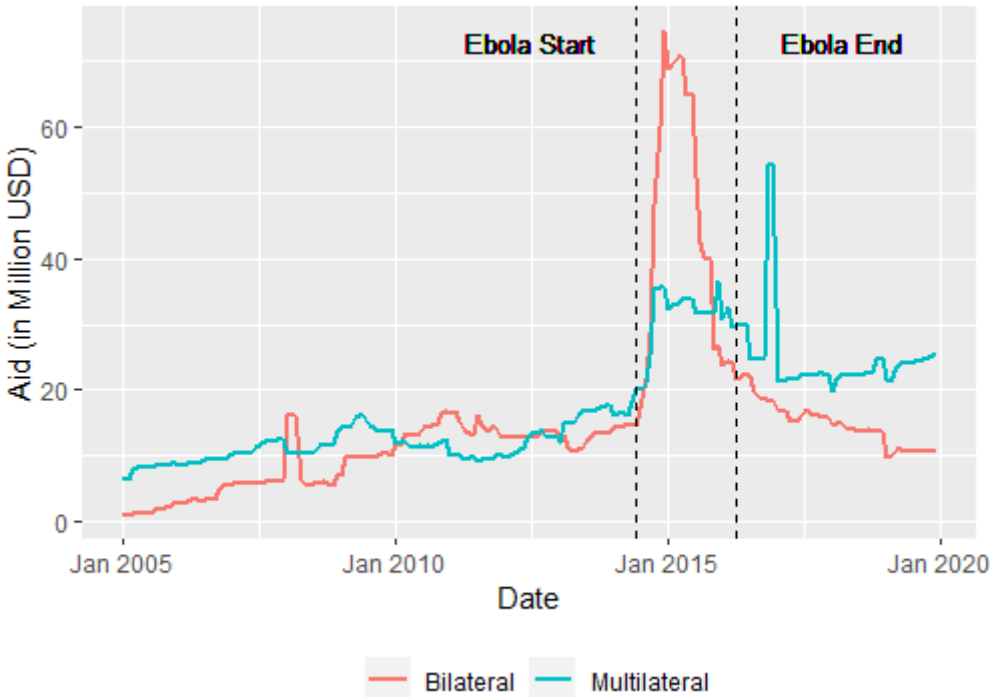
¹¹ Overall Aid is not a dependent variable in the analysis but is included in the table as a reference value.

evaluate the intervention effect. Plotting variables alone does not provide robust indication if fluctuations in trend can be traced back to the intervention or if other time varying confounders are at play.

Donor-specific Aid

Lastly, the descriptive statistics for the main control variables donor and donor type are examined. As shown in Table 3, bilateral and multilateral aid have a similar mean in monthly disbursements. Bilateral aid, however, has a significantly higher maximum, range, and standard deviation. This could be in line with the generally higher reactivity of bilateral aid to external factors along strategic interests opposed to multilateral aid (Raschky & Schwindt, 2012). This is also confirmed when plotting the data over time (see Figure 2), which shows that the two have a similar trend prior to the intervention, but a significantly higher surge in bilateral than multilateral aid during the Ebola epidemic. It is also noticeable that while bilateral aid drops in the post-epidemic period, multilateral aid proceeds at higher level than in the pre-epidemic period. The visibly evident outlier in multilateral aid in November 2016 can be traced back in the raw data to an EU macroeconomic support project of over USD 28 million with a duration of 1 month. As it is not a measurement error, it is kept in the sample.

Figure 2
Bilateral and Multilateral Aid in Sierra Leone (2005-2019)



Broken down to major individual donors, UK, US, EU, and – to a lesser extent – also the World Bank all have a wide range and comparatively high standard deviation (see Table 3), which is also visible in Figure B.2 (see Appendix B), where all four donors experience a spike in aid during the epidemic period. It is also noticeable, that after the end of the epidemic World Bank aid continues at a significantly higher level than in the pre-epidemic period. UN aid, in contrast, appears to be fairly stable throughout the entire observation period, which is confirmed by the low standard deviation and comparatively narrow range (see Table 3).

Table 3

Monthly Aid in Sierra Leone by Donor 2005-2019 (in Million USD)

Donor Type / Donor	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bilateral	180	15.13	13.87	1.03	7.05	15.90	74.71
Multilateral	180	17.40	8.69	6.54	10.37	22.39	54.49
United Kingdom (UK)	180	9.38	9.34	0.23	2.87	10.57	41.57
United States (US)	180	2.13	4.11	0.22	0.76	1.87	23.83
European Union (EU)	180	7.51	4.90	2.62	4.14	9.45	39.91
United Nations (UN)	180	2.04	0.75	0.51	1.59	2.46	3.63
World Bank	180	4.74	2.79	1.20	2.83	6.44	13.17

N = Number of months

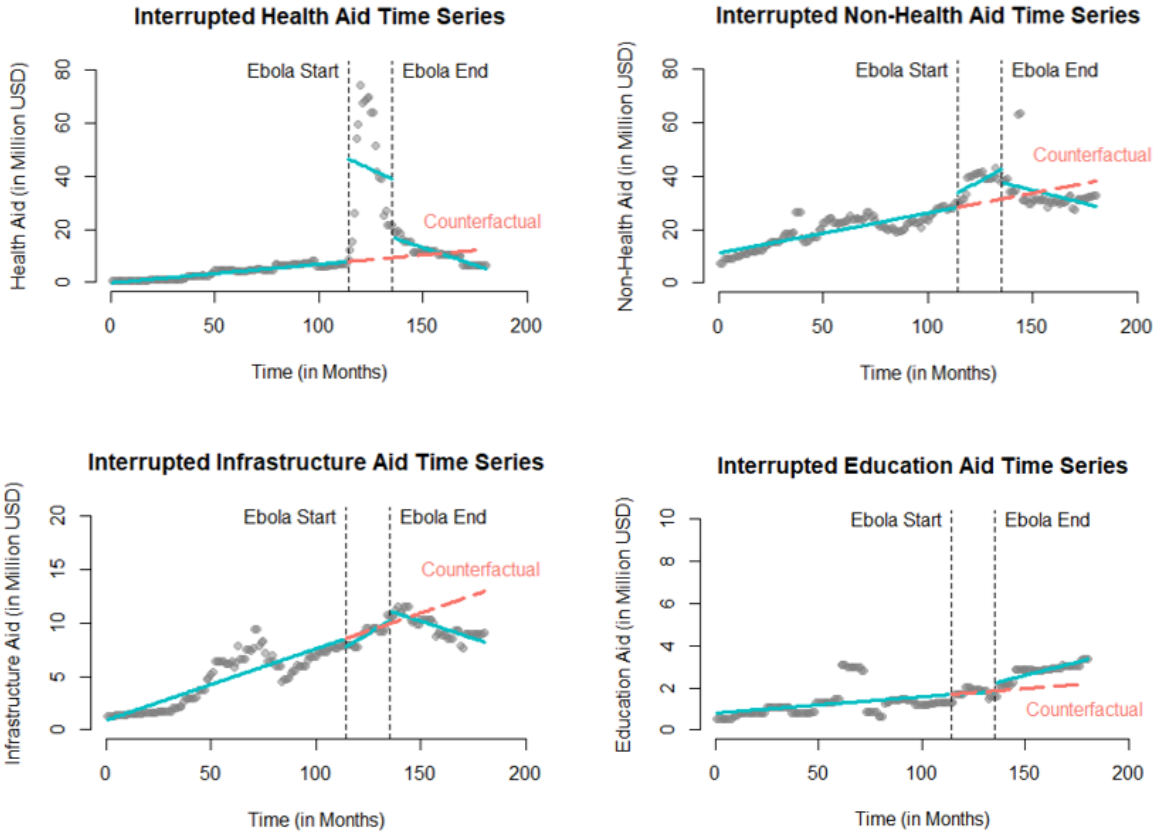
Apart from overall aid disbursements, donor aid disbursements also differ considerably across sectors. Tables A.6 to A.9 in Appendix A, present donor-specific distributions for each of four dependent variables. For health aid, bilateral aid is significantly higher than multilateral aid, while for non-health aid the opposite is observed, with multilateral notably exceeding bilateral aid flows. This hints towards a more balanced portfolio of multilateral donors, which again is in line with the argument that multilateral aid is less governed by strategic considerations (see Christensen et al. 2011; Rodrik, 1995, p. 15). This pattern also holds when comparing the largest individual bilateral (i.e., UK) and multilateral (i.e., EU) donors. It is also notable that while in 75% of months US health aid lies below USD 0.33 million, the peak value for monthly US health aid is far beyond at USD 21.85 million (see Appendix A, Table A.6). In both the infrastructure and education sector, bilateral and multilateral share similar distributions (see Appendix A, Tables A.8 and A.9). When disaggregating aid to the individual donor-level for these sectors distributions are extremely flat, thus confirming the methodological decision to not conduct separate donor-specific ITS analyses for hypotheses H3 and H4 (as discussed in Section 5.5).

6.2 Results

This Section turns to the results of the ITS analysis, which is broken down according to the main dependent variables described in hypotheses H1-H4. Apart from the overall model, differentiated models by donor type and largest individual donors are presented. When interpreting the coefficients, it is important to be aware that the effect variables measure changes in levels and slopes in reference to an absence of the intervention. The slope of the pre-intervention trend (also representing the trend for the counterfactual) is captured in the coefficient *Time*. For the effects at the start of Ebola the interpretation is fairly straightforward: *Intervention1* represents the change in outcome level from the intercept of the pre-epidemic trend at the last time point before the intervention to the intercept of the Ebola-period regression line at the first time point after the intervention. The coefficient *Time Since Intervention1* shows the difference between the pre-intervention slope and the Ebola-period slope. For the post-epidemic period the intervention effects are in comparison to a counterfactual (i.e., the continuation of the pre-epidemic trend throughout the Ebola period). *Intervention2* thus is the change in level from the intercept of the counterfactual at the last time point of the epidemic period to the intercept of the post-Ebola regression line at the first time point in the post-Ebola period. *Time Since Intervention2* captures the differences between post-epidemic slope and counterfactual slope. Interpretation of coefficients becomes clearer when consulting the plotted regression lines and counterfactuals in Figure 3.

Beyond the standard OLS segmented regression model, each model is also compared with a ‘best-fit’ automated ARIMA model (as described in Section 5.5) as a robustness check. If the ARIMA estimation shows statistically significant values in the same direction as in the respective segmented regression model, this is held to be a robust result. In cases where segmented regression and ARIMA coefficients vary in significance or direction, effects should be interpreted with caution.

Figure 3
Plotted Interrupted Time Series Data for Outcome Variables



6.2.1 Health Aid

Testing the impact of the Ebola intervention on health aid in Sierra Leone, Table 4 presents the following results in response to hypothesis H1: As captured in Model 1, the Ebola outbreak induces a significant surge (level change) in health aid of USD 39.27 million (significant at the 1% level) and a negative change in slope, which is significant at the 10% level. This indicates that towards the end of the epidemic levels of health aid are on average lower than at the outset of the epidemic. At the start of the post-epidemic period, the results show statistically significant (at the 5% level) higher levels of health aid than the pre-epidemic trend would predict, although these are far lower than during the epidemic. In comparison to the pre-epidemic trend, also post-Ebola health aid shows a significant negative slope change of USD -0.33 million per month.

When controlling for donor type (Models 3 and 5), the coefficients for all four effect variables remain statistically significant in the same direction, albeit partly at different levels of significance. The exception is that there is no statistically significant slope change in

multilateral aid at the beginning of the epidemic. This thus indicates that after the level increase, multilateral aid generally develops in line with the pre-intervention slope. When comparing the effect coefficients of bilateral and multilateral aid, it becomes clear that bilateral aid is responsible for the majority share of the surge in health aid at the outset of the epidemic. However, in the post-epidemic period, a comparatively larger share of the respective epidemic-surge persists in multilateral than bilateral aid.

Table 4
Regression Results of Ebola on Health Aid

	<i>Dependent variable:</i>		
	Health Aid	Bilateral Health	Multilateral Health
	<i>OLS</i> (1)	<i>OLS</i> (2)	<i>OLS</i> (3)
Time	0.07*** (0.02)	0.06*** (0.02)	0.001 (0.004)
Intervention1	39.27*** (3.67)	31.97*** (3.24)	7.64*** (0.71)
Intervention2	7.70** (2.98)	4.69* (2.63)	3.31*** (0.57)
Time Since Intervention1	-0.44* (0.26)	-0.41* (0.23)	-0.03 (0.05)
Time Since Intervention2	-0.33*** (0.09)	-0.24*** (0.08)	-0.08*** (0.02)
Constant	-0.16 (1.45)	-1.00 (1.28)	0.87*** (0.28)
Observations	180	180	180
R ²	0.74	0.70	0.74
Adjusted R ²	0.73	0.69	0.73
Residual Std. Error (df = 174)	7.65	6.75	1.47
F Statistic (df = 5; 174)	100.16***	81.23***	96.62***

It is also controlled for the largest bilateral and multilateral donors individually (see Appendix C, Table C.1). The significant level increase in health aid at the start of Ebola also holds for UK, US, EU, and World Bank health aid (all at the 1% significance level). No statistically significant changes during the epidemic period are observed in UN health aid. While the Ebola outbreak also induces a significant negative slope change in US and EU health aid, a *positive*

slope change is evident in World Bank aid. This means that while the EU and US decreased their levels in health aid the longer the epidemic lasted, World Bank health aid increased. In line with the overall health aid model, both UK and World Bank show a level increase in health aid at the beginning of the post-Ebola period as well as a negative slope change. It is noticeable that for World Bank health aid, the level increase at the end of Ebola (USD 2.99 million) is larger than the level change at the outset of the epidemic (USD 1.75 million). The only statistically significant change in UN health aid is a slope increase in the post-Ebola period.

As discussed in Section 5.5 possible sources for significance over-estimation within the results are autocorrelation, non-stationarity and/or seasonality. To detect non-stationarity an Augmented Dickey-Fuller Test is run on the dependent variables of each segmented regression model. For six of the eight H1-related models the Dickey-Fuller Test results in p-values > 0.05 , which indicates a failure to reject the null hypothesis that the variable has a unit root and allows us to conclude that the data is non-stationary.¹² To test for potential autocorrelation in the models, a Breusch-Godfrey test is conducted, detecting levels of autocorrelation in all segmented regression models. As explained in Section 5.5., both non-stationarity and autocorrelation can be accounted for through respectively fitted ARIMA models using the *auto.arima* function. Where non-stationarity was detected the term $d=1$ is pre-specified (as done in Schaffer et al., 2021). No indications of seasonality are detected in the STL decomposition when fitting the respective ARIMA models. However, even with ‘best-fit’ ARIMA models, autocorrelation is still present, as is shown in the rejection of the null-hypothesis of Ljung-Box tests conducted respectively for H1-related models.¹³ No robustness checks can thus be performed for these models.

Given this, all results regarding both hypotheses H1a and H1b need to be regarded as inconclusive, as interference of autocorrelation cannot be ruled out. Nevertheless, the results from the segmented regression models can provide some tentative indications, which is discussed further in Section 7.

6.2.2 Non-Health Aid

As described in hypothesis H2, Model 4 in Table 5 shows the intervention effects on non-health aid overall. The results indicate a significant level increase in non-health aid of USD 5.16 million at the start of Ebola. The difference of 0.26 between the slope of the trend before and

¹² This is the case for models 1, 2, and 3 in Table 4 and models 1, 4, and 5 in Table C.1 in Appendix C.

¹³ The null-hypothesis of the Ljung-Box test is rejected for models 1, 2, and 3 in Table 4 and models 2 and 3 in Table C.1 in Appendix C.

after the start of Ebola is statistically significant, indicating a sustained increase in non-health aid. After the end of the crisis period, the level is USD 6.29 million higher than what the pre-epidemic trend would have predicted (1% significance level). However, the end of the epidemic also induces a negative slope change, causing non-health aid to decrease at USD -0.20 million per month throughout the post epidemic period.¹⁴

Table 5
Regression Results of Ebola on Non-Health Aid

	<i>Dependent variable:</i>					
	Non-Health Aid		Bilateral		Multilateral	
	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>
	(4)	(5)	(6)	(7)	(8)	(9)
MA1		-0.12*		0.01		-0.14**
		(0.07)		(0.07)		(0.07)
MA2		-0.59***		-0.19***		-0.69***
		(0.06)		(0.07)		(0.05)
MA3				-0.35***		
				(0.07)		
Time	0.15***	0.19**	0.07***	0.08	0.06***	0.08*
	(0.01)	(0.09)	(0.01)	(0.06)	(0.01)	(0.05)
Intervention1	5.16**	1.75	1.05	0.93	4.16**	1.56
	(2.02)	(2.75)	(1.10)	(1.23)	(1.63)	(2.18)
Intervention2	6.29***	6.85	-3.17***	-1.83	8.60***	7.75**
	(1.64)	(5.62)	(0.89)	(3.39)	(1.32)	(3.35)
Time Since Intervention1	0.26*	0.18	-0.17**	-0.13	0.33***	0.23
	(0.14)	(0.27)	(0.08)	(0.16)	(0.11)	(0.17)
Time Since Intervention2	-0.35***	-0.41**	-0.14***	-0.14	-0.13***	-0.18*
	(0.05)	(0.18)	(0.03)	(0.11)	(0.04)	(0.10)
Constant	11.16***		3.40***		7.58***	
	(0.80)		(0.43)		(0.64)	
Observations	180		180		180	
R ²	0.81		0.49		0.76	
Adjusted R ²	0.80		0.48		0.75	
Residual Std. Error (df = 174)	4.21		2.29		3.40	
F Statistic (df = 5; 174)	147.55***		33.80***		107.52***	

Note:

*p<0.1; **p<0.05; ***p<0.01

¹⁴ The new slope can be calculated by adding the slope change to the pre-epidemic slope: $0.15 + (-0.35) = 0.20$.

For bilateral non-health aid (see Table 5, Model 6), no significant level change is observed at the beginning of the epidemic. In contrast to overall non-health aid, bilateral non-health aid *decreases* in slope after the outbreak of Ebola (significant at the 5% level). At the end of the epidemic there is a significant drop in bilateral non-health aid of USD 3.17 million below the expected level. Like overall non-health aid, the end of the Ebola intervention causes a negative slope change in bilateral non-health aid. These effects are generally also confirmed when examining the two largest bilateral donors individually (see Appendix C, Table C.2): for both UK and US non-health aid no level change is evident to the start of the epidemic. While the beginning of the epidemic causes a negative slope change in US non-health aid, leading to a significantly lower level in non-health aid to begin of the post-epidemic period, these effects remain insignificant for UK non-health aid. Like overall bilateral non-health aid, both UK and US non-health aid experience a significant gradual decrease in the post-epidemic period (slope-change).

Multilateral non-health aid, in contrast, shows very different results (see Table 5, Model 8): The Ebola outbreak causes a significant *increase* in both level and slope in multilateral non-health aid. At the beginning of the post-epidemic period, the level of non-health aid is significantly higher than the counterfactual predicts. This, however, gradually decreases in the post-epidemic period. Looking at the largest multilateral donors individually (see Appendix C, Table C.2), the EU shows significant effects in the same direction as overall multilateral non-health aid for all intervention variables. Also, for UN non-health aid a positive level change is observed at the outset of the epidemic as well as a negative slope change at the end; for the remaining intervention effect variables, the changes in slope and level, however, remain insignificant (see Appendix C, Table C.2). The Ebola outbreak does not induce any significant level change in World Bank non-health aid flows, however, triggers a positive slope change, which also continues and increases at a faster slope in the post-epidemic period that the pre-epidemic trend would predict (see Appendix C, Table C.2).

As again both non-stationarity¹⁵ and autocorrelation are detected in the data, this is accounted for in the ARIMA models (Table 5, Models 5, 7, and 9) as robustness checks. This time for all models (except UN and World Bank non-health aid) the respective Ljung-Box test does not find any signs of persisting autocorrelation, indicating a good model fit of the specified ARIMA models. While the robustness checks generally confirm the direction and strength of coefficients, several effects are no longer significant, indicating a potential overestimation in

¹⁵ Non-Stationarity is detected in all H2-related models, except for UK and World Bank models.

the segmented regression model. With regard to overall non-health aid, the appliance of a best-fit ARIMA (0,1,2) model has the effect that only the post-Ebola negative level change remains significant (at the 5% significance level). In the ARIMA (0,1,3) estimation, the Ebola intervention variables have no statistically significant effect on bilateral non-health aid and can thus not be considered statistically robust. For multilateral non-health aid, both the positive level change and negative slope change in the post-Ebola period hold, although slightly less significant. The level and slope change at the outset of the epidemic cannot be confirmed. Furthermore, for donor-specific non-health aid, robustness checks are conducted (see Appendix C, Table C.2): The negative slope change in US non-health aid at the outset of the epidemic as well as the level decrease in the post-epidemic period both reach statistical significance in the fitted ARIMA (0,1,5) model. For EU non-health aid, both the level and slope increase in the post-epidemic period can be confirmed. All other effects do not achieve statistical robustness.

Considering these robustly significant intervention effects, hypothesis H2 – which predicts the Ebola outbreak to have caused a decrease in aid flows to non-health sectors that is also sustained in the post-Ebola period – cannot be confirmed on a general level. When differentiating, between donor type and large individual donors, some robust support for H2 is found in the US non-health data. These results and potential explanations thereof are further discussed in Section 7.

6.2.3 Infrastructure Aid

Table 6 (Models 10-15) shows the segmented regression models and respective ARIMA robustness checks for Ebola on infrastructure aid. The segmented regression intervention effects on overall infrastructure aid are captured in Model 10: The beginning of the Ebola epidemic triggers an abrupt level decrease of USD 0.87 million, significant at the 10% level. No statistically significant slope change is observed at the outset of the epidemic. The end of the Ebola epidemic causes a significant (at the 1% level) level increase of USD 1.20 million above the expected pre-epidemic trend. It also induces a statistically significant negative slope change of USD -0.13 million, resulting in a sustained decrease infrastructure aid throughout the post-Ebola period.

Table 6
Regression Results of Ebola on Infrastructure Aid

	<i>Dependent variable:</i>					
	Infrastructure Aid		Bilateral		Multilateral	
	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>
	(2,1,2)	(2,1,2)	(0,1,0)			
	(10)	(11)	(12)	(13)	(14)	(15)
AR1		-0.03 (0.10)		-0.17*** (0.06)		
AR2		-0.86*** (0.09)		-0.93*** (0.04)		
MA1		0.01 (0.15)		0.22** (0.10)		
MA2		0.68*** (0.13)		0.81*** (0.07)		
Time	0.07*** (0.003)	0.06* (0.03)	0.04*** (0.003)	0.03 (0.03)	0.02*** (0.002)	0.02 (0.02)
Intervention1	-0.87* (0.49)	0.003 (0.40)	-0.59 (0.46)	0.09 (0.28)	-0.18 (0.29)	-0.003 (0.25)
Intervention2	1.20*** (0.39)	1.67 (1.88)	-2.20*** (0.38)	-1.32 (1.44)	2.90*** (0.23)	2.60** (1.29)
Time Since Intervention1	0.05 (0.03)	0.06 (0.09)	-0.06* (0.03)	-0.07 (0.07)	0.10*** (0.02)	0.12** (0.06)
Time Since Intervention2	-0.13*** (0.01)	-0.10 (0.06)	-0.01 (0.01)	0.01 (0.05)	-0.09*** (0.01)	-0.08* (0.04)
Constant	0.89*** (0.19)		-0.28 (0.18)		1.05*** (0.11)	
Observations	180		180		180	
R ²	0.90		0.58		0.88	
Adjusted R ²	0.89		0.57		0.88	
Residual Std. Error (df = 174)	1.01		0.97		0.60	
F Statistic (df = 5; 174)	297.77***		48.59***		256.68***	

Note:

*p<0.1; **p<0.05; ***p<0.01

Model 12 shows the results for bilateral infrastructure aid: In contrast to aggregated infrastructure aid, the Ebola outbreak does not cause a statistically significant level change in bilateral infrastructure aid. Instead, a negative slope change, significant at the 10% level, is observed. At the end of Ebola there is a statistically significant drop in bilateral infrastructure aid. While bilateral infrastructure aid shows a general negative Ebola-induced change, intervention effects for multilateral infrastructure aid are inherently different (see Model 14): Following the outbreak of the epidemic, there is gradual *increase* (slope change) in multilateral

infrastructure aid. In the post-epidemic period, a level *increase* of 2.90 million (significant at the 1% level) is followed by a statistically significant (at the 1% level) negative slope change.

As with the previous models, non-stationarity and autocorrelation are detected in the data. The results from the segmented regression models are thus compared with the respective ARIMA models as robustness checks. Performed Ljung-Box tests confirm a good model fit and absence of autocorrelation for overall and multilateral infrastructure aid, however not for bilateral aid. No results for bilateral infrastructure can thus be considered robust and need to be regarded with extreme caution. When accounting for stationarity and autocorrelation, no intervention effects in overall infrastructure aid reach statistical significance (see Model 11). Although when comparing effect coefficients with the respective standard errors, the post-Ebola negative slope change in overall health aid (see Model 11) is not far away from statistical significance at the 10% level (p-value of 0.126). For multilateral aid, on the other hand, all results significant in the segmented regression model hold also in the ARIMA (0,1,0) model, albeit partly less significant (see Model 15).

To reiterate, hypothesis H3 describes a decline in infrastructure aid in the post-Ebola period. The (partly) robust negative post-Ebola slope change in overall infrastructure aid thus stands in general support with H3. The break down to bilateral and multilateral infrastructure aid offers a less clear-cut interpretation regarding H3 and is discussed extensively in Section 7.

6.2.4 Education Aid

Lastly, the segmented regression results of the Ebola epidemic on education aid are represented in Table 7. For overall education aid (see Model 16), no significant changes in education aid are found following the start of the epidemic. However, after the end of the epidemic an immediate level increase of USD 0.38 million in comparison to the counterfactual trend is observed (significant at the 10% level). The positive and significant (at the 1% level) *Time Since Intervention2* coefficient indicates a sustained increase in education aid throughout the post-Ebola period.

When controlling for donor type, these effects, however, do not hold, diverging evidently between bilateral and multilateral donors: Bilateral education aid (see Model 18) decreases gradually during the epidemic period (negative slope change). At the beginning of the post-Ebola period a negative level change of USD -0.52 million is observed. Both effects are significant at the 1% level. When only examining multilateral donors in contrast, the Ebola outbreak induces a *positive* slope change in education aid. In the post-epidemic period, there is

a level increase of USD 0.93 million (in comparison to the counterfactual prediction), which is sustained through an increase in slope. All of these changes have a significance level of 1%.

Table 7
Regression Results of Ebola on Education Aid

	<i>Dependent variable:</i>					
	Education Aid		Bilateral		Multilateral	
	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>
	(0,1,0)		(1,0,0)		(0,1,0)	
	(16)	(17)	(18)	(19)	(20)	(21)
AR1				0.89***		
				(0.03)		
Time	0.01***	0.01	0.01***	0.01***	-0.01***	-0.003
	(0.001)	(0.02)	(0.001)	(0.002)	(0.001)	(0.01)
Intervention1	0.001	-0.01	-0.01	0.02	0.10	-0.03
	(0.24)	(0.23)	(0.17)	(0.17)	(0.09)	(0.09)
Intervention2	0.38*	0.09	-0.52***	-0.70*	0.93***	0.76*
	(0.20)	(1.15)	(0.14)	(0.39)	(0.08)	(0.44)
Time Since Intervention1	-0.002	0.01	-0.04***	-0.03*	0.03***	0.04*
	(0.02)	(0.05)	(0.01)	(0.02)	(0.01)	(0.02)
Time Since Intervention2	0.02***	0.03	-0.002	0.003	0.02***	0.03*
	(0.01)	(0.04)	(0.004)	(0.01)	(0.002)	(0.01)
Constant	0.81***		0.05		0.87***	
	(0.10)		(0.07)		(0.04)	
Observations	180		180		180	
R ²	0.67		0.30		0.84	
Adjusted R ²	0.66		0.28		0.84	
Residual Std. Error (df = 174)	0.51		0.36		0.20	
F Statistic (df = 5; 174)	69.94***		14.59***		188.98***	

Note:

*p<0.1; **p<0.05; ***p<0.01

Again, non-stationarity (except in the bilateral data) and autocorrelation are detected. The results presented above are thus all tested for their statistical robustness, by adjusting for and autocorrelation and (where necessary) non-stationarity in ARIMA Models 17, 19, and 21. For overall education aid no coefficients reach statistical significance in the respective ARIMA (0,1,0) model. This implies that in the segmented regression models the level of significance of changes in overall education aid have likely been overestimated due to non-stationarity of the data, which is accounted for in the ARIMA models through a first-difference term (d=1). For bilateral education aid, on the other hand, the negative slope change after the start of Ebola as

well as the negative level change at the beginning of the post-Ebola period also reach statistical significance in the robustness check. For multilateral aid, effects in the opposite direction, namely the slope increase at the outset of epidemic as well as the level and slope increase in the post-epidemic period are all confirmed in the ARIMA-fitted Model 20. In the ARIMA modeling, the results for both bilateral and multilateral education aid, however, only hold at the 10 % significance level (opposed to the 1% significance level of the respective coefficients in segmented regression model).

As the robustly significant results for bilateral and multilateral education aid show effects in opposing directions, hypothesis H4, predicting an increase in education aid after the end of the epidemic, only holds conditionally. While the slope and level increases in multilateral education aid are generally in line with the hypothesized relationship, the negative coefficients in bilateral aid suggest the contrary. Potential explanations for this are fathomed in Section 7.

7 Discussion

After having presented the results of the empirical analysis and having checked for their robustness, this section discusses the results in the context of the broader scholarly literature.

Inconclusive Results for Changes in Health Aid

The persistence of autocorrelation in the data (also in the ARIMA models), limits the ability to draw conclusions regarding hypotheses H1a and H1b. This implies that neither the OLS segmented regression models nor the fitted ARIMA estimations are suitable to capture the complexity of the data.

When taking the results from the segmented regression models in context with the descriptive statistics (see Section 6.1.2) an increase in health aid during the epidemic-period is nevertheless apparent and probable. In line with both H1a and H1b the results in the segmented regression models show a level increase in health aid at the outset of the epidemic across bilateral, multilateral and largest individual donors (US, UK, EU, and World Bank). This is in line with all prior studies finding surges in aid in the wake of natural disasters (see Yang, 2008; David, 2011; Becerra et al, 2014). The UN health aid data does not appear to react to outbreak of Ebola (supported by both the OLS model and descriptive statistics). This could be possibly related to

the fact that the UN is involved many in multi-donor projects (see DAD, 2021), which, however, are not captured in the individual donor data (as discussed in Section 6.1.1).

For the post-Ebola period, H1a predicts a sustained increase, while H1b foresees a return to the pre-epidemic trend. The results from the segmented regression models show a positive level change but negative slope change, indicating that at the beginning of the post-Ebola period health aid levels remain above the predicted trend but these strongly decrease the more time passes. This would thus neither fully confirm the predictions in H1a nor H1b but suggest a reality somewhere in between. Therefore, neither needs-based and visibility concerns nor health security considerations seemed to have dominated aid allocation decisions; although, the drop of the post-Ebola trend below the predicted trend relatively soon after the end of the epidemic arguably makes the case for the latter (H1b) stronger (see Figure 3).

Due to the persisting methodological issues any interpretation of these models is highly uncertain and requires further examination and different modeling approaches. The discussion of these results is therefore kept to a minimum and the focus is rather set on hypotheses H2-H4, where autocorrelation and non-stationarity can be accounted for successfully.

Mixed Effects of Ebola on Non-Health Aid

The results on the impact of the Ebola intervention on non-health aid, differ considerably depending on donor type, exhibiting intervention effects in the opposing direction for bilateral and multilateral donors. Therefore, as these are likely to partly balance each other out in the effects on overall non-health aid, it is opted to rather discuss the results disaggregated by donor type from the start.

In the segmented regression model, the negative slope change in bilateral non-health aid during the epidemic as well as the decrease in level and slope in the post-Ebola period are in line with hypothesis H2.¹⁶ While the direction holds, the statistical significance of the intervention effects, cannot be confirmed when controlling for non-stationarity and autocorrelation in the robustness check. Hypothesis H2 can thus not be robustly confirmed for bilateral donors. In US-specific data, however, the statistically significant decline in non-health aid (slope decrease during the epidemic and negative level change at the start of the post-epidemic period) is found to be statistically robust, showing general support of hypothesis H2 for US non-health aid. Putting this in context with the indications from the changes in US health aid (as described

¹⁶ Hypothesis H2 predicts the Ebola epidemic to cause an abrupt drop in aid flows to non-health sectors, which do not recover in the post-epidemic period.

above), these results stand in strong support of cross-sectoral reallocation towards the health sector. This would also be in line with Becerra et al. (2015, p. 584) who find reallocation from other sectors towards humanitarian aid in the aftermath of natural disasters to be only significant for US aid. A possible explanation would be strategic (Bermeo, 2017) or egoistic (Berthélemy, 2006) patterns in US aid allocation, to which also cross-sectoral reallocation could possibly be related. For the affected recipient country, the reallocation of aid from non-health sectors could imply a neglect and slowed development in these sectors (see Benson & Clay, 2004, p. 35) or given the multisectoral consequences of the epidemic (see Smith et al., 2019) could potentially even impose a double jeopardy.

As described in Section 5.5, a coinciding change in government in the donor country must be considered as a potential co-intervention that could explain a change in prioritization in aid allocation. Considering, however, that the change in government in the US occurred in January 2017, a new government could only have had impact on the observed slope change in the post-Ebola period. So even if this were the case, the slope decrease during the epidemic as well as the negative level change at the beginning of the post-Ebola period alone (both having occurred before the change in government) already provide support for cross-sectoral reallocation.

In contrast to bilateral non-health aid, multilateral data shows a large, significant and robust level *increase* in non-health aid at the beginning of the post-Ebola period, standing in direct contradiction to the predictions put forth in hypothesis H2.¹⁷ This would generally be in line with the rationale that “[t]he international community should not be overly engaged with humanitarian and early recovery actions at the expense of tackling the root causes of EVD” (UNDP, 2014, p. viii). This would also correspond with the argument that multilateral aid is less likely to follow a strategic or political agenda than bilateral aid and thus generally has a more balanced portfolio (see Burnside & Dollar, 2000; Christensen et al., 2011).

Decline in Post-Ebola Infrastructure Aid

As discussed in Section 6.2.3, the empirical analysis shows partly robust support for hypothesis H3, predicting a decline in infrastructure aid in the post-Ebola period. These results are in line with the expectations and findings of the few prior studies on the impact of natural disasters on reallocation mechanisms (Benson & Clay, 2004, pp. 26, 36, 115; Becerra et al, 2015, p. 579; Kum et al., 2019, p. 86). It also stands in support of the priorities put forth in the GoSL (2015)

¹⁷ There also is a robustly significant negative slope change across the post-Ebola period, which, however, rather reflects the return to levels in line with the predicted trend after the large level increase.

Ebola Recovery Plan, where infrastructural investments play a secondary role. The empirical findings here thus support the theoretical argument that the cost-intensive, slowly implemented, and arguably less urgent infrastructure projects become less of a priority for donors in the post-Ebola period (see Pietschmann, 2014, p. 84; Benson & Clay, 2004, p. 36).

When controlling for donor type, a decline in bilateral infrastructure aid – while evident in the segmented regression model – does not hold in the robustness checks, as autocorrelation also persists in the fitted ARIMA model. Nevertheless, the negative coefficients would allow to suspect that at least to some extent a reduction of infrastructure aid is also likely amongst bilateral donors. Multilateral infrastructure aid exhibits a robustly significant negative slope change in the post-Ebola period. However, this is preceded by a slope *increase* during the crisis period and *higher* levels in infrastructure aid at the start of the post-Ebola period than the pre-Ebola trend would predict. This may appear unintuitive but could be partly related to the need for increased water and sanitation projects as Ebola containment and prevention measures during and in the direct aftermath of the epidemic (GoSL, 2015, p. 8), which are also classified as infrastructure projects (see and Section 5.2.1). These projects potentially balanced out other planned infrastructure projects that were suspended during the hot phase of the epidemic and then potentially overlapped and accumulated once these projects were resumed towards the end of the crisis period / beginning of the post-Ebola period (GoSL, 2015, p. 9, 15). Support for this potential explanation is the strong and robustly significant decline in multilateral infrastructure aid (falling below the expected trend) in the post-epidemic period, underlining the temporary nature of the increase at the end of Ebola.

As mentioned in Section 5.5, the temporal overlap of the Ebola epidemic with the adoption of the SDGs could potentially induce a history bias. However, the SDGs' increased focus on economic development – mentioning infrastructure investment explicitly¹⁸ (Halişçelik & Soytaş, 2019, p. 560) – would in fact rather predict an effect in the opposite than the observed direction. It therefore can be argued that it is more plausible that the decline in post-Ebola infrastructure aid is associated with the epidemic rather than the adoption of the SDGs. Nevertheless, a history bias cannot be excluded entirely.

A sustained decrease in productive infrastructure aid can have wider implications for the country's economic development (Benson & Clay, 2004, p. 26, 39, 75). Especially when

¹⁸ “SDG 9: Build resilient infrastructure, promote inclusive, and sustainable industrialization“ (Halişçelik & Soytaş, 2019, p. 560). This is also reflected in the Sierra Leone UNDP Annual Report 2018 on SDG implementation (UNDP, 2019, p. 15).

considering the already existing challenges and deficits the country's infrastructure faced prior to the crisis (Pushak & Foster, 2011), a decline in critical infrastructure projects, such as roads, irrigation or energy infrastructure, can thwart the countries development considerably.

Diverging Impacts on Bilateral and Multilateral Education Aid

Hypothesis H4, predicting an increase in education aid after the end of the epidemic, receives support through the positive level and slope changes in overall education aid observed in the segmented regression model. When accounting for non-stationarity in the data, the effects are no longer statistically significant, and conclusions drawn from the results must be treated with caution. The increases in *multilateral* education aid, however, are statistically robust and thus provide strong support for hypothesis H4. The observed intervention effects are in line with the expectation that Ebola-induced damages are – at least partly – compensated for in high priority sectors. As explained in Section 4.4., achieving universal education is identified as a priority for donors in Sierra Leone, which has made the sector highly visible (Nishimuko, 2009, pp. 18; 21-22). An increase in education aid following the end of the epidemic thus would be in line with addressing the Ebola-induced setbacks (i.e., the 9-months shutdown of schools) in attaining this priority goal. Implications of increased multilateral education aid could be increased capacities to address the learning gap and counter the increase in school dropouts in the post-Ebola period (Smith, 2021).

For *bilateral* education aid, in contrast, statistically robust effects in the opposite direction than predicted in H4 are observed. This stands in opposition to the argumentation in Section 4.4, which expected a reluctance of donors to cut back in highly visible sector (see Knack & Rahman, 2008). This could be partly related to forced reallocations due to the interruption of certain projects through the crisis (Benson & Clay, 2004, p. 36), i.e., the shutdown of schools for 9 months. Further, recalling that education aid in Sierra Leone has been closely related with global education goals (i.e., EFA, MDGs, and later followed by SDGs) (Nishimuko, 2009, pp. 18; 21-22), it would also seem plausible that aid related to these targets is rather channeled through multilateral organizations. Given that bilateral and multilateral education aid show robustly significant slope changes during the epidemic period and level changes at the end of the epidemic but both in opposing directions, this could also imply that the changes cancel each other out. This is further strengthened when considering that the coefficient sizes of the opposing effects are fairly similar and that for overall education aid no intervention effects are robustly significant. In other words, this could imply that some donors simply switched the

channel of their aid from bilateral to multilateral or that the fall away of some bilateral projects was compensated by multilaterally funded ones.

Again, we cannot rule out potential history bias due to confounding with the adoption of the SDGs in January 2016. While the EFA and education-related MDGs were limited to achieving physical access to education, SDG 4 shifts the focus towards learning outcomes (Sayed & Moriarty, 2020, p. 201)¹⁹, thus offering a potential explanation for changes in education aid in the 2016-2019 period. As the results, however, show slope changes in bilateral and multilateral education aid already *during* the epidemic as well as immediate level changes at the *end* of Ebola (March 2016), there is a stronger case for association of these changes in education aid to the epidemic than the adoption of the SDGs (January 2016). The first draft of a national SDG action plan in Sierra Leone (GoSL, 2016) was only completed in July 2016, making any SDG-related change in education aid in the months directly surrounding the end of the epidemic unlikely.

8 Limitations and Future Research

While this study is designed and conducted to provide accurate and robust results, it naturally exhibits a number of limitations. Firstly, a general shortcoming of sector-specific aid data, is that aid reported as budget-support cannot be attributed to a certain sector thus possibly underestimating flows to certain sectors (see Eger et al., 2018, p. 1). Similarly, projects attributed to multiple sectors (“multi-sector”) or funded by multiple donors (“multi-donor”) cannot be captured in sector- or donor-specific aid variables (see Tables A.1 and A.2). This limitation in the data, can lead to an underestimation of aid flows to a specific sector or from certain donors. Despite relying on in-country reporting mechanisms and double-validation processes – as is common for national AIMS databases (Petras, 2009; OECD & World Trade Organization, 2011) – it of course cannot be guaranteed that some aid flows are not recorded in the DAD data. While other databases have similar or their own shortcomings (see Petras, 2009; Park, 2017) a replication of the analysis using different data (e.g., CRS data) could increase the validity of results. This would, however, go beyond the scope of this study. A further caveat when studying aid reallocation is, as Benson & Clay (2004, p. 25) explain, that reallocations may sometimes not be reported in available official accounts. This could have the effect that

¹⁹ Sayed & Moriarty (2020), however, also argue that the inclusion of ‘quality’ in SDG 4 is rather a ‘pseudo-technicism’ than a substantial turn in education goals.

some reallocations occur without being captured in the data. Reallocation through new projects (or the absence) thereof are, however, not affected by this.

As explained in Section 5.2.1, as part of the data preparation and transformation to the monthly level – which is prerequisite for an ITS analysis – the amount of aid allocated to a project is equally spread across the months of its activity. This, however, indirectly also implies a strong assumption, i.e., that a given project profited from the allocated aid across its entire duration. This shortcoming is again related to a general problem of reporting aid flows, potentially leading to inaccuracies when data transformation from the project level to the monthly level is necessary. This limitation is accepted, as in comparison to other transformation options it has the key advantage that it considers the large variance in duration between projects (as described in Section 6.1.1) and thus arguably is more representative of the aid levels in play at a given time point.

Beyond these general limitations of sectoral aid allocation research, the current ITS analysis is partially constrained by autocorrelation and/or non-stationarity in the data. While the ARIMA models account for this in most cases, for health aid data no suitable ARIMA model fit is found, leading to inconclusive results for hypothesis H1. Future research should thus consider different modeling options or further data transformations that may be needed to ensure a better model fit.

As mentioned in Section 5.5., a further issue in ITS analysis is the interference of possible co-interventions. Possible confounding through the adoption of the SDGs or change in government in donor countries were considered when discussing results, however, an exclusion of a potential history bias or other potential time varying confounders cannot be guaranteed. Given the complexity of recipient-specific determinants of aid allocation and related data constraints, finding a suitable control series for a natural control population (with balanced covariates but was not exposed to the intervention) is hardly practicable. The most promising option to account for this in future research, could be including a weighted synthetic control in the ITS modeling (see Bernal, Cummins & Gasparrini, 2018), but this, again, would require suitable data for a range of covariates and would exceed the scope of this paper.

This study aims to identify whether and how the Ebola intervention impacted cross-sectoral aid allocation, immediately and/or over time. It does not (nor aimed to) provide any evidence regarding the mechanism at play, i.e., why the epidemic caused a certain change. This should be kept in mind when interpreting the results of the study and thus also presents an important

avenue for future research. Lastly, given the case study nature of the analysis, and respective adaptation of hypotheses to the country-specific context, all findings should be limited to the Sierra Leone case. The similar courses of the epidemic in neighboring Guinea and Liberia (CDC, 2016), could, however, give reason to believe that findings of this study might also hold there. To increase the external validity of results, future research could thus pursue cross-country comparisons or examine whether similar dynamics also apply to different health crises.

9 Conclusion

Epidemics, like other natural disasters, remain highly disruptive events that can drastically shift circumstances and priorities. By extending the scholarly literature on sectoral aid allocation to the context of the 2014-2016 Ebola epidemic, this study examined how the Ebola crisis impacted donor aid allocation across sectors. By analyzing interrupted time series data of aid flows in Sierra Leone, this paper provides the first quantitative study on the impact of epidemics on sectoral aid allocation and addresses a crucial gap in the scholarly literature.

Through an interrupted time series analysis, controlling for differences across donor type and largest individual donors as well as accounting for potential non-stationarity, autocorrelation, and seasonality in a series of robustness checks, this paper presents the following findings: Despite indications of strong increases in levels of health aid at the start of the epidemic across donor type and donors, persisting autocorrelation in the data means no robust evidence can be presented for the impact of the epidemic on health aid. For the impact of Ebola on other sectors, the results show significantly different reactions in bilateral and multilateral aid, often also in opposite directions. Generally, multilateral aid shows to react with increases in aid to non-health sectors (i.e., infrastructure, education and non-health aid in general), while this is not observed for bilateral aid. As this study does not provide any evidence on the reason of an epidemic-induced change in aid allocation, conceivable explanations for these differences between bilateral and multilateral aid can only be discussed tentatively by drawing from prior literature. A theoretical argument that seems to hold is that multilateral aid is less likely to follow a strategic or political agenda than bilateral aid and thus generally has a more balanced portfolio. In the case of education aid, the significant effects in opposite directions, could potentially also imply some donors simply switching the channel of their aid from bilateral to multilateral. Beyond the differences along donor type, the epidemic causes significant and robust decreases in US non-health aid both during as well as in the aftermath of the epidemic. When taking this

in combination with the (strongly visible but inconclusive) indications of an increase in US health aid during the epidemic, the results suggest the reallocation of funds from other sectors towards health aid. In line with the findings from prior research, this study thus provides further evidence that the US responds to natural disasters in aid receiving countries through cross-sectoral reallocation. This could be an important implication for affected recipient governments to anticipate and respond to accordingly. For the impact of the epidemic on infrastructure aid, the partly robustly significant results indicate an association between the epidemic and a decline in infrastructure aid throughout the post-epidemic period. A sustained decline in infrastructure aid can have strong implications for the economic development of a country still in the process of recovering from civil war and with already significant gaps in road, irrigation and energy infrastructure.

Considering its limitations, the results and new insights this study provides should be viewed as preliminary and require further testing. To gain a more robust understanding of the impact of the Ebola crisis (and epidemics in general) on sectoral aid allocation, more or different data should be used with different methodologies and in other contexts. Especially, systematically studying the mechanism at play between the epidemic and changes in sectoral aid allocation is a promising avenue for future research. Nevertheless, considering the general lack of prior theoretical and empirical research on the epidemic–aid allocation interface, this study presents a novel contribution – both theoretically and methodologically – and a step forward in understanding cross-sector aid allocation in the context of epidemics. It thus also provides some important groundwork for studying aid allocation in the wake of other health crises, like the ongoing COVID-19 pandemic.

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Appendices

Appendix A

Table A. 1

Aid Projects in Sierra Leone Grouped by Sector (2005-2019)

Sector	N	Disbursed Aid (in Million USD)	Mean
Agriculture	156	519.94	3.33
Decentralization	22	71.99	3.27
Education	81	290.05	3.58
Environment	41	60.30	1.47
Gender	34	18.49	0.54
Gov Capacity Building	139	257.96	1.86
Health	370	1844.40	4.98
Infrastructure	165	1178.01	7.14
Justice	50	84.89	1.70
Macroeconomy	28	474.82	16.96
Private Sector	26	104.28	4.01
Public Finance	46	360.98	7.85
Security	18	39.01	2.17
Social Welfare	27	56.61	2.10
Transparency and Democracy	113	199.74	1.77
Youth	21	43.08	2.05
Multi-Sector	84	576.98	6.87
Other	39	113.36	2.91

N = Number of projects

Table A. 2*Aid Projects in Sierra Leone 2005-2019, Grouped by Donor*

Donor	N	Disbursed Aid (in Million USD)	Mean
African Development Bank (AfDB)	45	242.09	5.38
Arab Bank for Economic Development in Africa (BADEA)	5	21.18	4.24
Canada	17	13.86	0.82
China	3	47.31	15.77
ECOWAS	3	49.21	16.40
European Union (EU)	394	1243.52	3.16
Germany	50	184.95	3.70
Global Fund	2	6.35	3.17
India	1	0.15	0.15
International Monetary Fund (IMF)	1	43.11	43.11
Ireland	159	117.35	0.74
Islamic Development Bank (IDB)	21	113.05	5.38
Italy	7	14.26	2.04
Japan	38	108.30	2.85
Korean EXIM Bank	1	30.37	30.37
Kuwait Fund	10	25.45	2.54
Netherlands	3	1.10	0.37
Nigeria	1	0.5	0.50
Norway	15	3.98	0.27
OPEC	6	64.35	10.73
Sweden	5	20.19	4.04
Switzerland	2	0.13	0.07
United Kingdom (UK)	130	1715.59	13.20
United Nations (UN)	327	419.47	1.28
United States (US)	91	377.09	4.14
World Bank	76	860.34	11.32
Multi-Donor	32	557.32	17.42
Unspecified	15	14.34	0.96

N = Number of projects

Table A. 3*Pre-Ebola Monthly Aid in Sierra Leone Jan 2005 to May 2014*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Overall Aid	113	23.59	7.83	7.81	16.66	29.01	36.79
Health Aid	113	3.85	2.41	0.56	1.16	6.30	8.09
Non-Health Aid	113	19.74	5.80	7.25	15.50	23.91	29.93
Infrastructure Aid	113	4.71	2.50	1.26	1.68	6.81	9.46
Education Aid	113	1.25	0.66	0.54	0.80	1.31	3.11

N = Number of months

Table A. 4*During Ebola Monthly Aid in Sierra Leone Jun 2014 to Mar 2016*

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Overall Aid	22	80.94	24.56	38.78	61.14	105.45	114.16
Health Aid	22	42.87	21.99	8.61	22.57	64.06	74.35
Non-Health Aid	22	38.08	4.03	30.12	38.11	40.89	42.97
Infrastructure Aid	22	8.97	0.88	7.76	7.97	9.50	10.72
Education Aid	22	1.75	0.22	1.31	1.61	1.90	2.05

N = Number of months

Table A. 5*Post-Ebola Monthly Aid in Sierra Leone Apr 2016 to Dec 2019*

Dependent Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Overall Aid	45	44.20	9.28	34.30	39.11	43.09	79.01
Health Aid	45	11.01	3.71	6.46	6.65	11.79	19.36
Non-Health Aid	45	33.19	6.99	27.64	30.47	32.62	63.66
Infrastructure Aid	45	9.67	1.02	7.61	8.96	10.28	11.55
Education Aid	45	2.80	0.39	1.59	2.82	3.04	3.40

N = Number of months

Table A. 6*Monthly Health Aid in Sierra Leone by Donor (2005-2019)*

Donor Type / Donor	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bilateral	180	7.19	12.15	0.01	0.63	7.02	59.79
Multilateral	180	2.26	2.82	0.55	0.81	1.85	16.39
United Kingdom (UK)	180	5.41	8.43	0.00	0.10	5.33	36.04
United States (US)	180	1.14	3.86	0.00	0.06	0.33	21.85
European (EU)	180	0.47	1.09	0.00	0.20	0.45	8.64
United Nations (UN)	180	0.31	0.16	0.00	0.13	0.46	0.58
World Bank	180	1.07	1.29	0.00	0.32	1.30	4.29

N = Number of months

Table A. 7*Monthly Non-Health Aid in Sierra Leone by Donor (2005-2019)*

Donor Type / Donor	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bilateral	180	7.94	3.17	1.02	6.04	9.81	17.86
Multilateral	180	15.14	6.78	5.99	9.39	20.27	48.91
United Kingdom (UK)	180	3.97	1.89	0.22	2.79	5.05	12.71
United States (US)	180	0.99	0.70	0.12	0.30	1.73	2.19
European (EU)	180	7.04	4.69	2.38	3.74	9.22	39.21
United Nations (UN)	180	1.73	0.66	0.48	1.31	2.12	3.17
World Bank	180	3.67	1.90	0.91	2.41	4.72	9.01

N = Number of months

Table A. 8*Monthly Infrastructure Aid in Sierra Leone by Donor (2005-2019)*

Donor Type / Donor	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bilateral	180	2.25	1.47	0.00	0.78	3.19	6.14
Multilateral	180	3.40	1.72	1.02	1.86	4.62	6.89
United Kingdom (UK)	180	1.11	0.74	0.00	0.32	1.79	1.84
United States (US)	180	0.004	0.01	0.00	0.00	0.00	0.04
European (EU)	180	1.88	0.95	0.80	1.03	2.55	4.19
United Nations (UN)	180	0.10	0.19	0.00	0.00	0.15	0.74
World Bank	180	0.37	0.35	0.00	0.11	0.69	1.24

N = Number of months

Table A. 9*Monthly Education Aid in Sierra Leone by Donor (2005-2019)*

Donor Type / Donor	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bilateral	180	0.55	0.43	0.00	0.17	0.73	1.87
Multilateral	180	0.83	0.49	0.17	0.54	0.92	1.93
United Kingdom (UK)	180	0.33	0.30	0.00	0.00	0.60	0.67
United States (US)	180	0.004	0.01	0.00	0.00	0.00	0.03
European (EU)	180	0.21	0.38	0.00	0.00	0.16	1.20
United Nations (UN)	180	0.06	0.10	0.00	0.00	0.12	0.39
World Bank	180	0.29	0.14	0.00	0.27	0.38	0.55

N = Number of months

Appendix B

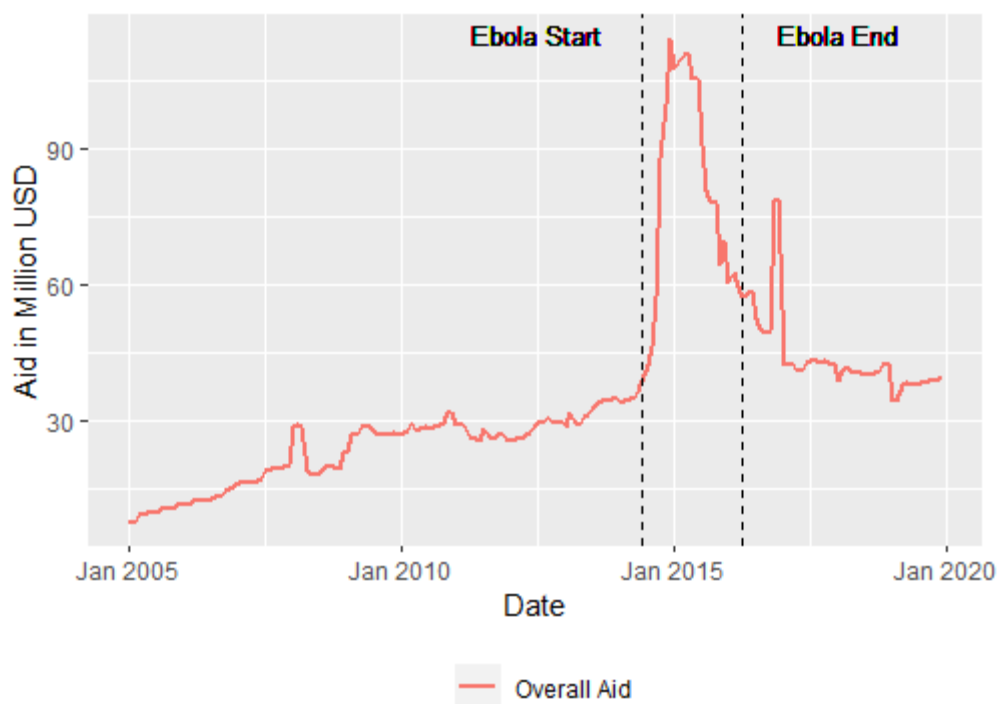
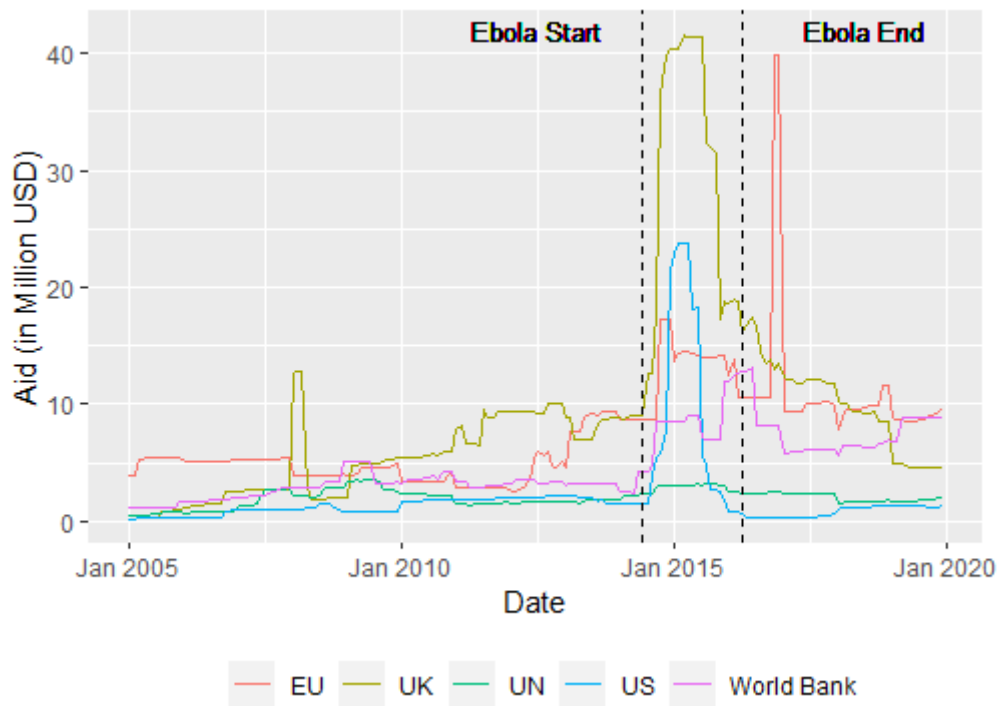
Figure B. 1*Overall Disbursed Aid in Sierra Leone 2005-2019*

Figure B. 2
Aid in Sierra Leone by Donor (2005-2019)



Appendix C

Table C. 1
Regression Results of Ebola on Health Aid by Donor

	<i>Dependent variable:</i>				
	UK (1)	USA (2)	EU (3)	UN (4)	World Bank (5)
Time	0.05*** (0.01)	0.001 (0.01)	0.0003 (0.003)	0.001** (0.0004)	-0.0001 (0.002)
Intervention1	19.36*** (1.98)	11.07*** (1.42)	2.80*** (0.45)	0.11 (0.07)	1.75*** (0.26)
Intervention2	4.94*** (1.60)	-0.15 (1.15)	0.23 (0.37)	-0.02 (0.05)	2.99*** (0.21)
Time Since Intervention1	-0.03 (0.14)	-0.31*** (0.10)	-0.13*** (0.03)	0.002 (0.005)	0.11*** (0.02)
Time Since Intervention2	-0.26*** (0.05)	0.03 (0.04)	-0.02 (0.01)	0.003* (0.002)	-0.07*** (0.01)
Constant	-1.06 (0.78)	0.04 (0.56)	0.32* (0.18)	0.20*** (0.03)	0.33*** (0.10)
Observations	180	180	180	180	180
R ²	0.77	0.43	0.26	0.28	0.83
Adjusted R ²	0.76	0.41	0.24	0.26	0.83
Residual Std. Error (df = 174)	4.12	2.96	0.95	0.14	0.53
F Statistic (df = 5; 174)	114.80***	26.12***	12.10***	13.66***	175.64***

Note: *p<0.1; **p<0.05; ***p<0.01

Table C. 2*Regression Results of Ebola on Non-Health Aid by Donor*

	<i>Dependent variable:</i>									
	UK		USA		EU		UN		World Bank	
	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>	<i>OLS</i>	<i>ARIMA</i>
	(0,0,3)		(0,1,5)		(0,1,2)		(0,1,0)		(1,0,4)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AR1										0.65*** (0.09)
MA1		0.91*** (0.07)		0.08 (0.07)		-0.05 (0.05)				0.21* (0.12)
MA2		0.78*** (0.08)		0.09 (0.07)		- 0.82*** (0.04)				0.15* (0.09)
MA3		0.12 (0.08)		-0.06 (0.08)						0.25*** (0.09)
Intercept		1.34*** (0.47)								1.46*** (0.55)
MA4				-0.07 (0.07)						0.25*** (0.09)
MA5				0.32*** (0.07)						
Time	0.04*** (0.004)	0.04*** (0.01)	0.02*** (0.001)	0.01 (0.01)	0.02* (0.01)	0.03 (0.03)	0.01*** (0.002)	0.01 (0.02)	0.02*** (0.003)	0.02** (0.01)
Intervention1	0.05 (0.69)	-0.08 (0.76)	-0.03 (0.13)	0.05 (0.11)	3.52** (1.62)	0.51 (1.75)	0.47* (0.27)	0.14 (0.17)	-0.14 (0.52)	-0.20 (0.62)
Intervention2	-0.55 (0.56)	-0.88 (0.91)	-2.30*** (0.11)	-1.31* (0.78)	7.84*** (1.32)	5.69** (2.81)	0.10 (0.22)	-0.17 (0.85)	0.57 (0.42)	1.09 (1.07)
Time Since Intervention1	-0.07 (0.05)	-0.04 (0.06)	-0.07*** (0.01)	-0.06* (0.04)	0.21* (0.11)	0.19 (0.14)	-0.01 (0.02)	-0.01 (0.04)	0.12*** (0.04)	0.06 (0.06)
Time Since Intervention2	-0.11*** (0.02)	-0.10*** (0.03)	-0.02*** (0.003)	-0.01 (0.03)	-0.14*** (0.04)	-0.17** (0.08)	-0.03*** (0.01)	-0.02 (0.03)	0.04*** (0.01)	0.01 (0.03)
Constant	1.37*** (0.27)		0.26*** (0.05)		3.73*** (0.64)		1.23*** (0.11)		1.58*** (0.21)	
Observations	180		180		180		180		180	
R ²	0.44		0.85		0.49		0.31		0.68	
Adjusted R ²	0.42		0.85		0.48		0.29		0.67	
Residual Std. Error (df = 174)	1.44		0.27		3.38		0.56		1.09	
F Stat. (df = 5; 174)	27.23***		199.29***		34.03***		15.34***		73.80***	

Note:

*p<0.1; **p<0.05; ***p<0.01

