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The Role of Aid on Peace Consolidation in Postwar Sri Lanka

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Abstract

The three-decade war in Sri Lanka left parts of the northern and eastern regions severely destroyed. Those regions are populated by minority and marginalized ethnic groups. The expectation is that aid flows to those regions to rebuild after the war as they need the aid more than other places. Nonetheless, the regions are underdeveloped, and the underlying issues which caused the war are yet to be addressed. Hence, this paper aims to answer the research question, 'Are conflict-affected districts a priority in aid allocation in postwar Sri Lanka?' This paper is primarily concerned about the aid allocation post-conflict. However, since the tsunami hit Sri Lanka in 2004, we use the aid allocation from the post-disaster environment to reveal aid patterns and potential biases. The paper uses GIS geocoding, mapping, spatial analysis, and econometric analysis to understand whether: (i) tsunami-affected districts received more aid than others, (ii) war-affected districts received more aid than others, (iii) economically developed districts receive less aid than others. The paper uses AidData on World Bank, Chinese, and the author's collected data on Asian Development Bank aid projects, 2002-2015. The study finds that donors do not respond to the needs of the recipient country. The maps and the analysis show that aid projects are predominantly in southern regions of the country and not in the war-affected districts.

Keywords: Aid donors, GIS, Post-conflict peacebuilding, Subnational aid allocation

Declarations

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1. INTRODUCTION

Whether foreign aid helps promote economic growth and development is a much-heated debate amongst economists and development practitioners. It is also contested whether aid combined with aid conditionality can bring about peace or sustain peace in conflict areas in the longer run. For instance, Boyce (2002) argues that there is a need for a complete restructuring of aid conditionality for it to succeed in peace consolidation, whereas Sindre (2014) argues that aid conditionality works as long as donors include the rebels in the decision-making process. However, most economists and politicians agree that aid rushes to countries after a natural disaster to give humanitarian relief (Rodella-Boitreaud & Wagner, 2011 and Strömberg, 2007). The objective assumption is that following a natural disaster, aid is allocated to the places most affected. For example, in January 2010, Haiti's capital Port-au-Prince was destroyed by an earthquake, and the aid allocated to this natural disaster was focused on rebuilding the most affected regions (Soden & Palen, 2014).

Similarly, one would assume that following a conflict, aid donors prioritize rebuilding the conflict-affected areas. Is this true?

While studies of aid allocation have mostly been cross-national (e.g., Gounder (2005), Nkurunziza, and Collier & Hoeffler (2014), Pritchett et al. (2012), Bohnke & Zurche (2013), and Kadirova (2014)), recent studies have started to explore within-country allocation (Öhler and Nunnenkamp (2014), Nunnenkamp et al. (2017), Briggs (2017) and Briggs, (2021)). These papers show that at the subnational level, aid does not target poorer regions. Unlike most previous work on subnational aid allocation, which spans larger spatial regions, this paper differs in investigating aid allocation within one country.

This paper uses Sri Lanka as a case study to investigate whether aid is allocated to places that need it the most. Sri Lanka saw a protracted war along ethnic, religious, linguistic lines from 1983 to 2009. Given the nature and scale of the conflict, the role of international aid in rebuilding the Sri Lankan economy became pivotal. In light of this, an empirical analysis of the spatial distribution of aid and its allocation across regions is important for many reasons. First, the Sri Lankan conflict did not end with a negotiated peace settlement. Instead, it was a 'winner-take-all' end to the conflict, which is not a common scenario. Most contemporary conflicts see an end with a negotiated peace. For example, Zambia, Namibia, and El Salvador ended with a negotiated peace.

Additionally, Sri Lanka has slowly moved away from traditional democratic society and closer towards a semi-authoritarian regime. Second, the Sri Lankan conflict was contained to particular geographical areas of the island. Hence, the districts affected by the conflict are easy to determine, making our identification strategy easier for empirical analysis[1]. Third, the majority of the marginalized ethnicities are also contained in somewhat precise geographic locations that mostly overlap with the geographical locations affected by the war. Lastly, one of the biggest donors in Sri Lanka at the moment is China. Other donors include the World Bank, Asian Development Bank, OECD, Iran, and India. The more 'traditional' donors from the West have conditionalities such as economic performance, governance reforms, and human rights conditionalities. However, donors like China have no aid conditionality. This makes aid conditionality less effective on the global scene and particularly less effective in Sri Lanka. All these aspects make aid to Sri Lanka a useful case study.

First, this paper investigates whether conflict-affected districts receive more aid than other districts. We use a newly added geocoded Official Development Assistance (ODA) dataset from the World Bank, and China combined with a collected and geocoded dataset by the author on aid from the Asian Development Bank. We use Geographical Information Systems (GIS) to geocode and extract this geocoded data at the district level and map the projects visually and analyze spatial clusters. Additionally, we do an econometric analysis to determine the validity of our visual maps. The visual maps show a significant lack of projects in the conflict-affected districts, and the empirical analysis shows that the conflict-affected districts do not receive more aid than other districts. The results are not surprising given the existing narratives by Sri Lankan scholars, activists, and the subnational aid literature. Even when accounting for economic development, we do not find that conflict-affected districts receive more aid than other districts. Therefore, this paper argues that donors do not prioritize their aid to areas within a country that desperately needs it. This is important because donors decide that a specific country needs aid, but they do not diligently research the country and decide where it could be most helpful. Based on the Sri Lankan case, it would seem that donors tend to take the path of least resistance, which ends up marginalizing the people they might have intended to give relief.

[1] The conflict districts are Ampara, Batticaloa, Jaffna, Kilinochchi, Mannar, Mullaitivu, Puttalam, Trincomalee, and Vavuniya (see figure 2)

This paper's contribution is both in the aid literature and literature on the conflict in Sri Lanka. It has been more than a decade since the conflict ended in Sri Lanka, but few studies on aid and donors after the tsunami exist. Additionally, it is commonly known by activists, Sri Lankan Tamil residents in northern and eastern parts of the country, and Sri Lankan scholars in various fields that the northeast has not been a priority in terms of rebuilding or reconciliation (Goodhand 2010, Ruwanpura et al. 2020, Tantrigoda 2017, Kadirgmar 2017 and many more). This paper uses visual and empirical evidence to fill the lacunae in the existing literature to show that systematic bias existed in aid allocation post-2009.

The methodology used for this study is another contribution to the aid literature. The interdisciplinary approach, using methods from economics and geography, has allowed us to visualize and investigate the aid projects allocated within a country, an approach most aid studies have not used. This paper underlines the importance of the geographical allocation of various aid projects. Finally, this paper urges aid donors to spend more time learning about a recipient country's internal history, especially in a post-conflict situation, to ensure that the aid actually goes to the places that need it the most.

1.1. Sri Lankan historical context

Sri Lanka saw a protracted ethnic and territorial conflict from 1983 to 2009. The Sri Lankan population of 20 million can be sub-grouped into 75% Sinhalese, 11% Sri Lankan Tamil, 9% Moors, and 4% Indian Tamils (Census 2011). The national liberation struggle was primarily fought between Liberation Tigers of Tamil Eelam (LTTE) and the Sri Lankan government – a conflict fought over the independence of the traditional Tamil homelands in the northern and eastern parts of the island. Horizontal inequality was a major cause of the Sri Lankan conflict as it impacted access to education, employment opportunities, disparities in urban development, distribution of benefits from agricultural development, and political exclusion of Sri Lankan Tamils. The conflict ended in 2009 when the Sri Lankan military defeated the LTTE. Subsequently, the government focused on rebuilding and developing the entire island with help from international loans and donors. However, the country still deals with many of the issues which existed in the pre-war period, such as high youth unemployment and Sinhala resettlements to the Tamil Homelands. In 2018, nine years after the violent conflict ended, around 8,000 Sri Lankans applied for asylum in other countries (worlddata.info). A deductive estimate would be that more than 200,000 Sri Lankans (mostly Tamils and Muslims who were targeted) left their motherland during this 26 year-long violent conflict[2]. More than 40,000 civilians died[3] during the last two weeks of the Sri Lankan conflict, which is now called genocide (see 'Tamil Genocide by Sri Lanka' by Francis Boyle, 2010). The end of the war also caused an additional 300,000 Tamils to be internally displaced and detained in camps (Amnesty International, 2009).

An important feature of the Sri Lankan post-conflict environment is that the government with the Rajapaksa family in the lead has moved towards soft authoritarianism (DeVotta, 2010). As Höglund and Orjuela (2011) write:

> "While a post-war context in many countries creates opportunities for a move towards further democratization, Sri Lanka instead appears to be consolidating a semi-authoritarian and highly centralized state. Activities are currently undertaken to reconstruct the war-torn areas. While such reconstruction is clearly required to alleviate the hardship experienced by the people in these areas, there is a great risk that these initiatives – due to their centralization and further domination and marginalization of minorities – will serve to exacerbate or create conflict in Sri Lanka, rather than serve as a vehicle for building trust". (p.34)

This paper explores this worrying statement of further marginalization of minorities due to reconstruction format by investigating aid project patterns in the war-torn areas.

2. SUBNATIONAL AID ALLOCATION

Most studies on aid have been cross-country studies or focused on large geographical spaces such as Sub-Saharan Africa. More studies have explored aid allocation within countries or what is also referred to as subnational aid allocation in more recent years, but the literature on this topic is still rather scarce. The scarce literature highlights that the main issue with subnational aid allocation is that aid does not go to the poorer or regions that need it the most. For example, Öhler and Nunnenkamp (2014), Nunnenkamp et al. (2017), Briggs (2017), and Briggs (2021) do not find any evidence that donor's aid allocation takes regional needs into

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[2] Author's estimate based on the 8,000 Sri Lankan asylum seekers in 2018 multiplied by the years of conflict (26) gives 208,000. A realistic assumption is that during the height of the conflict a lot more than 8,000 Sri Lankans sought asylum in other countries.

[3] There are no official numbers. The estimate ranges from 1,000 to 40,000. UN estimates 40,000 (Al Jazeera, Nov. 28th 2013).

account and that aid flow to wealthier and more accessible regions than others. Nunnenkamp et al. (2017) additionally underline that bilateral donors face the same challenge as multilateral donors such as the World Bank in that it is not enough to target aid to poor countries with appropriate governance for aid to be effective. The locations within recipient countries where the need for aid is most obvious are just as important.

Various studies find various reasons as to why regions that need aid are not targeted. Öhler and Nunnenkamp (2014) argue that the regional aid allocation may reveal personal, regional, and ethnic favoritism in the recipient countries. The authors highlight that political leaders in these countries may direct aid funds to their home regions irrespective of local needs. The authors also find that conflicts discourage World Bank projects, albeit not African Development Bank projects. Briggs (2021) finds that the World Bank Task Team Leaders (TTLs) face career pressure to get many projects approved, and less importantly, to make sure that their projects are rated well internally and by the WB's Independent Evaluation Group (IEG). TTLs think aid projects are harder to implement in poorer places, rural areas, and remote parts (tarmac bias). Briggs (2021) speculates that perhaps aid is steered away from such areas because implementation is time-consuming, and incentive structures within the WB encourage TTLs to select easy implementation projects.

Additionally, Briggs (2021) finds that TTLs believe that recipient governments target aid to presidential home regions and their supporters. However, TTLs in Africa think it is difficult to get approval for projects targeted to presidential home regions, which could be why in Africa, Chinese aid favors presidential home regions and not World Bank aid. Öhler et al. (2019) find that aid is allocated to areas with higher population density than poorer areas. They also find that capital cities receive disproportionally higher shares of World Bank funding on average, which the authors guess is due to political economy considerations in terms of the visibility of projects. Furthermore, the authors emphasize that security considerations are likely to affect aid allocation in countries with security risks. This obviously presents a clear trade-off as areas exhibiting less security tend to be poorer. Hence, aid allocation patterns may positively correlate with more prosperous, safer areas. Lastly, Öhler et al. (2019) find that the fungibility of aid across sectors within countries plays an important role. Because aid being fungible, it might not be possible for donors to target specific ethnic, religious, or income groups since governments tend to adjust their own spending according to the aid they receive.

Due to these conclusions reached by previous work, this paper investigates aid allocation within one country that has experienced conflict for almost 30 years.

In Sri Lanka, the major causes of the almost three-decade-long conflict were inequality in education, job opportunity, urban development, benefits from agricultural development, and political exclusion. Since the end of the war, the government has focused on rebuilding and developing the island with help from international loans and aid. However, the picture painted by global media, researchers, activists, and the Tamil diaspora shows that the country still deals with many of the issues that existed in the pre-war period. This means that horizontal inequality seemingly is not corrected in the decade following the end of the conflict.

The conflict has left the northern and eastern regions severely destroyed. Those regions are predominantly populated by minority and marginalized ethnic groups such as Sri Lankan Tamils and Muslims (of which the majority's mother tongue is Tamil as well). Ideally, the expectation in such a scenario is that aid flow to those regions to rebuild after the conflict and create initiatives to reconcile these war-affected minorities with the rest of the population. If aid plays a vital role in sustaining peace in a country, as the literature on aid suggests (Ndikumana 2015, Boyce 2002), then the distribution of aid within a country is also important. Unfortunately, the distribution of aid within a country is not something prevalent in the literature on aid. This study will give an example of how to study and evaluate aid distribution within a nation. If aid is not equally distributed across the country and ethnic groups, then the gains from aid will be unequal. Unequal gains from aid undermine peace consolidation in a post-conflict country.

To understand whether conflict-affected districts are a priority in aid allocation in postwar Sri Lanka, we examine how districts were prioritized.

Thus, this study's research question is investigated by testing the following hypotheses through GIS mapping/analysis and econometric analysis:

- Hypothesis I: war-affected districts receive more aid than other districts.

  Similar to a natural disaster, one would expect that districts affected by aid would receive more aid than districts not affected by the war. Money is needed to rebuild such districts and bring back internally displaced people.

- Hypothesis II: Economically developed/wealthy districts receive less aid than other districts.

  If Hypothesis II is rejected, one could argue that the war-affected districts receive less aid than other districts because they are economically developed.

3. DATA

For this study, we merged four data sets. We used AidData for both the World Bank and China. In addition, we collected data aid data from Asian Development Bank's project reports using AidData's methodology as much as possible, and we used economic indicators from the Sri Lankan National Statistical Bureau.

AidData is referred to as 'World Bank Geocoded Research Release, Version 1.4.2'. The data was published in 2017 and covers the period 1995 to 2014. It includes all approved projects of the World Bank IBRD/IDA lending lines. The dataset tracks 5,684 projects across 61,243 locations. Moreover, it tracks $630.2 billion in geocoded commitments and $389.6 billion in geocoded disbursements. The amounts are deflated into constant 2011 dollars, except for transactions in 2013 and after. Those numbers are reported in current USD. For Sri Lanka, the dataset covers 2002-2015.

The Chinese projects are in a dataset that includes 3485 China-funded development projects implemented in 6190 locations in 138 countries from 2000 to 2014. In particular, this paper takes advantage of the dataset called 'oda-like_flows.csv'. For Sri Lanka, this data covers 90 projects over the specified time. The amounts in this dataset are deflated into constant 2014 dollars.

The third data set is constructed using the information on projects funded by the Asian Development Bank. There are projects from 1968 to 2017. Since this data is combined with Chinese and World Bank aid data, the relevant years are 2002-2014. That means that approximately 119 projects were extracted from the ADB's website and geocoded manually by the author. The amounts are reported in current USD, as far as one can tell from the website.

We removed projects with no specific geospatial identification for the three aid data sets, such as projects labeled 'country-wide' instead of a district or address.

Lastly, Sri Lanka's National Statistical Bureau provided average economic development indicators on the district level, albeit only for three years; 2009/2010, 2012/2013, and 2016. There are statistics from earlier years, but the war-affected districts are not covered. Since those districts are essential in assessing positive peace, those initial surveys are not included in this study. The variables gathered as economic development indicators fall in the following categories: Gini, poverty gap, energy consumption, education, material things owned by the households, and gender.

The units of observation are district averages, and in 2010 there are 22 districts in the survey. However, in 2013, there are 25 districts. Mannar, Mullaitivu, Kilinochchi are added from the northern region. One can assume that those districts were excluded from the 2010 survey because of war vulnerability. Unfortunately, we were unable to attain the underlying household surveys of the district averages. These household surveys are available only in person at the National Statistical Bureau in Sri Lanka.

Since all three data sets on aid projects are reported in different prices (some in current and some in constant with different bases), the author deflated the current prices to constant 2014 USD prices, and the constant 2011 USD prices were rebased to 2014 USD prices. All of this was done using the 'Gross domestic product (implicit price deflator), Index 2012=100, Annual, Not Seasonally Adjusted' series from the Federal Reserve Bank of St. Louis. More details on how the data sets were merged can be found in the appendix. The aid data and the economic development indicators were merged successfully using 'year' and 'district' as identifiers. The final database spans from 2002 to 2015 and contains 25 districts and a max of 350 observations. It should be noted that there are some 'aid' observations, which are 0. In this study, those observations are interpreted as 'the given district did not receive aid that year' rather than a missing observation.

Lastly, we added population density to our data set. Unfortunately, we were only able to obtain population density across districts for 2012.

In this paper, we study commitments for projects rather than disbursement. The biggest reason for this choice is because this is the data that is available for most donors. Briggs (2017) goes through some of the biases related to using commitments for projects. The author mentions two biases which are the following: (i) using commitments instead of disbursements will likely bias the results towards exaggerating how much aid, in fact, reaches the poor, (ii) using data on project aid will also likely lead to bias if one is trying to conclude the degree to which aid, in general, is controlled or targeted by donors. In particular, Briggs (2017) emphasizes that the biases might exaggerate how aid is targeted to the poor and aid reaches poor people.

3.1. Descriptive statistics

This section presents descriptive statistics of the data used for regressions.

Table 1 presents the summary statistics of all the variables used in the model estimations.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Aid (2014 USD, millions)	325	78400	133000	0	1120000
Computer (%)	47	12.08	7.18	1.4	38.8
No school (%)	47	4.13	1.84	.9	9.1
Kcal	47	2142.17	143.305	1825	2419
Poverty Gap	47	1.79	1.29	.3	6.2
Gini	47	.45	.045	.37	.57
Female (%)	47	52.57	1.11	49.7	54.5
Fridge (%)	47	34.71	15.56	3.2	74.7

A study on energy and nutrients amongst Sri Lankan adults by Jayawardena et al. (2014) finds that calorie intake by males was about 1900 compared to 1500 for women. Hence, the average across districts of 1541 seems very reasonable.

The poverty gap index is a measure of the intensity of poverty. It is defined as the average poverty gap in the population as a proportion of the poverty line. The poverty gap index estimates the depth of poverty by considering how far, on average, the poor are from that poverty line. According to the Department of Census and Statistics, the national poverty line in Sri Lanka in 2019 is Rs. 4849[4] PPPM, equivalent to approximately 27 dollars. A high poverty gap index means severe poverty.

A Gini coefficient of 1 (or 100%) expresses maximal inequality, whereas 0 expresses maximal equality. The national Gini coefficient was estimated to be approximately 0.4 in 2016[5], which suits the summary statistics.

Table 2 presents aid by the three donors included in the data set and the average amount of money they have committed to over the entire time period (2002-2014).

Table 2. Aid by donor over 2002-2014, in billion, 2014 USD

	N	Sum	Mean	Std .Dev
Asian Development Bank	157	17100	109	151
China	26	2100	80.9	130
World Bank	156	6300	40.4	52.5
Total	339	25500	230.3	333.5

[4] http://www.statistics.gov.lk/poverty/monthly_poverty/index.htm
[5] https://tradingeconomics.com/sri-lanka/gini-index-wb-data.html

As shown in Table 2, the ADB is the biggest donor, which intuitively makes sense since ADB has had a longstanding relationship with Sri Lanka. Both the World Bank and ADB have about the same number of projects during the selected time. China has few projects, but they are expensive.

Table 3 shows the average amount of aid committed to war-affected districts all years.

Table 3. Aid amount to war-affected areas over 2002-2014, in billion, 2014 USD

War affected districts (binary)	N	Sum	Mean	Std.Dev.
Not affected	208	17100	82.2	151
Affected	117	8360	71.5	95
Total	325	25460	78.4	133

Source: Author's computations

Table 3 shows that war-affected districts overall, on average, received less aid than non-war-affected districts.

Table 4 below shows the averages of the various variables for war and non-war districts and the differences in those means.

Table 4. Difference in means of variables, war/non-war

	Non-war districts	War districts	Difference
Computer (%)	13.647	8.740	4.907*
No school	4.491	3.347	1.144*
Kcal.	2160.000	2104.133	55.867
Gini	0.454	0.441	0.014
Poverty gap	1.472	2.460	-0.988*
Income	39351.219	30565.400	8785.819**
Fridge (%)	39.834	23.780	16.054***
Female (%)	52.719	52.253	0.465
Aid (billion USD)	38.37	36.37	2.00
Tamil share	0.030	0.586	-0.556***
Observations	47		

Table 4 shows a significant difference in the means of six variables; computers, no schooling, poverty gap, income, fridge, and share of Sri Lankan Tamils. In war districts, the share of households with computers is 4.9 percentage points lower than in non-war districts. It is not surprising that the poverty gap, on average, is higher in war districts. This is, similarly, true for income and the percentage of households with fridges. It is also not surprising that the share of Sri Lankan Tamils is significantly higher, on average, in war districts. It is puzzling that the average difference in means of no schooling is significantly higher in no-war districts.

One plausible explanation for this could be that the non-war districts are also the southern districts, still highly preoccupied with rural agriculture.

4. EMPIRICAL SPECIFICATION AND VARIABLES

The paper uses GIS analysis for geocoding, mapping, and analyzing spatial clusters combined with econometric analysis.

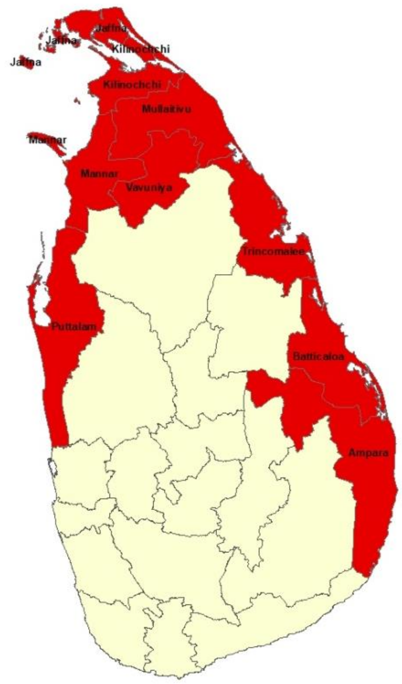
4.1. Econometrics methodology

One would assume that aid would flow to war-affected districts after a war. To investigate whether this is true, the following model is estimated using ordinary least squares (OLS):

$$\log\,(Aid\ amount)_{it} = \beta_0 + \beta_1 war\_affectd\_areas_{it} + \epsilon_{it} \qquad (1)$$

The period is, of course, different. In this regression, the time period is post-2009. The districts affected by the war are shown in Figure 1 below: Ampara, Batticaloa, Jaffna, Kilinochchi, Mannar, Mullaitivu, Puttalam, Trincomalee, and Vavuniya.

Figure 1. War affected districts



Notes: Created by the author using GIS and data from Sri Lanka National Statistical Bureau and Uppsala Conflict Data Program (Date of retrieval: 21/09/14) UCDP Conflict Encyclopedia: www.ucdp.uu.se, Uppsala University

This study specifies a second model to be estimated to investigate any potential bias further. The reasoning is that districts already doing well economically (or development-wise) should be expected to receive less aid than other districts. The model is specified as follows:

$$\log\,(Aid\ amount)_{it} = \beta_0 + \beta_1 war\_affectd\_areas_{it} + \boldsymbol{\beta}'\boldsymbol{X_{it}} + \epsilon_{it}, \qquad (2)$$

where $\boldsymbol{X_{it}}$ is a vector factor that includes development indicators such as education, poverty levels, and inequality, i indicate the districts, t indicates the year. The dependent variable' aid amount' is the log of aid in constant 2014 dollars, '*war_affected_areas*' is a binary variable taking the value 1 if the district was affected by the war and 0 otherwise. The districts included in that category are Ampara, Batticaloa, Jaffna, Kilinochchi, Mannar, Mullaitivu, Puttalam, Trincomalee, and Vavuniya.

In order to take time fixed effects and spatial correlation into account, all the models include year dummies and district clustering.

The econometrics in this study might suffer from some endogeneity problems. In particular, the models might have omitted variable bias since data is limited. The regressions on aid and war-affected districts include controls that are district averages instead of household-level because this is how the Sri Lankan National Statistical Bureau publishes their data. The endogeneity might cause somewhat biased results. This is why the GIS methodology adds a new layer of robustness to the results. If the pattern revealed by GIS and the results from econometrics are similar, we could conclude that the results tell a true story.

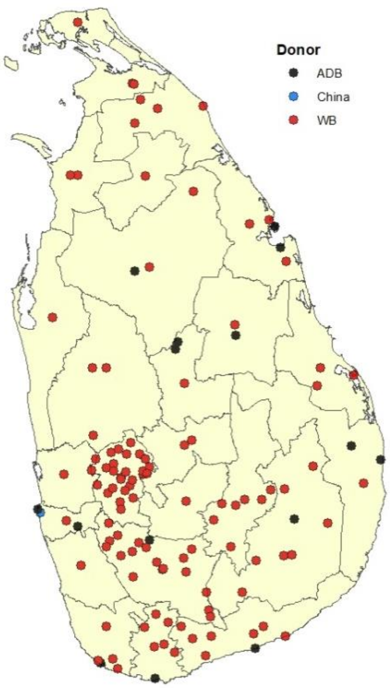
5. RESULTS

This section presents the findings from GIS and the econometric analysis. The first section presents the development in aid allocation over the years in Sri Lanka. Sri Lanka experienced a tsunami in 2004, which changed the aid allocation patterns in the country drastically. Hence, we show maps from before the tsunami, after the tsunami, and after the war.

5.1. The geographical allocation of aid projects

Figure 2 shows the aid projects sponsored by the World Bank, China, and the Asian Development Bank from 2000 to 2004. These are projects approved/committed to before the tsunami in late December 2004.

Figure 2. Project commitment, 2002-2005



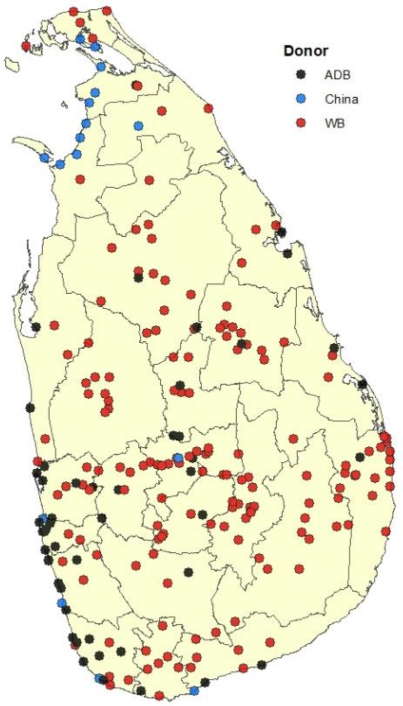
Source: Author's construction
Note: Sri Lanka district boundaries and the geocoded aid projects before the tsunami in December 2004 are the layers in this map. Aid projects are mostly prevalent in the southern part of the country, and the most active donor is the World Bank.

The map shows the geographical distribution of aid historically. The points shown on the map are simply the geographical indication without considering the amounts of money committed. The different symbols indicate different donors. It is worth noting that there are no Chinese projects reported on this map. This is because Chinese involvement in Sri Lanka only really started from approximately 2005 with President Mahinda Rajapaksa.

This map shows that most donor projects were allocated in the southern part of the country. There are very few projects scattered in the North, East, and Central regions.

One can explain this disparity by war. During this time period, the war in Sri Lanka was intense, and the LTTE had gained control over large parts of the northern and eastern regions. Aid could still come through to these areas, but because the LTTE wanted aid to go through them, the bureaucracy could have made those regions less attractive for aid projects from the donor's perspective. Furthermore, few NGOs would be interested in working in highly volatile war zones.

Figure 3. Project commitments in the post-tsunami period, 2005-2009



Source. Author's construction

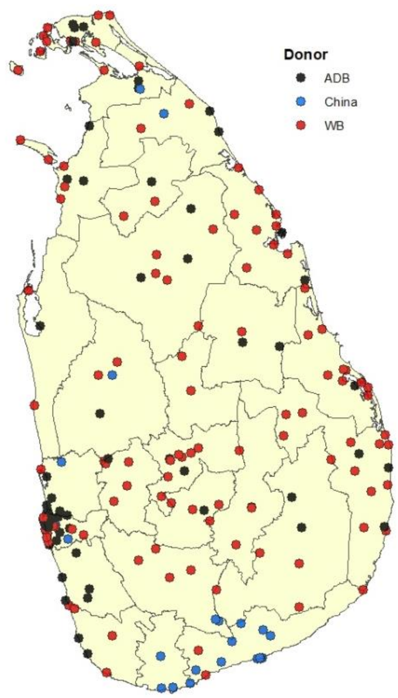
Notes: The layers included are Sri Lanka district boundaries and geocoded aid projects, 2005-2009. The number of projects on the island has increased and is more widely disbursed, but the southern part still dominates the aid projects.

The map in figure 3 shows the location of aid projects from 2005-2009. These are projects approved/committed after the tsunami until the year the war ended. After the tsunami, we can see that China became more involved in the Sri Lankan aid environment. Most projects are still located in the South and the Southwest regions, but there is a definite increase in projects in the central part of the island and some Chinese projects on the northern coast. However, there are fewer coastal projects than one would have expected.

This is surprising given the massive inflow of aid during this time after the tsunami. Everyone wanted to help tsunami victims. Holt (2011) estimated almost a doubling of aid from before to after the tsunami. McGilvray and Gamburd (2010) support the notion that this seemingly unequal distribution of aid could be due to what is popularly known as 'tarmac bias' in the development and disaster literature: "… the better roads and airport access meant that organizations and individuals with money – whether local or international – could more easily and quickly deliver aid to the south and west" (p. 29, McGilvray and Gamburd, 2010.

Additionally, patronage politics and corruption are essential factors in how aid was allocated during the post-tsunami period. Patronage and corruption continue to influence aid allocation even today. The Sri Lankan patronage political system allows powerful politicians to funnel money to where they want to. Since most Sri Lankan powerful politicians are Sinhalese, they assured that the majority of aid was allocated in the South and West of the country (McGilvray and Gamburd, 2010).

Figure 4. Project commitments in the post-war period, 2010-2014

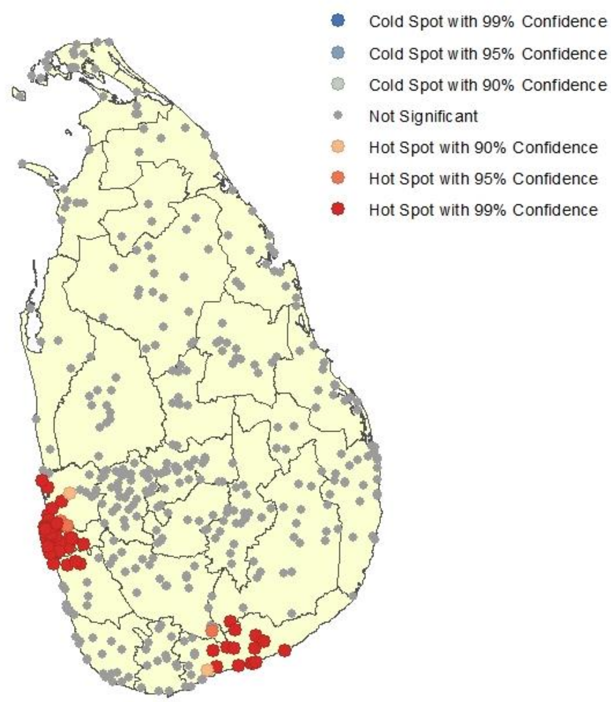


Notes: The layers included here are Sri Lanka district boundaries and geocoded aid projects. More activity from China and Asian Development Banks as donors, and more projects seem allocated to the northern and eastern parts.

The projects depicted on the map in figure 4 are the ones approved from 2010 to 2014. Similar to the maps in figures 2 and 3, the points shown are the geographical locations of aid projects, and the various symbols indicate donors.

It seems that projects are more concentrated in Colombo. From the map, an increase in Chinese projects in the South is obvious. Additionally, there are more projects in the North and the East than before and immediately after the tsunami.

Figure 5. Hot spot map of aid commitment amounts, 2002-2014



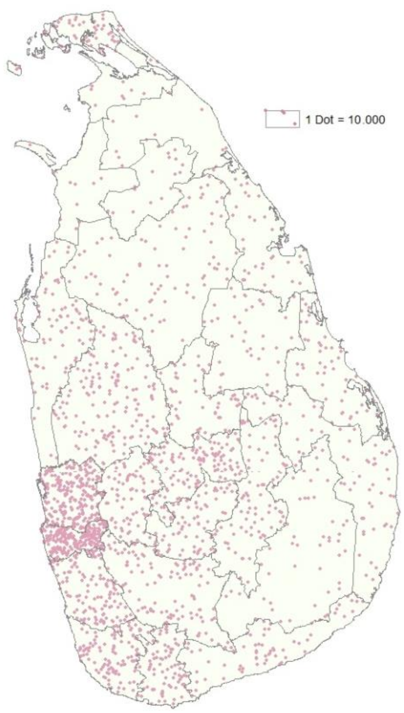
Notes: The layers included here are Sri Lanka district boundaries and geocoded project amounts analyzed into clusters. The ArcGIS website explains the methodology behind hot spot maps as follows "The Hot Spot Analysis tool calculates the Getis-Ord Gi* statistic (pronounced G-i-star) for each feature in a dataset. The resultant z-scores and p-values tell you where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features. A feature with a high value is interesting but may not be a statistically significant hot spot. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and when that difference is too large to be the result of random chance, a statistically significant z-score results. When the FDR correction is applied[6], statistical significance is adjusted to account for multiple testing and spatial dependency." (source: https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-hot-spot-analysis-getis-ord-gi-spatial-stati.htm).
The aid hotspots are in Colombo and Hambantota, which did not suffer through the conflict.

The map in figure 5 illustrates clusters of projects in terms of the amounts approved/committed, both significant and insignificant clusters. Up until now, we have only looked at the location of projects. However, this map is based on the amount of money in various places and tells us a more vibrant story. The map shows two highly significant clusters of projects throughout the 2002-2014 period, namely Colombo and Hambantota. The significant cluster of donor money in the Colombo district makes sense since many capacity-building projects would be allocated to the public sectors. Most public sector headquarters are located in the

[6] FDR is an abbreviation of False Discovery Rate. It is the expected proportion of type I errors or so-called false positives. A type I error is where one incorrectly rejects a null hypothesis.

capital city of Colombo. The money cluster in Hambantota., however, is a little surprising. However, it is commonly known that President Mahinda Rajapaksa is from that district and had a personal agenda in wanting to develop the region. He was also the President who brought China in as a significant donor to Sri Lanka. Hence, he likely played a role in influencing where the Chinese and other donations went.

Figure 6. Population density map, 2012



Notes: The layers included here are Sri Lanka district boundaries and population on districts from Sri Lankan Census 2012. The author constructed the map. The population is much denser in the southwest part of the country.

The map in figure 6 presents the population density in Sri Lanka in 2012. We might see clusters of projects or the absence of projects in individual districts because of high or low population density. Each dot in figure 6 is equivalent to 10,000. As can be seen from the map, there is a high population density in the Colombo district, where there are also many aid projects. Another thing to note is how sparsely the Northern region is populated. This, of course, is because of internal displacement due to the war and the tsunami. We will add population density to our regressions to make sure we control for the population.

5.3. Regression results

Table 5 presents the results of the estimation of equation (1) specified in the methodology. There are two variations of equation (1) shown in this table.

Table 5. War aid allocation, 2010-2014

	(1) Post-war	(2) Post-war
War	2.400	
	(2.474)	
Population density	0.003***	0.003***
	(0.001)	(0.001)
War*share_tamil		2.376
		(2.677)
Constant	19.013***	19.456***
	(2.385)	(2.160)
Obs.	47	47
Year dummies	Yes	Yes
R-squared :		
Within	0.66	0.66
Between	0.21	0.20
Overall	0.50	0.49

Note: The dependent variable is the log of real aid. (1) is the regression for the years 2010-2014. The binary variable War is not significant. (2) is also for 2010-2014, where the interaction term between the binary variable War and the share of Tamils in those districts is not significant. Population density is positive and significant in both regressions, while all regressions include year dummies.

Column (1) presents results from a simple regression of war-affected districts and aid commitments, accounting for population. The regression helps answer the question: 'Did war-affected districts get more aid?' War-affected districts include Ampara, Batticaloa, Jaffna, Kilinochchi, Mannar, Mullaitivu, Puttalam, Trincomalee, and Vavuniya. The model is estimated for 2010-2014, and it involves time-fixed effects.

Column (2) is the same as column (1) – the only difference is that the war-affected districts are split into predominantly Tamil and predominantly other ethnic groups. The predominantly Tamil war-affected districts are Batticaloa, Jaffna, Kilinochchi, Mannar, Mullaitivu, and Vavuniya.

The results of regressions (1) and (2) show that war does not have a statistically significant effect on aid allocation. Hence, the null hypothesis I is rejected. It is surprising and not following the original hypothesis, which assumed that war-destructed districts would receive more aid. However, our results follow the results from other literature on subnational aid allocation when accounting for population. Our results show that population density is positive and significant, which means that aid goes to densely populated places.

Since hypothesis I was rejected, there is scope to test hypothesis II: Does aid go to poorer districts? Many multilateral organizations, including the World Bank, want to target aid to poor people.

Table 6 presents the results from estimating equation (2) specified in the methodology section. The table includes eight variations of equation (2).

Table 6. Aid allocation, war, and level of development, post-conflict (2010-2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
War	2.400	2.406	0.536	0.677	2.612	2.016	1.537	3.577	3.072	0.728
	(2.474)	(2.538)	(2.725)	(2.492)	(2.611)	(2.443)	(2.388)	(2.970)	(2.503)	(3.666)
Population density	0.003***	0.003	0.002	0.002	0.003***	0.004***	0.003***	0.002	0.004***	0.002
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)
Computer (%)		0.003								-0.355
		(0.363)								(0.602)
No school			-1.168							-0.950
			(0.831)							(0.792)
Kcal.				-0.015						-0.012
				(0.013)						(0.022)
Gini					18.911					34.712
					(20.305)					(26.605)
Poverty gap						0.475				-0.116
						(0.851)				(1.678)
Female (%)							-1.593**			-1.378
							(0.652)			(1.263)
Fridge (%)								0.114		0.153
								(0.156)		(0.265)
Leader's birthplace									8.411***	7.456**
									(1.913)	(3.394)
Constant	19.013***	18.995***	25.348***	53.403*	10.475	18.109***	102.635***	15.769***	18.260***	106.166
	(2.385)	(3.560)	(4.948)	(27.546)	(10.468)	(3.451)	(34.002)	(5.475)	(2.472)	(97.448)
Obs.	47	47	47	47	47	47	47	47	47	47
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared :										
Within	0.66	0.66	0.65	0.66	0.67	0.66	0.69	0.66	0.65	0.71
Between	0.21	0.21	0.29	0.21	0.21	0.21	0.19	0.22	0.27	0.35
Overall	0.50	0.50	0.53	0.53	0.51	0.51	0.52	0.51	0.52	0.59

Robust standard errors are in parenthesis

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Dependent variable is the log of real aid. Regression (1) through (10) are for 2010-2015 (post-conflict). The variable of interest is the binary variable War since we want to know if conflict-affected districts receive more aid than others. The variable War is insignificant in all nine iterations of the regression. Population density is positive and significant, female (%) is negative and significant, and leader's birthplace is positive and significant.

Table 6 shows an OLS regression of aid commitment on household-level development indicators for the years after the war (post-2009). This exercise aims to investigate whether some districts did not receive aid because they were already wealthy. The development indicators include owning computers, fridges, education, calories, poverty gap, Gini coefficient, and female percentage in the district. We have also included population density and the birthplace of the leader. Öhler and Nunnenkamp (2014) include a similar variable in their analysis and find that areas where political leaders were born, were more likely to see more aid. Our maps in the GIS part of this analysis have already shown us that it looks like Hambantota receives more aid than others. The district of Hambantota is where the then President Mahinda Rajapaksa was born.

Because there are only about 47 observations of each economic indicator, the OLS regression is split up into nine regressions: (1) with just war and population density as regressors, and (2)-(9) with various development indicators. Each indicator is included separately to avoid a reduction of degrees of freedom. The regressions also include a time dummy to take time fixed effects into account. Additionally, the regressions are robust to district clusters.

We see across all the regressions that the 'war' dummy, indicating whether a district was affected by the war or not, is insignificant. This again suggests that in the case of Sri Lanka, war-affected areas did not receive more aid than peaceful districts.

In regression (1), (5), (6), (7), and (9), population density is positive and significant, again telling the story that aid flows to places that are more densely populated. In column (7), a one-unit increase in the percentage of females leads to an approximately 1.6 unit decrease in aid. Finally, in regression (9), we note that if the district is Rajapaksa's birthplace, then the district is 8.4 times more likely to get aid than another district.

The following tables show us the same regressions from table 6 but for each individual donor included in the sample, i.e., World Bank, Asian Development Bank, and China. We want to explore if the different donors prioritize different aspects of a country when deciding where allocation should go.

Table 7. Aid allocation, war, and level of development, post-conflict (2010-2014), World Bank

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
War	3.254**	3.453**	2.357	2.042	2.913**	3.059**	3.267**	4.340**	3.564**	3.355*
	(1.410)	(1.518)	(1.661)	(1.363)	(1.395)	(1.445)	(1.464)	(1.942)	(1.524)	(2.021)
Population density	0.002*	0.001	0.001	0.000	0.002*	0.002*	0.002*	0.000	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Computer (%)		0.110								-0.062
		(0.166)								(0.191)
No school			-0.566							-0.251
			(0.656)							(0.706)
Kcal.				-0.011						-0.002
				(0.007)						(0.014)
Gini					-32.085					-30.016
					(25.454)					(27.244)
Poverty gap						0.245				0.839
						(0.470)				(1.354)
Female (%)							0.025			0.194
							(0.680)			(0.706)
Fridge (%)								0.106		0.134
								(0.089)		(0.144)
Leader's birthplace									3.862**	4.048**
									(1.659)	(1.948)
Constant	16.919***	16.236***	19.988***	41.304***	31.413***	16.454***	15.611	13.899***	16.574***	20.324
	(2.633)	(3.076)	(4.035)	(15.827)	(10.767)	(2.887)	(35.805)	(4.255)	(2.762)	(52.450)
Obs.	47	47	47	47	47	47	47	47	47	47
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared :										
Within	0.82	0.82	0.82	0.82	0.84	0.82	0.82	0.82	0.82	0. 84
Between	0.45	0.46	0.49	0.50	0.43	0.45	0.45	0.49	0.47	0.51
Overall	0.73	0.73	0.73	0.74	0.74	0.72	0.73	0.73	0.73	0.76

Robust standard errors are in parenthesis

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Dependent variable is the log of real aid for the World Bank. Regression (1) through (10) are for 2010-2014 (post-conflict). The variable of interest is the binary variable War since we want to know if conflict-affected districts receive more aid than others. The variable War is significant and positive 8 out of 10 regressions. Population density is positive and significant in 5 out of 10, and the leader's birthplace is positive and significant.

Table 8. Aid allocation, war, and level of development, post-conflict (2010-2014), Asian Development Bank

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
War	4.956	5.804*	1.654	4.399	5.160	5.538	3.179	6.429	5.415*	1.759
	(3.109)	(3.228)	(3.231)	(3.504)	(3.214)	(3.383)	(3.441)	(4.181)	(3.209)	(6.608)
Population density	0.001	-0.003	-0.001	0.000	0.001	0.001	0.001	-0.001	0.001	-0.006
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.005)
Computer (%)		0.467								0.442
		(0.419)								(0.776)
No school			-2.084***							-1.603
			(0.692)							(1.181)
Kcal.				-0.005						-0.003
				(0.010)						(0.026)
Gini					19.167					38.691
					(32.613)					(37.436)
Poverty gap						-0.731				-0.295
						(0.908)				(2.304)
Female (%)							-3.418***			-4.155**
							(1.057)			(1.748)
Fridge (%)								0.144		0.054
								(0.168)		(0.389)
Leader's birthplace									5.698***	-1.511
									(1.917)	(4.107)
Constant	9.060***	6.159	20.368***	20.274	0.401	10.447***	188.585***	4.967	8.551***	222.417*
	(3.182)	(4.426)	(5.255)	(23.050)	(14.906)	(3.577)	(55.990)	(5.804)	(3.253)	(121.469)
Obs.	47	47	47	47	47	47	47	47	47	47
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared :										
Within	0.13	0.17	0.21	0.14	0.15	0.13	0.36	0.14	0.13	0. 51
Between	0.17	0.19	0.23	0.16	0.15	0.21	0.04	0.22	0.20	0.17
Overall	0.14	0.16	0.23	0.14	0.15	0.15	0.25	0.16	0.15	0.38

Robust standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Note: Dependent variable is the log of real aid for the Asian Development Bank. Regression (1) through (10) are for 2010-2014 (post-conflict). The variable of interest is the binary variable War. The variable War is significant and positive in (2) and (9). Leader's birthplace is positive and significant, no_school and female (%) are significant and negative.

Table 9. Aid allocation, war, and level of development, post-conflict (2010-2014), China

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
War	0.244	-0.487	0.326	0.683	0.364	-0.211	0.051	-0.986	0.719	-0.240
	(1.422)	(1.310)	(1.387)	(1.317)	(1.445)	(1.231)	(1.276)	(1.282)	(1.189)	(1.033)
Population density	-0.001	0.002**	-0.000	-0.000	-0.001	-0.000	-0.001	0.001	-0.000	0.003**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
Computer (%)		-0.358**								-0.416*
		(0.148)								(0.214)
No school			0.051							-0.496
			(0.229)							(0.313)
Kcal.				0.004						0.004
				(0.005)						(0.007)
Gini					11.314					14.007
					(8.889)					(10.053)
Poverty gap						0.514				0.199
						(0.591)				(0.826)
Female (%)							-0.355			0.633
							(0.371)			(0.629)
Fridge (%)								-0.113*		-0.021
								(0.064)		(0.081)
Leader's birthplace									7.664***	9.424***
									(0.598)	(1.129)
Constant	0.349	2.536**	0.070	-8.459	-4.762	-0.648	19.012	3.518*	-0.399	-42.699
	(0.443)	(1.227)	(1.101)	(11.932)	(4.014)	(1.330)	(19.298)	(1.954)	(0.467)	(45.448)
Obs.	47	47	47	47	47	47	47	47	47	47
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared :										
Within	0.09	0.14	0.09	0.11	0.12	0.09	0.07	0.10	0.09	0. 21
Between	0.22	0.35	0.22	0.20	0.23	0.21	0.26	0.30	0.30	0.61
Overall	0.09	0.18	0.09	0.09	0.09	0.10	0.10	0.14	0.23	0.40

Robust standard errors are in parenthesis
*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Note: Dependent variable is the log of real aid for China. Regression (1) through (10) are for 2010-2014 (post-conflict). The variable of interest is the binary variable War. The variable War is insignificant in all instances. Leader's birthplace is positive and significant, computer (%) and fridge (%) are significant and negative.

Table 7, showing regressions for World Bank, we see that war is significant and positive and, on average, about 3 times more likely to get aid than other districts. This is the result we were hoping to see. We also see that population density still seems to be an important explanatory factor in several instances. Lastly, the results show that the leader's birthplace is 3.9 times more likely to receive aid than other districts.

Table 8, with results from Asian Development Bank, shows that 'war' is only significant in (2) and (9), but in both instances, the coefficient is positive, indicating that war districts are 5 times more likely to receive aid than other districts. We do, however, also find in (3) that 'no_school' is significant and negative, which is also true for 'female (%) in (8). 'No_school' being negative could indicate that Asian Development Bank does not prioritize poorer districts, as those districts would have less educated people. Lastly, on account of the leader's birthplace, we see that Hambantota is 5.7 times more likely to receive aid than any other district.

Looking at China as a donor in table 9 shows us that 'war' is insignificant and that population density is only positive and significant in regression (2) and (10). However, in (2), we find that a 1% increase in population with computers leads to a 0.36 decrease in aid. Similarly, (8) shows that a 1% increase in the population with fridges leads to a 0.11 decrease in aid. Both regressions could indicate that at least China does not target aid to wealthier districts. Nonetheless, the leader's birthplace is also here positive and significant and suggests that the district is 7.6 times more likely to receive aid than other districts,

6. DISCUSSION

The results from the analysis, both GIS and econometric, showed that donors do not follow the needs of the war-affected districts when deciding where to allocate aid. There could be many reasons for this pattern, and one of the most common explains in the aid literature is that the poorer districts are harder to reach than the more infrastructurally developed places. However, Moramudali (2019) writes that from 2009 to 2013, 221 billion Sri Lankan rupees (equivalent to 12 billion USD) were spent on infrastructure development programs. In fact, the Sri Lankan government made the biggest public investment in the Vanni of the Northern province (>USD 2 billion) since independence between 2010 and 2014. Additionally, the A9 highway from Kandy to Jaffna was renovated and opened in 2009. In this author’s opinion tarmac bias does not seem very plausible compared to the explanation given by Sarvananthan (2016). He gives the following explanation for why development continues to lack behind in the conflict affected districts:

> "It [infrastructure development] was a blanket approach throughout the country. There were no attempts to identify the specific circumstances and priorities circumstances and priorities of the people of different provinces and districts, especially of the former conflict affected provinces." (p.574, Sarvananthan 2016).

The government has been focused on infrastructural rebuilding after the war and high-cost beautification development projects in Colombo city that are not focused on the reconciliation of the ethnic groups or rebuilding the war-affected districts. These beautification development projects in Colombo city may be why we see big clusters of aid projects in the Colombo district.

Another big cluster of aid projects was found in Hambantota, where the then President Mahinda Rajapaksa is from. Looking at both the aggregate aid level and at the individual donors, we see that Hambantota has had a very high influx of aid projects. The district is not very densely populated, nor did it already have the potential for becoming a significant trade port compared to other coastal districts. The district only distinguishes itself from other districts in that it is the home district of the entire Rajapaksa family that has taken over the Sri Lankan government.

Political patronage is a crucial thing in Sri Lankan public resource allocation. For example, when this author traveled to Vanni in 2017(one of the areas that were most affected by the war), the author spoke with some women who had lived in the same house throughout the war. These women told the author that the central government allocated (and continues to allocate) plenty of money to the Northern Province after the war. However, because the politicians were unqualified to manage the budget and spend it on job creation or education, or other rebuilding programs, most of the budget was sent back to the Central Government at the end of every year. Whether this is true or not is less important than the fact that this is what they believed about the allocation of resources in Sri Lanka and the capacity of their own politicians. It so happens that these women were entirely correct. In addition, I spoke with an activist from Jaffna, who told me that immediately after the first election in the Northern Province for the Northern Province Council (NPC) in 2013, there was a substantial discussion of the NPC's failure to utilize the funds provided to them. The activist remembers that approximately 40 % of the funds were sent back to the central government. This is an area where more aid projects focusing on training the politicians to make long-term plans and administer big budgets in sustainable ways and informing about democracy would have been fruitful.

It does seem that donors value the path of least resistance when deciding aid allocation (Briggs (2017) goes over several reasons why this is the pattern amongst donors). First, the war-affected districts should have been a priority for donors and the central government in the postwar environment. Because at the end of the day, donors and recipient governments are both involved in aid allocation decisions. However, simply throwing money at a problem has rarely resolved anything, especially when it is not combined with proper guidance. Second, donors need to know a country's history and the intricate political situation that exists after a conflict. Third, donors need to do a better job working with more local governments and grassroots organizations, ensuring that the local populations are part of the decision-making process and help donors identify where they can make a difference. Finally, if aid is given to help or maintain country relations, donors and central governments must prioritize reconciliation when allocating aid in post-conflict countries.

7. CONCLUSION

Our study contributes to filling a crucial gap in the aid allocation literature, which has mostly focused on cross-national aid allocation, whereas our paper focuses on aid allocation within one single post-conflict country.

Our study does not find that aid is targeted to the areas that actually need it on an aggregate level. Additionally, our results support the notion that aid tends to find its way to the country's leader's birthplace. This is a very problematic result.

However, the aggregate aid accounted for in this study makes out approximately 40 percent of total aid commitments from all donors in the 2002-2014 period. Therefore, our findings may not carry over when all donors are included. Moreover, when we broke down aggregated aid by donor, the World Bank allocation behavior does seem to differ from the China and Asian Development Bank.

Future work could include more on recipient government preferences over aid targeting. Maybe the governments are the problem and not the donors. Another important angle in within country aid allocation for future research could be the type of aid projects allocated to poorer regions. Could the types of projects be targeted even if the aggregated amounts of aid are not?

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Appendix

Further Data Details

The subset data called 'level 1a' from the 2017 data set provided by AidData was used for the World Bank aid data. The time indicator chosen in this study is the variable named 'approval year' while the variable of interest (aid amounts) is the variable named 'even_split_commitments'. This particular variable was selected because some donors commit an amount for several projects without clarifying how much is going to which project. To avoid looking through several hundred project reports, the 'even_split_commitments' variable averages the total amount committed by the donor on the total number of projects.

For the Chinese aid, the time indicator is 'transaction start year'. A variable similar to 'even_split_commitment' was created based on 'project_total_commitment'.

This study uses a variable containing commitments instead of disbursement because the Chinese data and the Asian Development data have little information on disbursements. One issue with this is that there is often a significant difference between what donors commit to and what gets disbursed. Thus, this study will not be able to evaluate aid projects in the traditional sense. However, we will be able to comment on the donors' political agendas intentions based on their aid commitments.

Collecting aid data from the Asian Development Bank required going through all project reports in Sri Lanka by the Asian Development Bank from 2002 to 2014. The data collected consists of commitment amount, year of project approval, project categories, and geographical locations (districts).

The three data sets were merged using 'year'. After merging projects categorized as 'Nation-wide' or 'Sri Lanka' were excluded. All projects without geolocation were also removed.

To include the economic development indicators, which are district averages, the aid data needed to be on the district level as well. Therefore, the aid data was coded at precise GPS location and not divided into districts (except for the ADB data). GIS was used to transform the data into district-level data. In particular, the ArcGIS 'Intersect' tool was used: a layer of districts only was created and then 'intersected' with the geocoded layer, which allowed the geolocations to be sectioned out on districts.

After extracting the aid data on district levels, the aid series had to be within donor, within a district, and within a year to be merged with the economic development indicators.