Illuminating the Economic Costs of Conflict: A Night Light Analysis of the Sri Lankan Civil War

Nicholas Kiran Wijesekera

Professor Charles Becker, Faculty Advisor
Professor Michelle Connolly, Faculty Advisor

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Abstract

This paper investigates the economic consequences of the Sri Lankan Civil War (1983-2009) by using event-based data on civilian and combatant fatalities in addition to night light imagery as a proxy for economic activity. By looking at regional economic activity across the island of Sri Lanka, this paper seeks to identify how violence led to declines or undershoots of economic activity in the areas in which it was most prevalent. The use of night light data gives a hyper-localized proxy measurement of this activity for each year of the war. The investigation finds that government and rebel deaths have strong, negative effects on economic activity, and that these effects spill over across time and space. Additionally, the manner in which civilian deaths occur is an important determinant of their subsequent economic impact. The paper offers new findings on the economic legacy of the Sri Lankan Civil War and extends existing work on the use of night light data to measure economic activity during conflict.

JEL Codes: H56, N45, O53

Keywords: Sri Lanka, Civil War, DMSP-OLS Night Lights

I. Introduction

For 26 years Sri Lanka suffered the brutal consequences of a civil war sparked by ethnic tensions that claimed the lives of up to 100,000 people- including tens of thousands of civilians. The Liberation Tigers of Tamil Eelam (LTTE, also known as the Tamil Tigers) launched a multi-year insurgency (1983-2009) against the Sri Lankan government with the strategic aim of creating an independent Tamil state in the north and east of the country. At its peak, the LTTE controlled 76% of the Northern and Eastern provinces of Sri Lanka (United Kingdom: Home Office, 2016). While the conflict featured sporadic attacks on government and civilian targets throughout the country, the worst effects were faced by the north and east of the country. Here, the population experienced direct violence, constant threats of future violence, and various restrictions on the movement of people and goods.

Estimating the extent of the economic devastation caused by conflicts is always difficult. Data on the intensity of conflicts are often hard to measure, subject to misreporting incentives, or generally impeded by the ‘fog of war’. Similarly, data on economic activity during wars are notoriously difficult to collect. This holds with regard to the Sri Lankan Civil War as well. The 1991 census was canceled, and the 2001 census omitted the north and northeast. No other major household survey covered the entire country during the war. LTTE administration of large areas also means that firm records, tax receipts, or other measures are not readily available.

This paper seeks to address this issue in two ways: event-based data on fatalities from the Uppsala Conflict Data Program (UCDP) serve as a measure of conflict intensity, and Defense Meteorological Program-Operational Linescan System (DMSP-OLS) night light imagery is used as a proxy for economic activity. The UCDP is a widely cited authority on armed conflict and civil wars, while the use of DMSP-OLS night light data to measure GDP is well-established in the literature (Henderson, Storeygard, and Weil, 2012; Ebener et al., 2005). The latter has proved particularly useful in cases where available data may be unreliable. This includes countries experiencing natural disasters, authoritarian regimes, and most notably, conflict.

Figure 1: Map of Sri Lanka and areas claimed for independent Tamil state (Olason, 2010)

This paper investigates the extent to which outbursts of violence suppress economic activity in surrounding areas during the war and in its immediate aftermath. The use of night lights data gives a hyper-localized proxy measurement of this activity each year from 1992 onwards. This approach is particularly important because of the rapid growth the country as a whole experienced during the civil war years. Sri Lanka's economy grew significantly from 1983 to 2009, with real per capita GDP rising at an average annual pace of approximately 4.5% (World Bank Open Data n.d.). This eclipses most of the country's South Asian neighbors and greatly exceeds the growth seen by other countries that have suffered from major internal conflicts. Therefore, there are certainly challenges when evaluating the response of the wider economy to the conflict. By looking at regional economic activity across the island, this paper seeks to identify how violence led to declines or undershoots of economic growth in the areas in which it was most prevalent. The legacy of this fighting can still be seen today in the economic struggles of the affected areas. Poverty rates in the Northern and Eastern provinces are roughly triple the levels along Sri Lanka's western coast, and per capita manufacturing output in the Northern Province was just $72 in 2014 compared to $1,262 in the Western province where the capital is located (Mundy, 2017).

Overall, this paper makes three primary contributions. First, it adds to the literature on the economic consequences of civil wars, helping to highlight what elements of conflict may be most costly. Second, it extends work using Nighttime Lights (NTLs) as a means through which to study economic activity during wars. Finally, it adds to the sparse available research on the economic costs of the Sri Lankan Civil War. The paper finds that rebel and government deaths are strongly associated with a decrease in nighttime lights, with 100 deaths implying changes of -23% and -14% respectively. Significant effects are also found for temporally and spatially lagged violence. Further, once civilian fatalities are separated by war zone deaths and deaths resulting from targeted attacks, the former exhibits a very large negative impact on lights while the latter is positively associated with luminosity, likely reflecting the endogeneity of these attacks.

The rest of the paper proceeds as follows. Section II offers a brief historical overview of the Sri Lankan Civil War. Section III reviews the existing literature on night lights, economic activity during conflicts, and the Sri Lankan Civil War. Section IV describes the data used in the paper. Section V outlines the empirical strategy. Section VI presents the results, and section VII discusses the findings. Section VIII concludes.

II. Historical Background

From 1983 to 2009, the Sri Lankan Civil War varied dramatically in both its intensity and geographic scope. The fighting consisted of conventional warfare, guerilla tactics, terrorist attacks, and retaliatory killings. War was preceded by years of ethnic tension and mistreatment of the minority Tamil population that eventually led LTTE leader Velupillai Prabhakaran to launch a violent quest for independence (Haelig, 2017). Other pro-Tamil groups also emerged during this time including the PLOTE, EPRLF, and LTTE-K, although their influence was limited.

The roots of the conflict can be traced back to British colonialism, following the conclusion of which in 1948, the majority Sinhalese population felt angered by what they perceived as favoritism by the colonial rulers towards Tamils. In the following years, the Sinhalese majority government passed numerous laws disadvantaging and disenfranchising the Tamil minority. Examples include the Sinhala Only Act in 1956- making Sinhala the only official language and creating barriers for Tamils entering the civil service- as well as the standardization policies of the 1970s, which made admission into universities disproportionately difficult for Tamils (Anandakugan, 2020).

The eruption of hostilities was marked by an LTTE ambush that killed 13 Sri Lankan Army soldiers in the north of the country in July 1983. This sparked anti-Tamil riots across Sri Lanka, killing thousands and displacing many more. The following years involved a series of suicide bombings by the LTTE and retaliatory killings by the Sri Lankan Army and Sinhalese mobs. In 1987, India- having been involved in arming both sides of the conflict- sent in peacekeepers to enforce an agreed disarmament deal. Meanwhile, the Sri Lankan government turned its attention to quashing an armed insurrection in the south by the Marxist-Leninist group the Janatha Vimukthi Peramuna (JVP) from 1987 to 1989. The Indian presence lasted three years before the force was withdrawn following heavy losses during clashes with the LTTE. In the spring of 1995, a second ceasefire- agreed in January of that year- collapsed, and the government launched a major counter-offensive to retake Jaffna (the largest city in the north). Eventually, a Norwegian-negotiated ceasefire in 2002 was able to hold, partially due to the devastation the country experienced at the hands of the 2004 Indian Ocean tsunami. The pause lasted until 2006 when more fighting erupted. The war entered its final stages in 2008 when a newly-elected government launched a massive offensive, taking back most of the northern and eastern territory including the insurgents' capital of Kilinochchi. The official conclusion of the war was declared in May 2009 after the government encircled the final LTTE fighters and killed Prabhakaran (Williams & Weaver, 2009). Estimates of civilians killed in the final stages of the war are as high as 40,000, as the LTTE trapped them as human shields and the Sri Lankan government proceeded to indiscriminately shell the small pocket of land on the north-east coast occupied by the LTTE and civilians alike (United Nations, 2011).

During the 26 years, the war saw numerous high-profile events, from the assassinations of former Indian Prime Minister Rajiv Gandhi and Sri Lankan President Ranasinghe Premadasa to suicide bombings on civilian targets across the country. Since its conclusion, the country has remained remarkably peaceful, with the violence of the previous decades virtually nonexistent (Sundberg & Melander, 2013).

III. Literature Review

Nighttime Lights and Economic Activity

The relationship between satellite measures of night lights and economic activity is well-established in the literature. The underlying framework for this relationship is that electricity use, and thus lighting, increases with income and therefore can be used as an indicator of economic development. Using night lights can capture this development through two mechanisms: expansion across space and intensification (Hu & Yao, 2019). In the seminal paper on this issue, Henderson et al. (2012) use night lights from the United States Air Force Defense Meteorological Satellite Program (DMSP) to augment official GDP statistics for 188 countries from 1992-2008. They find a statistically significant elasticity of around 0.3, indicating that a 1% increase in night lights corresponds to a 0.3% increase in GDP. Additional research has shown that this relationship holds at the subnational level (Ebener et al., 2005) and can further be used to predict a host of other well-being indicators such as poverty rates and technology access (Ghosh et al., 2013).

The value of night lights in measuring economic activity lies in their availability in contexts where other sources of data might be unavailable or unreliable. Martínez (2018) uses night lights to study the extent to which dictators 'lie' about official GDP statistics. The author finds that the night light elasticity of GDP- the increase in officially quoted GDP corresponding to an observed unit increase in night lights- is significantly higher for autocratic regimes and uses this as evidence of manipulation. Gillespie et al. (2014) study the applicability of night lights in a post-disaster setting. Looking at the 2004 Indian Ocean Tsunami in Indonesia, the authors find that night lights track closely with per-capita expenditure data and can be used to assess the path of recovery across different areas in lieu of a more costly and delayed household-level survey.

Night Lights and Conflict

War zones are a natural application for the use of night lights in studying economic activity because of the extreme difficulties in obtaining accurate data. Ongoing clashes, the threat of violence, or the administration of areas by non-state forces means that traditional data collection methods are often impossible. Though not the focus of the study, Henderson et al. (2012) makes reference to the potential use of night lights in studying conflict. The paper shows images of Kigali from 1993-1996 to exhibit the extent of the decline in night light activity during the Rwandan Genocide and civil war. A study of the wars in Georgia and Russia's Caucus regions between 1992-2009 finds that nighttime lights could accurately detect major refugee movements during the conflicts (Witmer & O'Loughlin, 2011). Further, using night light data from Somalia, Shortland et al. (2013) finds a significant 'peace dividend' for poorer households whereby night lights in lower-income areas rebound strongly during low-violence years. The study also notes that violence in the capital- Mogadishu- has positive effects in absolute terms on night lights in cities with international aid networks.

This paper will seek to examine the effect that conflict intensity has on nighttime lights in Sri Lanka. This dynamic has been explored by Dodd (2021) and Kanj (2022) in the context of the Bosnian Civil War and the Ukrainian War in the Donbas, respectively. Both authors find an initial decrease in night lights during the onset of the war, followed by a slow recovery. Dodd also finds that the type of conflict (siege, conventional, etc.) has a significant impact on the effect on night lights.

Impact of Civil Wars on Economic Activity

The impact of wars on economic activity has been widely studied due to the frequency with which conflict interrupts economic development. Wars typically damage economies through two primary mechanisms: the opportunity cost of factors employed in war, and the direct destruction of capital (physical, human, social, etc.). The former has been studied extensively, primarily through the lens of increased defense spending crowding out other productive investments. Developing countries tend to increase defense spending on average from 2.8% to 5% of GDP during civil conflicts and there is evidence that governments disproportionately divert funding from important public goods to finance these wars (Collier et al., 2003). The latter mechanism includes the loss of human capital (through casualties and outmigration), social capital, infrastructure, and other capital goods. Analogously, the looming threat of violence alone can have a host of consequences that hurts the economic prospects of a country. Cullen & Colleta (2000) find that during wartime, people invest less and return to subsidence activities that are less vulnerable to the destruction of war. Evidence from the Rwandan Civil War shows that these effects can be lasting, with households that experienced more intense conflict lagging behind six years later and high-conflict zones having persistently different returns to land and labor than low-conflict zones (Serneels & Verpoorten, 2015). Overall, countries experiencing civil war grow around 2.2 percentage points more slowly than during times of peace in real terms (Collier 1999).[1] This implies that a seven-year war would leave incomes 15% lower than the corresponding counterfactual and result in absolute poverty being 30% higher.

For the purposes of this study, finding similar conflicts in terms of scope, scale, and duration is important when considering the economic impact of the Sri Lankan Civil War. Looking at the outbreak of fighting in the Basque Country- a long-lasting but lower-intensity conflict- Abadie and Gardeazabal (2003) find that GDP in the region declined by 10% compared to a synthetic control. Further, they use a truce as a natural experiment to show that a high degree of deviation in stock prices of companies with significant business in the region could be explained by levels of violence. Another paper shows that in Pakistan the elasticity between

[1] Collier's study is based on a sample of 92 countries between 1960 and 1989, 19 of which experienced civil wars. Collier's work is a seminal paper on the impact of civil conflicts

terrorist attacks and percapita GDP was -0.39 (Hyder et al., 2015). This is noteworthy because terrorism is in some ways analogous in form to the guerilla tactics and suicide attacks used by the LTTE.

There are still gaps in the literature on the economic effects of long-term guerilla-style conflicts. Some evidence from Afghanistan suggests that the duration and nature of wars may alter their economic impact. Bove and Gavrilova (2014) find that while impacts from insurgent attacks are limited, International Security Assistance Force (ISAF) troop deployments have a much larger effect on commodity prices and wages. The authors propose that because of the ongoing insurgencies over the past 30 years of the conflict, locals have developed coping mechanisms that limit the impacts of these events. The arrival of ISAF soldiers presents a novel challenge that introduces more uncertainty.

Economic Impacts of the Sri Lankan Civil War

Current literature on the economic effects of the Civil War in Sri Lanka remains limited. Several studies conducted during the war attempted to estimate costs incurred by Sri Lanka up to that point in time. Arunatilake et al. (2001) find that the cost of the conflict between 1983-1996 may have been at least twice the country's 1996 GDP. The authors examine direct costs (military expenditure, destruction of infrastructure, etc.) and indirect costs (lost foreign investment, reduced tourist arrivals, forgone public investment, etc.) to arrive at this estimate. They find that foreign investment, military expenditure, and reduced tourism were the most impactful channels. However, the lack of available data forces the authors to make numerous simplistic assumptions such as new remittance flows exactly offsetting losses from emigration, half of displaced people finding work, and output declining by 50% in the north. Further, the analysis does not extend through the end of the war.

Other studies suffer from similar limitations imposed by the availability of data. Richardson and Samarasinghe (1991) estimate the cost of the war between 1983-88 as 62% of GDP but rely on assuming a counterfactual growth rate based on pre-war GDP growth from 1978-1982. Bandara (2007) cites trade group claims that the tourism industry could have made SL Rs 16.5 billion ($330 million at 1995 exchange rates) in additional foreign exchange in 1995 if Sri Lanka's security and economic conditions had been better. Another study looking at military spending and growth finds that defense spending, in comparison to non-military spending, only minimally increases GDP and that therefore Sri Lanka might enjoy significant economic benefits by ending the war (Wijeweera & Webb, 2009). Finally, writing after the war, Ganegodage and Rambaldi (2014) construct a measure of 'war effort' using ratios of military expenditure to GDP and armed forces personnel to labor force participants and find that a one percent increase in war effort leads to a corresponding 0.09 percent decrease in GDP. These effects are detectable in both the short and long run.

IV. Data

Nighttime Lights Data

To measure nighttime lights, this paper uses the Defense Meteorological Program's Operational Linescan System (DMSP-OLS). The program was established in the 1970s for the original purpose of detecting moonlit clouds but has found a new use in its ability to record nighttime lights. Archived data are available from 1992 through 2013. Each night, between the hours of 8:30 and 10:00 pm local time, DMSP satellites record imagery of visible and near-infrared (VNIR) emissions from human activity. This imagery is then cleaned by the National Oceanic and Atmospheric Administration (NOAA), removing the interference introduced by fires, auroral activity, and lunar luminescence, before being released (Henderson et al., 2012). Light emissions from gas flares are still present in the data, though the lack of such installations means this is not an issue for studying Sri Lanka. Typically, annual composites are used to smooth noise introduced by seasonality.

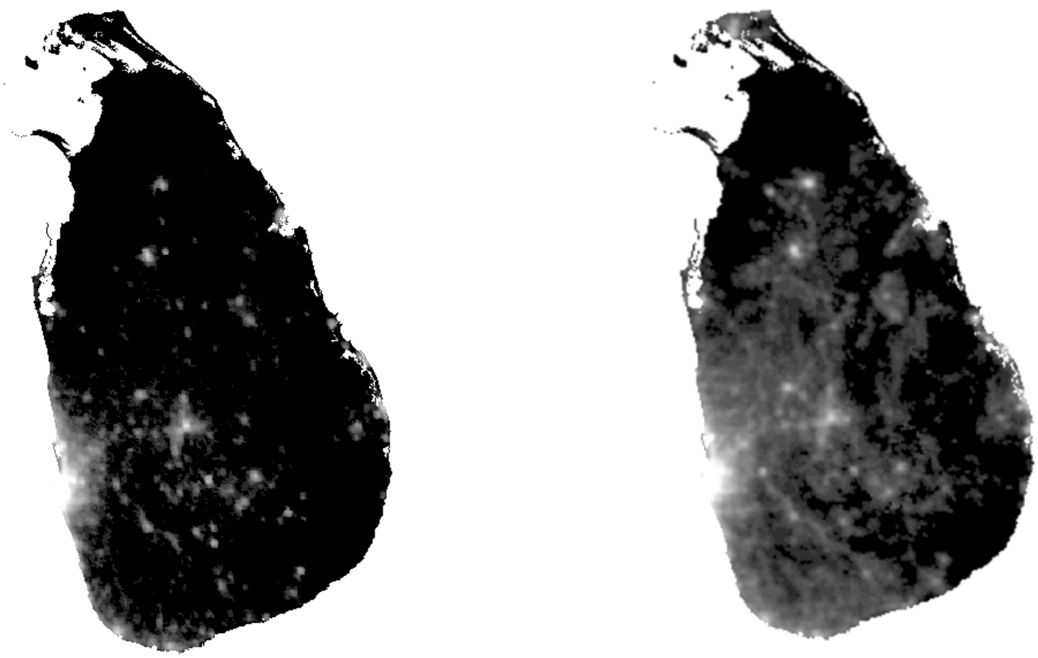

Figure 2: DMSP-OLS imagery of Sri Lanka from 1992 (first available data) and 2009 (final year of war)

Individual pixels in the released imagery correspond to 30 arc-second grids or around 0.86 km^2 at the equator. As the satellites have no onboard calibration mechanism, a Digital Number (DN) is reported rather than radiance. This number ranges from 0-63, with 0 representing a remote area like a jungle or agricultural field, and 63 representing a dense urban core. These arc-second grids span from -180 to 180 degrees longitude and -65 to 75 degrees latitude (Observation Group n.d.). For the purposes of this study, a given district's luminosity value will be calculated as the natural logarithm of the sum of its constituent pixels. The natural logarithm is used to reduce heteroskedasticity as conducted by Henderson et al. (2012). There are 77,679 individual pixel measurements for Sri Lanka each year, ranging from values of 0 to 63. The mean pixel value in 1992 was 1.78 as compared to 4.24 in 2009.

Satellite Calibration

The DMSP-OLS Nighttime Lights Series requires calibration for two main reasons. First, the satellites taking measurement change every few years, which may affect measured luminosity because, without on-board calibration, different devices may report different luminosity values.[2] Secondly, even if measurements from the same satellites are used, factors such as varied atmospheric conditions and sensor degradation may impact annual measurements. To rectify this, this paper employs the stepwise calibration technique developed by Li and Zhou (2017) for the entire DMSP-OLS series.

First, the estimates recorded by satellite F14 are adjusted upwards based on the years of overlap with satellite F12 (1997, 1998, 1999) to correct systematic underestimation. A regression of each F14 pixel *p* in each of the overlap years *t* on the corresponding F12 pixel is used to derive coefficients. These are then applied to the F14 measurements, including for years not covered by F12. A quadratic term is included because it adds more explanatory power. This regression is as shown below:

$$F14_{p,t} = \beta_1(F12_{p,t}) + \beta_2(F12_{p,t})^2$$

Second, measurements taken by F15 from 2003 to 2007 are similarly adjusted upwards based on the authors' finding of underestimation. This is conducted in the same manner based on the adjusted F14 pixel values for the overlapping year 2003. Next, a two-step process is

[2] Details on satellite-year coverage are shown in Figure A.1 in the appendix.

employed to adjust the measurements of F16 which do not show a "temporally consistent pattern". The first step uses pixel values from Sicily, Italy to adjust the F16 series, with 2007 being the reference year. This follows from the widely used method developed by Elvidge et al. (2009), which identified Sicily- due to its near-zero change in lighting over time and favorable spread of DN values- as an ideal candidate to calibrate cross-year measurements. Night lights for the region are assumed to be constant over time, and coefficients are generated to adjust the F16 years accordingly. These are then applied to the pixel values for Sri Lanka. After the inconsistent variation among F16 measurements is stabilized, the next step accounts for the underestimation of the F16 years as a whole relative to other satellites. The overlap with F15 in 2007 is used to generate coefficients, and the entire F16 series is then adjusted. Finally, the values for F18-2010 are adjusted to deal with overestimation. As F18 has no overlap years with other satellites, coefficients are generated by regressing the calibrated pixel values for Sicily from F16-2009 on the F18-2010 values. During all calibration steps, a cap of 63 and a floor of 0 are imposed on all pixels following the minimum and maximum values of the original data. After calibration, multiple satellite measurements for the same years are averaged. Figure 3 shows the results of the calibration process for the countrywide sum of lights in Sri Lanka.

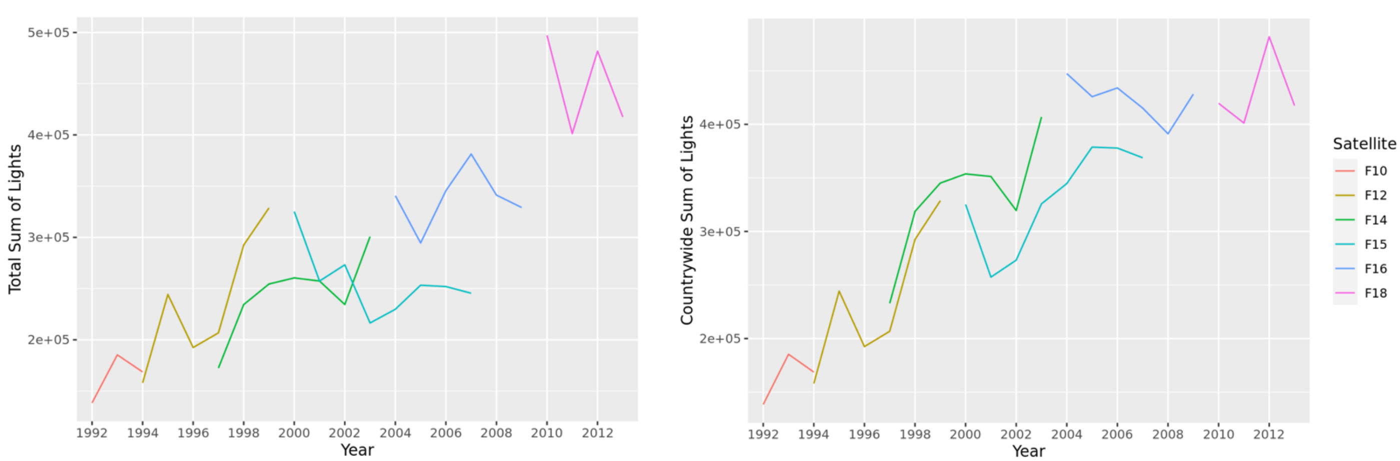

Figure 3: Pre-calibration (left) and post-calibration (right) sum of lights for Sri Lanka

Data on Violence

Event-based data on fatalities are available from the Uppsala Conflict Data Program (UCDP), which focuses on data collection on organized violence. It maintains the longest ongoing data collection project on civil wars. Data on individual violent events in Sri Lanka are available from 1989 through to the present day (for the period 1983-89, only annual, countrywide estimate totals are available). For each recorded violent event, data are available on the organizations involved, deaths suffered by each combatant side, civilian deaths, date, province, district, and coordinates in some cases. The dataset also includes a brief description of the source article headline, and an index indicating how precisely each of the event details, date, and location are known.

The data in the UCDP dataset are sourced from three sets of sources: global newswire reporting, global monitoring and translation of local news performed by the BBC, and secondary sources such as local media, Non-Governmental Organization (NGO) and Intergovernmental Organization (IGO) reports, field reports, and books. The process of compiling the dataset is done in a "two-pass" system, where the first pass involves consulting global newswire sources for the whole world and the second pass involves consulting local and specialized sources based on the information obtained from the first pass. Approximately 60% of the data comes from global newswire reporting. Various automatic checks are then applied to verify the data (Croicu & Sundberg, 2016).

In total, there are 4,573 violent events listed in the UCDP dataset for Sri Lanka from 1989-2009. Adding in the UCDP yearly death estimates from 1983-89, the total fatalities come to 76,000 as compared to UN estimates of 80,000-100,000 for the war (Ethirajan, 2021). This represents remarkably high coverage of fatalities during the war. The vast majority of events

(~4000) are coded as engagements between the Sri Lankan Government and the LTTE, with the residuals being made up of LTTE-civilian, government-civilian, or other engagements representing mostly skirmishes between different Tamil militant groups. Government-LTTE-coded events often carry large civilian death tolls, with these engagements totaling 7,480 non-combatant deaths. In total, the event level data cover 65,365 deaths, 10,928 noted as civilian deaths, and 52,948 attributed to a combatant group (Sundberg & Melander, 2013).

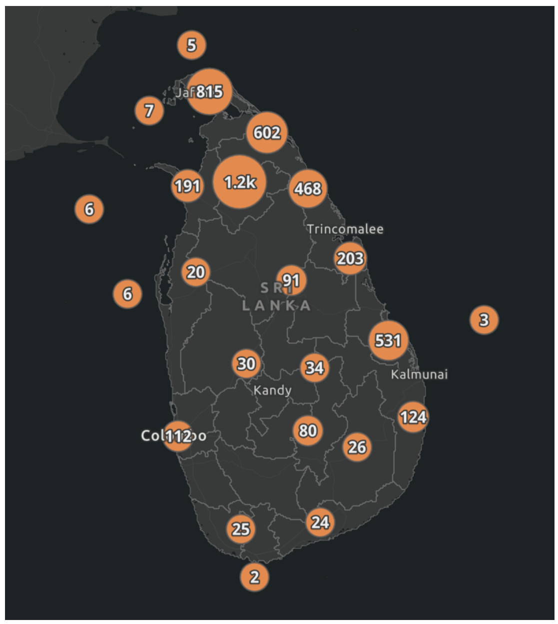

Figure 4: Geographic distribution of number of violent events recorded in the UCDP dataset (1989-2009)

With regard to precision, 91% of all events can be traced to the exact day, while 8% are traced to a two to six-day period, and the remainder less precisely. Some 95% are denoted as high clarity events- as opposed to low clarity where data on many events has already been aggregated by the source. The UCDP also includes information for each event on how precisely they can pin down the coordinates. For Sri Lanka, of all violent events recorded, 30.5% are traced to an exact location, 29.2% to a nearby area within 25km, and 29.7% can be traced to a second-order administrative division (districts in Sri Lanka's case). The remainder is only traced to the province level, national level, or occurred at sea (Croicu & Sundberg, 2016).[3]

This paper will primarily analyze night lights and casualties within Divisional Secretary's (DS) Divisions, which dissect the island into 331 administrative units. Additional analysis will be conducted at the district level of which there are 25 in the country. The district level analysis is less geographically precise and contains fewer observations. However, it is acts as an additional robustness check, and further allows for the inclusion of the 29.7% of deaths that cannot be located to a specific DS division. The average land area of a DS division is 189 km^2 while the average land area for a district is 2,508 km^2.

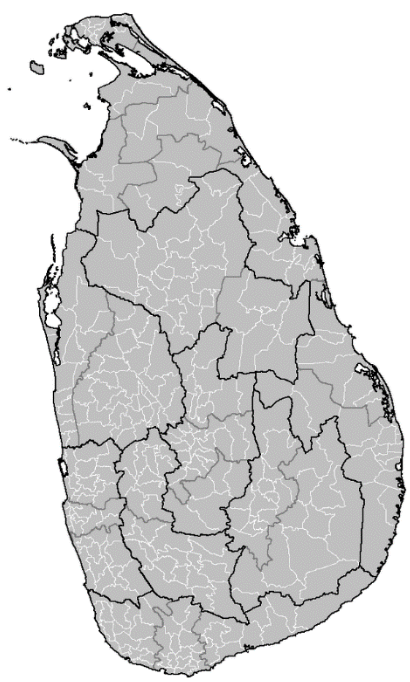

Figure 5: Sri Lanka administrative divisions including: Provinces (black), Districts (grey), and Divisional Secretary's Divisions (white)

[3] From 1988-2006 the Northern and Eastern Provinces were combined to make the Northeastern Province. Events that can only be classified at the province level and are marked as 'Northeastern' have their violence stats split between the Northern and Eastern Province in proportion to the percentage that were attributed to each.

The key variables of interest from the UCDP dataset are rebel deaths, Sri Lankan government deaths, civilian deaths, and the number of attacks.[4] The last will be proxied for by the number of reported events and is intended to capture the frequency of violence, which is important as it seems plausible that a single high casualty event might have a different impact on economic activity than a few dozen, smaller outbursts. However, this is not a perfect measure as many events represent an aggregation of attacks when they are recorded from the source (i.e. a government spokesperson lists casualty numbers for the day along a section of the frontline).

V. Empirical Framework

As this paper seeks to investigate the economic effects of the Sri Lankan Civil War, an ideal empirical framework would measure the response to localized conflict intensity of production measures, household-level economic well-being, or other factors. However, in the absence of such data due to the difficulty of wartime collection efforts, night lights are employed as a proxy for economic activity, while seasonally adjusted changes indicate economic growth. As outlined in the literature review, the relationship between nighttime light intensity and GDP growth is well established at both the national and sub-national levels.

Nonetheless, even with the availability of a valuable proxy for economic activity, limitations are imposed by the lack of available pre-war and early-war data. Event-based casualty data are first available in 1989 while night light data exist from 1992 onwards. The possibility of inferring luminosity estimates for Sri Lanka prior to 1992 is complicated. Dodd (2021) similarly lacks pre-war DMP-OLS data for Bosnia but, using a matching procedure, estimates counterfactual luminosity values with night light data from other Yugoslavian republics that did

[4] ~2% of deaths are not classified as combatant or civilian and are excluded.

not experience conflict. A pre-war value for each Bosnian municipality is calculated using the coefficients obtained from regressing a set of municipality characteristics on 1992 luminosity values in neighboring republics. However, a similar approach in Sri Lanka's case faces three major obstacles.

First, the nature of Sri Lanka's geography means that there are no neighboring countries in the traditional sense, and the closest candidate- southern India- may be structurally different in many ways.[5] Rama & Beyer (2017), in a review of night lights in South Asia, show a moderately different relationship between ln(GDP) and ln(luminosity) between the two countries. Second, the war started nine years before DMSP-OLS became available and obtaining pre-war luminosity values would require making predictions across this long time frame. The country did conduct a census almost immediately before the war in 1981, providing valuable population and demographic data. Nevertheless, later censuses during the war were either canceled altogether as in 1991 or did not include the north and east of the country as in the 2001 census. This renders making predictions of NTL values difficult because countrywide data that could be used to establish a relationship between municipality characteristics and night lights are first available only after the war from the census in 2012 (*Statistical Abstract*, 2021). Given the thirty-year difference and structural changes caused by the war, computing 1983 luminosity values based on these data would be unwise. Finally, casualty data for the conflict years before 1989 are only available on an annualized countrywide basis from the UCDP or other data programs such as the Correlates of War project (COW) (Wayman & Sarkees, 2010). This represents a significant dimensionality reduction from post-1989 event-based data and does not allow for the study of the impact of regional differences in violence.

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[5] For example, the fact that fact that many Sri Lankan population centers are situated on the coast may affect the amount of light pollution these areas exert on their surroundings.

Instead of calculating pre-war figures, this paper aims to parse the relationship between war and night lights by exploiting the extensive variation in conflict intensity observed during the conflict. During the 26 years of hostilities, three official ceasefires were implemented: from 1989-1990, during early 1995, and from 2002-2006. In addition, extensive variation in conflict intensity persisted outside of these ceasefires, as shown below in Figure 6. This paper also examines night light and fatality data from the post-war period until 2013, during which deaths were near zero.[6]

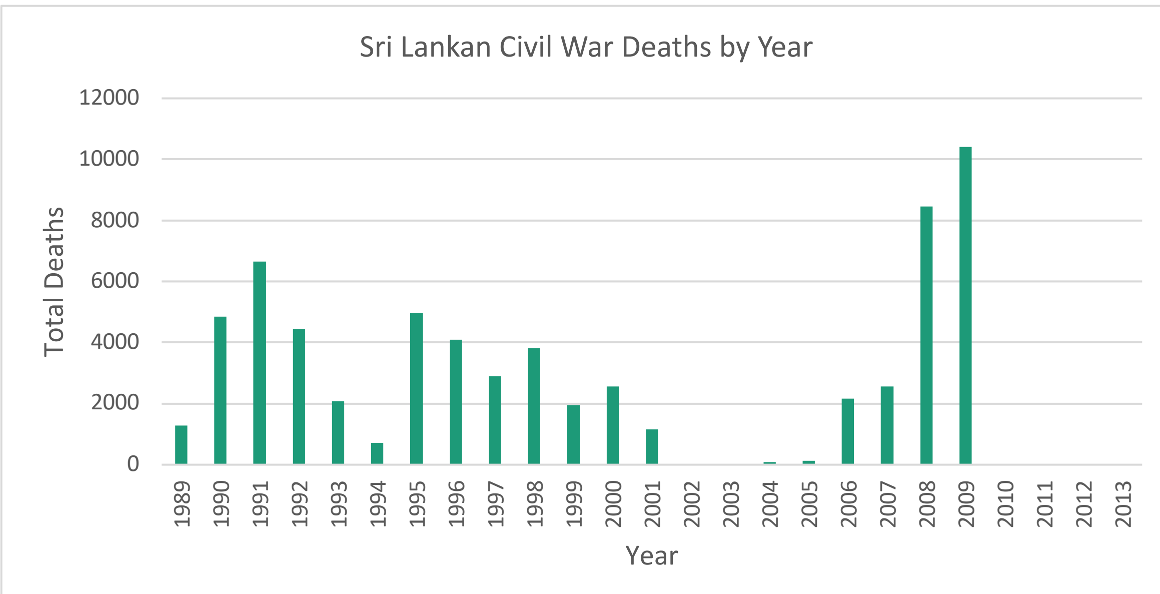

Figure 6: Yearly sum of total deaths from Sri Lankan Civil War (Croicu & Sundberg, 2016)

This variation in the intensity of the fighting means that the impact of elevated violence on night lights each year can be studied relative to years with comparatively less violence. This approach means that some mechanisms through which war affects economic activity on the extensive margin will not be captured. These mechanisms include potentially heightened

[6] 2013 is chosen as the final year of study because from 2014 onwards, DMSP-OLS data is not available. Visible Infrared Imaging Radiometer Suite (VIIRS) data can be used to measure NTLs, but significant cross-calibration is required between the two (Li et al., 2020).

uncertainty regarding investments in a 'war zone', collapse of institutions, and other cumulative effects of the war. However, this approach allows for the study of how the intensity of the war (intensive margin) impacted economic activity in different Sri Lankan municipalities. This should capture a wide range of mechanisms through which this might occur from the destruction of physical and human capital to increased civilian fear and anticipation of future violence.

Temporal Lags

The DMSP-OLS annual composites represent averages of around 365 nightly images taken by the satellites each year.[7] Given this collection method, events occurring part way through the year only have the potential to influence the images taken on the nights after their occurrence and thus impact should be proportional to how early in the year an event occurred. To account for this, violence variables in the finalized model are weighted by the proportion of days remaining in the year from the date on which they occur. Additionally, the remainder is added to the following year so that all deaths are weighted equally overall. If an attack kills 365 civilians on January 1st, 1990, this will contribute 364 to the weighted total of civilian deaths in 1990 and 1 to the total in 1991. A death occurring exactly halfway through the year would contribute 0.5 to the year in which it occurred and 0.5 to the next.

While this weighting approach effectively incorporates deaths from the previous year into the weighted total for the current year, weighted deaths from year *t-1* are also included to incorporate a temporal lag effect of violence, which has been found to be of consequence with regards to household welfare (Justino, 2009). Incorporating weighted deaths from *t-1* means that

[7] Some nightly measurements may be omitted during the bright half of the lunar cycle and in the presence of forest fires so the composites have slightly less than 365 inputs (Henderson et al., 2012).

deaths from years t, $t-1$, and $t-2$, will factor into the final form regression as a result of the weighting strategy outlined above.

Spatial Lags

In addition to temporal lags, spatial lags are also included to capture the effect of violence nearby on night lights in a given municipality. De Groot (2010) finds significant economic impacts of violent conflict on neighboring countries in a study of conflict in Africa. Meanwhile, Burgess et al. (2015), studying the effect of war in Sierra Leone on deforestation, find that the presence of battles in a higher administrative unit (district) has a larger effect size than battles directly in a chiefdom, an effect the authors attribute to the existence of more widespread conflict disrupting key infrastructure such as roads and markets. Dodd (2021) finds more mixed results with different types of nearby conflict having varying degrees of significance and directional impact on night lights.

It should be noted that the sign of impacts of spatial lags in Sri Lanka is not obvious based on theory. Deaths nearby may dim lights through channels such as anticipation of future violence and outmigration, sequestration of resources by warring parties, or increased civilian fear. On the other hand, nearby violence could potentially increase lights if commercial activity or fleeing civilians relocate from war zones to nearby areas. This paper measures nearby violence as the sum of total deaths and attacks that occurred in the wider district n (a higher-level administrative unit) minus those that occurred in the Divisional Secretariat (DS) m. This offers an estimate of the intensity of violence in the proximity of DS division m. The finalized model is as follows:

$$\ln(lum_{m,t}) = \beta_0 + \beta_1 Gov_{m,t} + \beta_2 Rebel_{m,t} + \beta_3 Civilian_{m,t} + \beta_4 Attacks_{m,t} + \delta_1 Gov_{n-m,t} + \delta_2 Rebel_{n-m,t} + \delta_3 Civilian_{n-m,t} + \delta_4 Attacks_{n-m,t} + \gamma_1 Gov_{m,t-1} + \gamma_2 Rebel_{m,t-1} + \gamma_3 Civilian_{m,t-1} + \gamma_4 Attacks_{m,t-1} + \varphi M + \rho T + \mu$$

Here *lum* refers to the sum of luminosity measures in the constituent pixels of the DS *m* in period *t*. The natural logarithm of luminosity is taken to reduce heteroskedasticity (Henderson et al., 2012).[8] Consequentially, the interpretation of each coefficient is that: $\%\Delta lum = 100 \times (e^{\beta_i} - 1)$. *Gov* refers to deaths suffered by the Sri Lankan Government, while *Rebel* is deaths suffered by all other combatant parties, consisting mostly of the LTTE, but with some other militant groups as well.[9] *Civilian* represents civilian fatalities while *Attacks* is the number of recorded events (a proxy for frequency of attacks). The δ coefficients represent the sum of each variable total in district *n* less the total for DS *m*. The γ coefficients measure the effect of violence in period *t-1*. All variables are weighted as outlined above. A time trend (*T*) is employed to account for the expected growth in nighttime lights over time. Finally, the model includes DS fixed effects (*M*) to account for time-invariant characteristics of each administrative units that affect luminosity.[10]

VI. Results

The results section proceeds as follows. First the results of the primary model setups with and without spatially and temporally lagged terms are presented. These results will be discussed, including a review of the signs and significance of the coefficients, the impact of the addition of

[8] Municipalities for which the sum of lights is equal to zero are assigned a ln(*lum*) value of zero.
[9] The figure for the government includes the Sri Lankan Armed Forces as well as police.
[10] A Hausman test was performed to confirm the use of fixed effects instead of more powerful random effects. The main regressions were also run with random effects as a check, and the results were robust.

lags, and an interpretation of the magnitudes. Then two new specifications of the model are run to investigate the unintuitive impacts of the civilian death's variable. Finally, alternative setups are assessed to test the robustness of the model.

Main Results

Table 1 shows the impact of the relevant violence variables on the natural logarithm of total luminosity for each Divisional Secretariat. The table includes the results of the baseline model, a specification with spatial lags, one with temporal lags, and one with both spatially and temporally lagged terms. All deaths and attacks variables are re-scaled by 100 to make the coefficients more readable. Therefore, the interpretation of the marginal effect for Gov Deaths, for example, is the corresponding change in the natural log of lights for 100 government deaths. All four specifications include DS fixed effects.

Table 1: Primary Regression Results

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.375***	-0.367***	-0.262***	-0.264***
	(0.09)	(0.09)	(0.09)	(0.09)
Rebel Deaths	-0.098**	-0.075	-0.183***	-0.148***
	(0.05)	(0.05)	(0.06)	(0.05)
Civilian Deaths	0.089***	0.087***	0.125***	0.109***
	(0.03)	(0.03)	(0.03)	(0.04)
Num Attacks	-2.010***	-1.173***	-1.299***	-0.580
	(0.42)	(0.44)	(0.44)	(0.45)
Time Trend	0.071***	0.067***	0.071***	0.067***
	(0.00)	(0.00)	(0.00)	(0.00)
Spatial Lags:				
Gov Deaths Near		-0.097***		-0.094***
		(0.03)		(0.03)
Rebel Deaths Near		-0.110***		-0.108***
		(0.01)		(0.01)
Civilian Deaths Near		0.043***		0.043***
		(0.01)		(0.01)

Num Attacks Near		0.032		0.036
		(0.10)		(0.10)
<u>Temporal Lags:</u>				
Gov Deaths Prev.			-0.348***	-0.324***
			(0.09)	(0.09)
Rebel Deaths Prev.			0.168***	0.139***
			(0.05)	(0.05)
Civilian Deaths Prev.			0.138***	0.123***
			(0.03)	(0.03)
Num Attacks Prev.			-2.144***	-1.633***
			(0.46)	(0.46)
Constant	5.593***	5.673***	5.596***	5.674***
	(0.02)	(0.02)	(0.02)	(0.02)
N	7273	7273	7273	7273
R^2	0.287	0.314	0.292	0.318

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

Across the specifications, government deaths are found to have a negative effect on night lights that is highly significant (1% level). Rebel deaths are also negatively associated with luminosity and are significant in the baseline model at the 5% level, and in both models that include temporal lags at the 1% level. The effect sizes for government deaths are consistently larger than those for rebel deaths. This may be indicative of the favorable attrition ratios experienced by the Sri Lankan Armed Forces given their advantage in equipment and training (Layton, 2015). In the UCDP dataset for the years under study, 14,731 deaths are attributed to the Sri Lankan government in comparison to 38,217 to rebel combatants. Therefore, 100 government deaths likely signify heavier fighting than 100 rebel deaths and thus the marginal effect is larger. As outlined in section V, the interpretation of each coefficient is that:

$$\%\Delta lum = 100 \times (e^{\beta_i} - 1)$$

For the model with spatially and temporally lagged terms, this consequentially implies that 100 government deaths are associated with a -23.20% change in the sum of lights. The same model suggests that for rebel combatants, 100 deaths result in a -13.76% change in the sum of lights. For the baseline model, the implied changes in lights for 100 government and rebel deaths are -31.27% and -9.33% respectively.[11] The direction of these effects makes sense with regard to the theory of conflict and economic activity. Deaths of combatants in a given administrative division means that fighting is occurring, and this would be expected to subdue economic activity and thus observations of nighttime lights.

On the other hand, the civilian death coefficient exhibits a somewhat unintuitive sign. Across all the specifications, these coefficients indicate a positive relationship between civilian deaths and nighttime lights and are highly significant. The coefficient for the baseline model implies a 9.31% increase in the sum of lights for each additional 100 civilian deaths. This number is 11.52% for the model with spatial and temporal lags. The positive association between civilian fatalities and luminosity will be investigated further in this section.

The effect of the number of attacks is negative and significant across three of the four models. The large effect size relative to the other variables may be related to the fact that 100 attacks will ultimately result in far more than 100 deaths, and as such the marginal impact of an attack is larger. For the 1989-2013 data, the average number of total deaths from each reported event is 14.29. Separately, a high degree of correlation was found between the number of attacks variable and the civilian and rebel death counts. To address potential issues arising from multicollinearity, the model was rerun without the number of attacks variable in either the direct, temporally lagged, or spatially lagged terms. The results of this regression are shown in Table A.2 in the appendix. Overall, the results are robust to this exclusion. None of the coefficient

[11] A full breakdown of the implied luminosity changes from the relevant coefficients is provided in table A.1 in the appendix.

signs change, and there is minimal impact to the magnitudes. The direct impact of civilian deaths loses significance, and the effect size of rebel deaths increases moderately.

Lagged Terms

The coefficients for the impacts of nearby violence are generally smaller than the direct effects but are still highly significant. Government and rebel deaths are negatively associated with luminosity, implying respective decreases of -9.24% and -10.24% in the model with only spatial lags. Unlike for deaths in Divisional Secretariat *m*, the impact of rebel deaths nearby is larger than that of government deaths, though the difference is minimal. Civilian deaths in the wider district *n*, like their direct effect, are positively associated with night lights and significant. The number of attacks variable is positive, but not significant. The spatially lagged terms are not altered much once temporal lags are included as well. Except for the number of attacks variable, the impact of the inclusion of spatial lags on the direct violence coefficients is also minimal.

While the difference between the spatially lagged effects and the direct effects might be expected to be larger, this could be related to the fact that since the area of each division is so small, a DS may lie in the warzone but experience little to no fighting if it does not have strategic objectives (e.g., high ground, roads, etc.). Therefore, the spatial effects would be capturing the disruptions to economic activity from war nearby, while direct impacts would not be observed.

The coefficients for the temporal lags are relatively large in magnitude, even compared to the direct effects. Previous government deaths are significant at the 1% level and have negative coefficients across both models where deaths from *t-1* are included. This implies that there are persistent impacts from violence in previous years. Conversely, rebel deaths are positive and significant in both models. One potential explanation for this is that these variables could be correlated with control of terrain changes. If high rebel deaths indicate the capture of a given municipality by the Sri Lankan Armed Forces, night lights might be expected to rebound in the following year as the government has several advantages in administering areas that might lead to higher night lights and economic activity. These advantages include access to foreign fuel imports, larger public coffers, and existing governance structures.

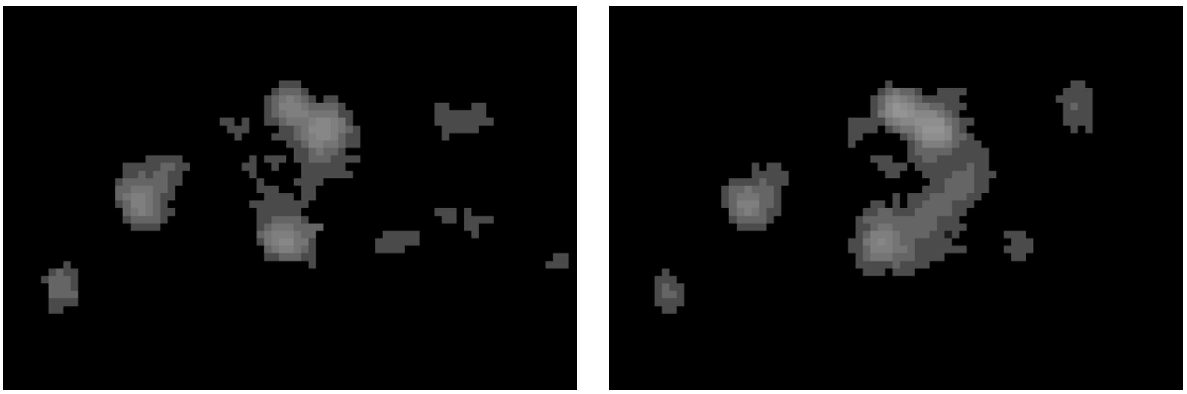

Figure 7: Jaffna NTLs 1995 (left) and 1996 (right) pre and post-capture by SL government

Figure 7 shows the change in lights following the government recapture of the Jaffna peninsula in late 1995 as a supporting case study, though it should be noted that further testing this theory would require additional data on control of territory. The civilian deaths variable is positive in both regressions and significant. This is as observed in the direct and nearby effects. The number of attacks variable exhibits a negative and a strong significance. Some of this may be due to correlation with previous rebel and civilian deaths. In the specification excluding the number of attacks variable (Table A.2), the effect sizes of previous civilian and rebel deaths are lessened. The significance of rebel deaths is also weakened.

The temporally lagged terms are not altered significantly by the inclusion of the spatial lags into the model as well, however, temporal lags do seem to impact the estimates of the direct coefficients. The effect size of government deaths is reduced, while for rebel and civilian deaths it is increased. This may indicate that these coefficients, being correlated with violence in period *t-1*, were absorbing some of the impact from violence in the previous year. Finally, temporal lags also seem to add less explanatory power than spatial lags.

Investigating the Civilian Death Coefficient

The direction of the coefficient on civilian deaths warrants further exploration because it seems to run counter to what the theory might suggest. Across the models, civilian deaths are positively associated with nighttime lights at varying degrees of significance. This relationship holds for the spatial and temporal lag coefficients (though for the lagged variables the assumed relationship is less clear as mechanisms such as the 'bounce-back' effect and the movement of refugees could explain this). Two potential causes for this positive coefficient are investigated.

First, a significant portion of the civilian deaths occurred in the final year of the war, which ended in May 2009, so it was hypothesized that the positive coefficient may have been capturing a post-war rebound. In total, 6,800 of the nearly eleven thousand civilian deaths occurred in 2009.[12] The remaining seven months of the year offered time to rebuild. Further some of these deaths are also shifted to 2010 given the weighting approach. This in turn might partially explain the temporally lagged civilian deaths coefficient effect being larger than the direct effect. Table A.3 in the appendix reports the results of the primary regressions, excluding data from 2009 and 2010. When this change is made, the coefficient for civilian deaths turns negative in the baseline model, and the specification with only temporal lags. For the model with both lags it is 0.003 and not significant. The spatially lagged civilian term becomes negative and

[12] Separately, it is also likely that the UCDP undercounts the civilian death toll in this year because the Sri Lankan Government went to great lengths to obscure the number of civilians killed in the "safe zones" that were shelled and the UCDP cannot account for vague estimates made years later by human rights groups (United Nations, 2011).

significant while the temporally lagged term is positive and significant. These results indicate that the 2009 and 2010 deaths may have played a role in driving the positive civilian death coefficients in the model. However, this is not conclusive, and it is important to note that excluding them also greatly reduces the number of civilian deaths in the data.

Second, additional analysis is conducted to see whether the manner of civilian death is important in determining its positive sign in the primary regressions. Many of the civilians killed died because of strategic and terror attacks on government and civilian infrastructure (a popular tactic employed by the LTTE) or one-off retaliatory massacres. The attack locations are endogenous because they are likely correlated with various factors such as government-controlled areas, big cities, wealthy areas, and locations receiving an influx of refugees, which are in turn related to night lights. This would be expected to yield different results than civilian deaths resulting from intense shelling of an area for example. Events in the UCDP dataset contain information on the 'sides' involved. For example, 'Government of Sri Lanka – LTTE', 'LTTE – Civilians', and 'Government of Sri Lanka – Civilians' are all potential values for this variable. However, if government officials are killed in an event, it would fall under the former, even if civilians are killed. A bomb blast at a police station might kill many civilians and be an example of an endogenously chosen attack location, but this would be classified as a government LTTE engagement. Therefore the 'sides' variable is limited in usefulness for this analysis.

Instead, a different approach is taken to parse out the type of civilian death. An indicator variable *Fighting* is created, being equal to one if there were more combatant deaths than civilian deaths in DS m in year t. Analogous indicator variables are created if the same condition is met in the wider administrative district n-m and year t-1. These variables are then interacted with the direct, spatially lagged, and temporally lagged civilian totals, respectively.

Table 2: Fighting Interaction Included

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.376***	-0.360***	-0.263***	-0.257***
	(0.09)	(0.09)	(0.09)	(0.09)
Rebel Deaths	-0.083*	-0.064	-0.167***	-0.133**
	(0.05)	(0.05)	(0.06)	(0.05)
Civilian Deaths	0.085***	0.082***	0.104***	0.083**
	(0.03)	(0.03)	(0.04)	(0.04)
Civilian*Fighting	-1.245**	-1.040**	-1.751***	-1.636***
	(0.51)	(0.50)	(0.54)	(0.54)
Num Attacks	-2.005***	-1.212***	-1.238***	-0.558
	(0.42)	(0.44)	(0.44)	(0.45)
Time Trend	0.071***	0.066***	0.070***	0.066***
	(0.00)	(0.00)	(0.00)	(0.00)
Spatial Lags:				
Gov Deaths Near		-0.059**		-0.054**
		(0.03)		(0.03)
Rebel Deaths Near		-0.112***		-0.112***
		(0.01)		(0.01)
Civilian Deaths Near		0.040***		0.041***
		(0.01)		(0.01)
Civilian Near*Fighting Near		-0.601***		-0.607***
		(0.11)		(0.11)
Num Attacks Near		0.117		0.117
		(0.10)		(0.10)
Temporal Lags:				
Gov Deaths Prev.			-0.360***	-0.336***
			(0.09)	(0.09)
Rebel Deaths Prev.			0.170***	0.135***
			(0.05)	(0.05)
Civilian Deaths Prev.			0.157***	0.145***
			(0.03)	(0.03)
Civilian Prev.*Fighting Prev.			0.566	0.772
			(0.49)	(0.48)
Num Attacks Prev.			-1.943***	-1.422***
			(0.47)	(0.46)
Constant	5.593***	5.688***	5.597***	5.690***
	(0.02)	(0.02)	(0.02)	(0.02)
N	7273	7273	7273	7273
R^2	0.288	0.318	0.293	0.322

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

Table 2 shows the results with the inclusion of these new interaction terms. The direct effect of the interaction term is negative across the models and significant at the 1% level for all specifications. The regular civilian coefficient- representing cases where *Fighting* = 0- is positive for all four models and significant. The interaction term for the spatial lag is similarly negative while the regular coefficient is positive. Both are significant. For the temporally lagged terms, both civilian coefficients are positive, though the interacted term is not significant. The magnitude of the interaction term is larger than the coefficients for government and non-government deaths across the models. For the model with both lag types included, 100 civilian deaths in a DS experiencing fighting are associated with a -80.52% decline in NTLs. Meanwhile the regular coefficient implies that 100 civilian deaths in an area where *Fighting* = 0 is correlated with an 8.65% increase in lights. Overall, this evidence supports the hypothesis that the type of violence that induces civilian fatalities is a major determinant of the effect on night lights and that endogenous attacks may have been driving the positive and significant coefficient for civilian deaths in the primary regression models.

Robustness checks

A number of robustness checks are performed to confirm the findings of the paper. First, the DS level models are run again using only observations from the Northern and Eastern Provinces- where the LTTE claimed an independent state and much of the fighting occurred. As shown in table A.4, the results are largely similar to the original model in terms of the magnitudes and direction of the coefficients. However, government deaths go from being weakly significant to no longer significant once temporal lags are included, and rebel deaths are only weakly significant. This may partly be due to the reduction in statistical power given the smaller sample. Civilian deaths are still positive and significant.

Second, primary regressions are rerun at the district level as an additional check, and to allow for the inclusion of deaths that can only be geolocated at this level of specificity. In this case, the spatially lagged term represents the number of deaths in province *m*, less those in district *n*. District fixed effects are also included. The results are reported in table A.5 in the appendix. The effect sizes are much smaller than the DS level effects. This makes sense as the average size of a DS division is 189 km^2 as compared to 2,508 km^2 for a district. This in turn means that the impact of violence would be expected to be much less direct at the district level as deaths in a DS division mean they occurred in the immediate proximity of everyone within the area, whereas an attack in the same district could be several towns away. Overall, the signs remain relatively consistent with government and rebel deaths having negative coefficients and civilian deaths having positive ones. The significance of civilian and government deaths is reduced. This may be due to the fact that there are fewer observations, with only 25 districts in the country. None of the spatial lags are significant. This seems reasonable as the spatial lag variables for the district regressions are the totals outside division *m* in province *n*. Sri Lanka's provinces are quite large, with only nine across the whole country.[13] As such, there are likely fewer mechanisms through which such nearby violence would affect luminosity if the impact is assumed to be inversely proportional to distance. There is also limited variation in this variable given the small number of provinces.

Finally, an additional specification is run, including the value for the previous year's luminosity in DS *m* as a regressor. The lagged dependent variable is used in this alternate setup

[13] See Figure A.2 in the appendix for a visual comparison of provinces and districts.

because it improves the model fit and can help pick up cumulative effects of violence.[14] DS fixed effects are included, however, the time trend is dropped as the assumed increase in NTLs over time is accounted for by the lagged term. The results of this regression are reported in table A.6. Other than the spatially lagged number of attacks variable (which is insignificant), none of the coefficient signs change. The magnitudes are mostly unaffected as well. For the model with both lags the government and rebel coefficients are -0.251 and -0.158 as compared to -0.264 and -0.148 in the primary regressions. Only nearby rebel deaths and direct number of attacks lose significance. The lagged dependent variable is highly significant.

VII. Discussion

Overall, using night lights as a proxy for economic activity, the violence during the Sri Lankan Civil War is shown to have a clear negative effect both directly, and indirectly through lagged effects in time and space. This is particularly evident for government deaths which are shown to be the most impactful in the primary regression with an implied change in luminosity of -23.20% per 100 deaths for the model with both lags. These magnitudes are comparable to the findings of Dodd (2021) which, looking at the extensive margin, found an average decrease in night lights of 63% for the presence of hybrid conflict, 48% for civil war, and 54% for conventional conflict.[15] Rebel deaths are also impactful across different specifications modeled, leading to luminosity declines of 13.76% in the primary regressions when spatial and temporal lags are included. The generally larger impact of government deaths may well be a result of

[14] This setup, known as a dynamic panel data model, is not used for the primary results because it introduces the possibility of Nickell bias. This occurs as the demeaning process of fixed effects leads to a correlation between the lagged dependent variable and the error term. This is significant in instances where the number of cross-sectional units is large and the number of time periods is small (Nickell, 1981).

[15] These are based on the classification of different periods of the Bosnian Civil War via. principal components analysis performed by Becker et al. (2022).

favorable attrition ratios experienced by the Sri Lankan Armed Forces. This would make sense if combatant deaths are assumed not to mechanically affect night lights, but rather signify a level of fighting intensity that impacts night lights through mechanisms such as collateral damage to physical and human capital or increased fear.

Civilian deaths are positively associated with nighttime lights, which seems to run counter to what theory might suggest. A closer analysis investigated two potential factors at work. First, the concentration of deaths in the final year of the war may have meant that this was reflecting a ‘bounce-back' effect. With the war conclusively over in 2009, people could return to their homes and pursue economic endeavors that might otherwise have been suppressed. Excluding data from 2009 and 2010 resulted in the direct civilian death coefficient being either negative or near zero depending on the specification. This is similarly true only for the spatial lags. This mechanism seemed to contribute to, but not be a major determinant of, the unintuitive sign.

Additional analyses suggested that the manner of civilian death is a key driver of the positive relationship. Including the *Fighting* interaction term to decompose civilian deaths into war zone and sporadic attack deaths reveals large, significant effects of the former on nighttime lights. The estimates imply that 100 civilian deaths in a Divisional Secretariat where fighting is occurring is associated with a -80.52% change in lights. This is highly significant. The effect sizes for the lagged interaction terms are also large and negative. Meanwhile the remaining civilian deaths (those not in war zones) exhibited a positive correlation with night lights that was significant. This seems to suggest two things. First, the correlation between sporadic attacks and night lights reflects the endogeneity of the former, as such violent events are correlated with unobserved factors that also affect the level of lights. Second, civilian deaths sustained from conventional war are among the most harmful component of violence with regard to economic activity. This could be because such deaths indicate much higher collateral damage (assuming civilians are not the target then large death tolls would mean lots of other infrastructure being unintentionally destroyed) or because they result in depopulation through casualties and fleeing.

Throughout the analysis, spatial effects are found to be significant. Additional analysis at the district level suggests these effects may be inversely related to distance. Government and rebel deaths nearby were negatively associated with nighttime lights. On the other hand, civilian deaths nearby seemed to imply a positive effect on lights, although this dissipated once 2009 and 2010 data were excluded and reverses once the *Fighting* interaction was added. For the temporal lags, both civilian and rebel deaths are positively related with luminosity while government deaths are negatively related. These effect sizes seemed to be relatively large as well. The potential for changes in control of terrain to be driving the positive rebel death coefficient was discussed, but more data would be required to reach a definitive conclusion. It is not apparent from the conceptual framework what these effects should be. On the one hand, physical destruction of the stock of infrastructure or long-term outmigration might mean that deaths in period *t-1* exert a negative pull on lights. On the other hand, municipalities might experience a rebound effect if people and economic activity return in year *t*.

Limitations and Future Research

The study faces several limitations imposed by the available data. First, while night lights are a good proxy for economic activity they certainly have some shortcomings. Hu and Yao (2019) find that DMSP-OLS-based estimates of real GDP work best for middle-income countries- a status Sri Lanka only achieved in 2010 (Government of Sri Lanka, 2010). Particularly towards the start of the study period, there are large areas of the country that are dark, including the de facto LTTE capital of Kilinochchi. Additionally, other LTTE bases may have actively sought out such 'dark' areas as the remote jungle provided cover. From 2013 onwards, Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) is available which provides better low-light detection capabilities and captures more detailed spatial variation. Future studies focusing on more recent conflicts would benefit from the use of this satellite data.

Additionally, this study was unable to control for several variables that might have been of interest to the investigation. For example, strategic infrastructure such as roads or ports would likely have informed peoples' expectations of future violence as they are very likely to be contested in the future and may thus have influenced luminosity. Further, accurate population data would have enabled an assessment of how the movement of people acted as a causal mechanism between violence and lights. Witmer & O'Loughlin (2011) find lights to be a significant predictor of such movement. Finally, the number of events in the UCDP data served as a crude proxy for the frequency of attacks and may have been a less accurate proxy for certain areas of the country more affected by the 'fog of war'. An alternative approach might have been to construct a measure of the number of weeks in a year with a reported event, though this might suffer from some of the same limitations.

Future research could extend this work by compiling data on control of terrain data or the location of the frontline and incorporating it into the analysis to explore the effects. This would address some of the issues relating to the potential endogeneity of deaths which was hypothesized to be a concern for civilian deaths as well as previous rebel deaths. Additionally, the exact mechanisms through which violence translates to lower economic activity might be explored in more depth. More granular data on the war effort such as localized munition expenditure or mine placement, along with data on the movement of refugees would help parse out the different factors at play. Finally, an extension of this research might be to investigate the post-war recovery paths of Divisional Secretariats based on different levels of violence experienced during the war. This would help reveal the existence of any lasting scarring from the conflict.

VIII. Conclusion

This paper employed DMSP-OLS nighttime light measurements as a proxy for economic activity to investigate the economic impact of violence during the Sri Lankan Civil War. The main findings indicate that conventional conflict- through government deaths, non-government deaths, and civilian deaths in war zones- has a large and significant negative effect on nighttime lights in Sri Lanka during the war. An additional 100 government deaths results in a corresponding decline in luminosity of 23% to 31% depending on the specification. Additionally, violence is shown to generally lower luminosity in both the following period and in neighboring areas. This paper contributes to the literature by offering findings on the forms of violence that most hamper economic activity. It also offers new findings on the economic impacts of the Sri Lankan Civil War in particular.

Understanding the mechanisms through which conflict hurts economic activity is important for measuring the devastation of war. Naturally, casualty figures and the loss of life take center stage in the discussion of such devastation. However, it is important to remember that even those who do not sustain physical wounds from war still suffer. At a very rough estimate using the elasticity from Henderson et al. (2012), a 23% difference in night lights might imply a

7% decline in real GDP.[16] The wide availability of both UCDP event-level violence data and DMSP-OLS satellite data means that this investigation is easily replicable for other conflicts that fit within the range of the respective data sources.

Since the conclusion of the war, Sri Lanka has remained remarkably peaceful. With that being said, the north and east have yet to catch up to the rest of the country in terms of economic development and the country has faced new economic challenges in recent years. Much work is left to be done to heal the deep economic inequities that years of violence and underdevelopment have created large areas of the country. Doing so is imperative to building a fairer Sri Lanka for the Tamil minority and wider population alike and thereby, hopefully, avoiding future outbursts of violence.

[16] This should only be taken as a rough gauge of scale as Henderson et al. (2012) was examining economic growth, unrelated to conflict or intra-national NTL changes. It is conceivable that luminosity overstates GDP declines in active war zones as a portion of the decline may be evasive action to avoid being targeted (Kappner et al., 2022).

References

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, *93*(1), 113–132.

Anandakugan, N. (2020, August 31). *The Sri Lankan Civil War and Its History, Revisited in 2020*. Harvard International Review. https://hir.harvard.edu/sri-lankan-civil-war/

Arunatilake, N., Jayasuriya, S., & Kelegama, S. (2001). The Economic Cost of the War in Sri Lanka. *World Development*, *29*(9), 1483–1500. https://doi.org/10.1016/S0305-750X(01)00056-0

Bandara, J. (2007). The impact of the civil war on tourism and the regional economy*. *South Asia: Journal of South Asian Studies*, *XX*, 269–279. https://doi.org/10.1080/00856409708723315

Becker, C., Devine, P., Dogo, H., & Margolin, E. (2022). *Marking Territory: Modeling the Spread of Ethnic Conflict in Bosnia and Herzegovina, 1992-1995* (SSRN Scholarly Paper No. 3160015). https://doi.org/10.2139/ssrn.3160015

Bove, V., & Gavrilova, E. (2014). Income and Livelihoods in the War in Afghanistan. *World Development*, *60*, 113–131.

Burgess, R., Miguel, E., & Stanton, C. (2015). War and deforestation in Sierra Leone. *Department of Economics, Working Paper Series*, Article qt83h9d9gb. https://ideas.repec.org//p/cdl/econwp/qt83h9d9gb.html

Collier, P., Elliott, V. L., Hegre, H., Hoeffler, A., Reynal-Querol, M., & Sambanis, N. (2003). Breaking the Conflict Trap: Civil War and Development Policy. In *World Bank Publications—Books*. The World Bank Group. https://ideas.repec.org/b/wbk/wbpubs/13938.html

Croicu, M., & Sundberg, R. (2016). *UCDP Georeferenced Event Dataset Codebook Version 5.0*. Department of Peace and Conflict Research, Uppsala University. https://ucdp.uu.se/downloads/ged/ucdp-ged-50-codebook.pdf

Cullen, M., & Colleta, N. (2000). *Violent conflict and the transformation of social capital: Lessons from Cambodia, Rwanda, Guatemala and Somalia*. The World Bank. https://www.researchgate.net/publication/313819980_Violent_conflict_and_the_transformation_of_social_capital_Lessons_from_Cambodia_Rwanda_Guatemala_and_Somalia

De Groot, O. J. (2010). The Spillover Effects of Conflict on Economic Growth in Neighbouring Countries in Africa. *Defence and Peace Economics*, *21*(2), 149–164. https://doi.org/10.1080/10242690903570575

Dodd, S. (2021). *The Impact of Conflict on Economic Activity: Night Lights and the Bosnian Civil War*. Duke Economics Honors Theses Archive. https://sites.duke.edu/econhonors/2021/11/18/the-impact-of-conflict-on-economic-activity-night-lights-and-the-bosnian-civil-war/

Ebener, S., Murray, C., Tandon, A., & Elvidge, C. C. (2005). From wealth to health: Modelling the distribution of income per capita at the sub-national level using night-time light imagery. *International Journal of Health Geographics*, *4*(1), 5. https://doi.org/10.1186/1476-072X-4-5

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., Erwin, E. H., & Zhizhin, M. (2009). A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data. *Energies*, *2*(3), Article 3. https://doi.org/10.3390/en20300595

Ethirajan, A. (2021, March 23). *UN to collect evidence of alleged Sri Lanka war crimes*. BBC News. https://www.bbc.com/news/world-asia-56502221
Ganegodage, K. R., & Rambaldi, A. (2014). Economic consequences of war: Evidence from Sri Lanka. *Journal of Asian Economics*, *30*(C), 42–53.
Ghosh, T., Anderson, S. J., Elvidge, C. D., & Sutton, P. C. (2013). Using Nighttime Satellite Imagery as a Proxy Measure of Human Well-Being. *Sustainability*, *5*(12), Article 12. https://doi.org/10.3390/su5124988
Gillespie, T. W., Frankenberg, E., Chum, K. F., & Thomas, D. (2014). Nighttime lights time series of tsunami damage, recovery, and economic metrics in Sumatra, Indonesia. *Remote Sensing Letters (Print)*, *5*(3), 286–294. https://doi.org/10.1080/2150704X.2014.900205
Government of Sri Lanka. (2010, January 21). *IMF Upgrades Sri Lanka's Status to Middle Income Emerging Market*. PR Newswire. https://www.prnewswire.com/news-releases/imf-upgrades-sri-lankas-status-to-middle-income-emerging-market-82250897.html
Haelig, C. (2017, September 9). The Sri Lankan Civil War: Turning COIN on Its Head and Learning to Adapt. *Small Wars Journal*. https://smallwarsjournal.com/jrnl/art/the-sri-lankan-civil-war-turning-coin-on-its-head-and-learning-to-adapt
Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring Economic Growth from Outer Space. *American Economic Review*, *102*(2), 994–1028. https://doi.org/10.1257/aer.102.2.994
Hu, Y., & Yao, J. (2019). *Illuminating Economic Growth*. International Monetary Fund.
Hyder, S., Akram, N., & Padda, I. (2015). Impact of Terrorism on Economic Development in Pakistan. *Pakistan Business Review*, *16*, 704–722.
Johnson, S. (2017). The Cost of War on Public Health: An Exploratory Method for Understanding the Impact of Conflict on Public Health in Sri Lanka. *PLOS ONE*, *12*, e0166674. https://doi.org/10.1371/journal.pone.0166674
Justino, P. (2009). The Impact of Armed Civil Conflict on Household Welfare and Policy Responses. *HiCN Working Papers*, Article 61. https://ideas.repec.org//p/hic/wpaper/61.html
Kanj, R. (2022). *Economic Effects of the War in Donbas: Nightlights and the Ukrainian fight for freedom*. Duke Economics Honors Theses Archive. https://sites.duke.edu/econhonors/2022/06/03/economic-effects-of-the-war-in-donbas-nightlights-and-the-ukrainian-fight-for-freedom/
Kappner, K., Szumilo, N., & Constantinescu, M. (2022, June 21). Estimating the short-term impact of war on economic activity in Ukraine. *Centre for Economic Policy Research (CEPR)*. https://cepr.org/voxeu/columns/estimating-short-term-impact-war-economic-activity-ukraine-0
Layton, P. (2015, April 9). How Sri Lanka Won the War. *The Diplomat*. https://thediplomat.com/2015/04/how-sri-lanka-won-the-war/
Li, X., & Zhou, Y. (2017). A Stepwise Calibration of Global DMSP/OLS Stable Nighttime Light Data (1992–2013). *Remote Sensing*, *9*(6), Article 6. https://doi.org/10.3390/rs9060637
Li, X., Zhou, Y., Zhao, M., & Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, *7*(1), Article 1. https://doi.org/10.1038/s41597-020-0510-y
Martínez, L. R. (2018). How Much Should We Trust the Dictator's GDP Growth Estimates? *Journal of Political Economy*, *130*(10), 2731–2769. https://doi.org/10.1086/720458
Mundy, S. (2017, November 7). Sri Lanka counts high cost of war and peace. *Financial Times*.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, *49*(6), 1417–1426. https://doi.org/10.2307/1911408

Observation Group. (n.d.). *DMSP Nighttime Lights*. Payne Institute for Public Policy, Colorado School of Mines. Retrieved December 12, 2022, from https://eogdata.mines.edu/products/dmsp/

Olason, E. (2010). *Sri Lanka Civil War Maps*. Behance. https://www.behance.net/gallery/35391907/Sri-Lanka-Civil-War-Maps

Rama, M., & Beyer, R. (2017, October 25). *Measuring South Asia's economy from outer space* [World Bank Blogs]. https://blogs.worldbank.org/endpovertyinsouthasia/measuring-south-asia-s-economy-outer-space

Richardson, J. M., Jr., & Samarasinghe, S. W. R. de A. (1991). Measuring the economic dimensions of Sri Lanka's ethnic conflict. In *Economic dimensions of ethnic conflict*. St. Martin's Press.

Serneels, P., & Verpoorten, M. (2015). The Impact of Armed Conflict on Economic Performance: Evidence from Rwanda. *Journal of Conflict Resolution*, *59*(4), 555–592. https://doi.org/10.1177/0022002713515409

Shortland, A., Christopoulou, K., & Makatsoris, C. (2013). War and famine, peace and light? The economic dynamics of conflict in Somalia 1993–2009. *Journal of Peace Research*, *50*(5). https://journals.sagepub.com/doi/full/10.1177/0022343313492991

Statistical Abstract (Chapter II-Population). (2021). Department of Census and Statistics. http://www.statistics.gov.lk/abstract2021/CHAP2

Sundberg, R., & Melander, E. (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research*, *50*(4), 523–532. https://doi.org/10.1177/0022343313484347

United Kingdom: Home Office. (2016). *Country Information and Guidance Sri Lanka: Tamil Separatism*. https://www.refworld.org/docid/573eab154.html

United Nations. (2011). *Report of the Secretary-General's Panel of Experts on Accountability in Sri Lanka: UN Documents: Security Council Report*. Security Council Report. https://www.securitycouncilreport.org/un-documents/document/poc-rep-on-account-in-sri-lanka.php

Wayman, F., & Sarkees, M. R. (2010). *Resort to War: 1816—2007*. CQ Press. https://us.sagepub.com/en-us/nam/resort-to-war/book236426

Wijeweera, A., & Webb, M. J. (2009). Military Spending and Economic Growth in Sri Lanka: A Time Series Analysis. *Defence and Peace Economics*, *20*(6), 499–508. https://doi.org/10.1080/10242690902868301

Williams, R., & Weaver, M. (2009, May 18). Timeline: Sri Lanka conflict. *The Guardian*. https://www.theguardian.com/world/2009/may/18/sri-lanka-conflict

Witmer, F. D. W., & O'Loughlin, J. (2011). Detecting the Effects of Wars in the Caucasus Regions of Russia and Georgia Using Radiometrically Normalized DMSP-OLS Nighttime Lights Imagery. *GIScience & Remote Sensing*, *48*(4), 478–500. https://doi.org/10.2747/1548-1603.48.4.478

World Bank Open Data. (n.d.). The World Bank. Retrieved December 8, 2022, from https://data.worldbank.org/

Appendix:

Figure A.1: DMSP Satellite Year Coverages

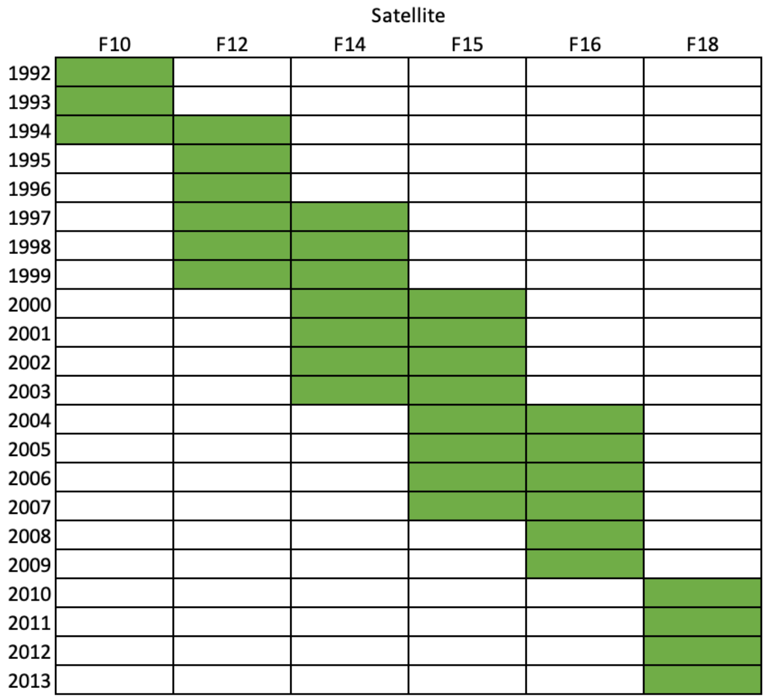

Figure A.2: Provinces and Districts in Sri Lanka (Johnson, 2017)

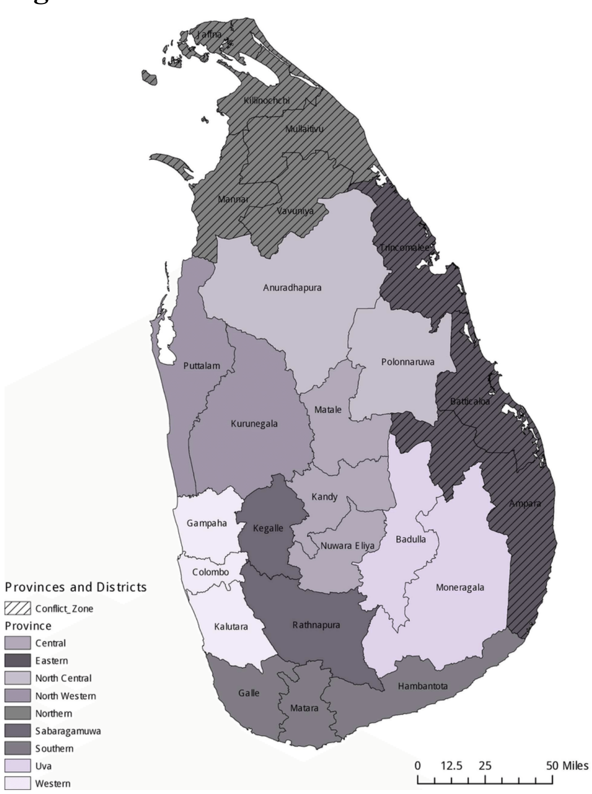

Table A.1: Implied Percentage Change in *ln(lum)* from Primary Regression Results

	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-31.27%	-30.72%	-23.05%	-23.20%
Rebel Deaths	-9.34%	-7.23%	-16.72%	-13.76%
Civilian Deaths	9.31%	9.09%	13.31%	11.52%
Num Attacks	-86.60%	-69.06%	-72.72%	-44.01%
Time Trend	7.36%	6.93%	7.36%	6.93%
Spatial Lags:				
Gov Deaths Near		-9.24%		-8.97%
Rebel Deaths Near		-10.42%		-10.24%
Civilian Deaths Near		4.39%		4.39%
Num Attacks Near		3.25%		3.67%
Temporal Lags:				
Gov Deaths Prev.			-29.39%	-27.67%
Rebel Deaths Prev.			18.29%	14.91%
Civilian Deaths Prev.			14.80%	13.09%
Num Attacks Prev.			-88.28%	-80.47%

Table A.2: Without Number of Attacks

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.348***	-0.352***	-0.246***	-0.261***
	(0.09)	(0.09)	(0.09)	(0.09)
Rebel Deaths	-0.224***	-0.144***	-0.251***	-0.165***
	(0.04)	(0.04)	(0.05)	(0.04)
Civilian Deaths	0.032	0.056*	0.011	0.037
	(0.03)	(0.03)	(0.03)	(0.03)
Time Trend	0.070***	0.066***	0.070***	0.066***
	(0.00)	(0.00)	(0.00)	(0.00)
Spatial Lags:				
Government Near		-0.091***		-0.087***
		(0.03)		(0.03)
Rebel Deaths Near		-0.112***		-0.112***
		(0.01)		(0.01)
Civilian Deaths Near		0.045***		0.044***
		(0.01)		(0.01)
Temporal Lags:				
Gov Deaths Prev.			-0.374***	-0.331***
			(0.09)	(0.09)
Rebel Deaths Prev.			0.085**	0.066*
			(0.04)	(0.04)
Civilian Deaths Prev.			0.092***	0.086***
			(0.03)	(0.03)
Constant	5.592***	5.674***	5.595***	5.675***
	(0.02)	(0.02)	(0.02)	(0.02)
N	7273	7273	7273	7273
R^2	0.285	0.314	0.288	0.316

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

Table A.3: 2009 and 2010 Excluded

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.340***	-0.340***	-0.203**	-0.214**
	(0.09)	(0.09)	(0.10)	(0.09)
Rebel Deaths	-0.060	-0.029	-0.134**	-0.093
	(0.05)	(0.05)	(0.06)	(0.06)
Civilian Deaths	-0.208	0.081	-0.282	0.003
	(0.41)	(0.40)	(0.41)	(0.40)
Num Attacks	-1.778***	-1.128**	-1.253***	-0.653
	(0.43)	(0.45)	(0.45)	(0.47)
Time Trend	0.071***	0.067***	0.071***	0.067***
	(0.00)	(0.00)	(0.00)	(0.00)
<u>Spatial Lags:</u>				
Gov Deaths Near		-0.059**		-0.055**
		(0.03)		(0.03)
Rebel Deaths Near		-0.107***		-0.106***
		(0.01)		(0.01)
Civilian Deaths Near		-0.274***		-0.287***
		(0.09)		(0.09)
Num Attacks Near		0.146		0.135
		(0.11)		(0.11)
<u>Temporal Lags:</u>				
Gov Deaths Prev.			-0.426***	-0.397***
			(0.09)	(0.09)
Rebel Deaths Prev.			0.149***	0.126**
			(0.05)	(0.05)
Civilian Deaths Prev.			0.399***	0.407***
			(0.09)	(0.09)
Num Attacks Prev.			-1.707*	-1.311
			(0.93)	(0.92)
Constant	5.588***	5.671***	5.592***	5.674***
	(0.02)	(0.02)	(0.02)	(0.02)
N	6611.000	6611.000	6611.000	6611.000
R^2	0.282	0.306	0.287	0.311

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

Table A.4: Northern and Eastern Provinces Only

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.279*	-0.280*	-0.179	-0.183
	(0.15)	(0.15)	(0.15)	(0.15)
Rebel Deaths	-0.062	-0.060	-0.163*	-0.149*
	(0.08)	(0.08)	(0.09)	(0.09)
Civilian Deaths	0.080	0.086*	0.132**	0.120**
	(0.05)	(0.05)	(0.06)	(0.06)
Num Attacks	-2.380***	-1.464**	-1.617**	-0.813
	(0.68)	(0.71)	(0.71)	(0.74)
Time Trend	0.111***	0.101***	0.112***	0.101***
	(0.00)	(0.00)	(0.00)	(0.00)
Spatial Lags:				
Gov Deaths Near		0.007		0.010
		(0.04)		(0.04)
Rebel Deaths Near		-0.103***		-0.101***
		(0.02)		(0.02)
Civilian Deaths Near		0.035**		0.034**
		(0.01)		(0.01)
Num Attacks Near		-0.013		-0.005
		(0.17)		(0.17)
Temporal Lags:				
Gov Deaths Prev.			-0.289*	-0.292**
			(0.15)	(0.15)
Rebel Deaths Prev.			0.204***	0.174**
			(0.08)	(0.08)
Civilian Deaths Prev.			0.131***	0.123**
			(0.05)	(0.05)
Num Attacks Prev.			-2.544***	-2.012***
			(0.75)	(0.75)
Constant	3.787***	4.001***	3.796***	4.002***
	(0.06)	(0.07)	(0.06)	(0.07)
N	1731	1731	1731	1731
R^2	0.283	0.307	0.291	0.313

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

Table A.5: District Level Results

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.213**	-0.193**	-0.100	-0.097
	(0.09)	(0.09)	(0.09)	(0.09)
Rebel Deaths	-0.103**	-0.129**	-0.164***	-0.175***
	(0.05)	(0.05)	(0.05)	(0.06)
Civilian Deaths	0.067***	0.061**	0.039	0.017
	(0.03)	(0.03)	(0.03)	(0.03)
Num Attacks	-0.967***	-0.629	-0.729**	-0.438
	(0.34)	(0.51)	(0.35)	(0.52)
Time Trend	0.056***	0.054***	0.054***	0.054***
	(0.01)	(0.01)	(0.01)	(0.01)
<u>Spatial Lags:</u>				
Gov Deaths Near		-0.058		-0.045
		(0.04)		(0.04)
Rebel Deaths Near		0.034		0.025
		(0.02)		(0.02)
Civilian Deaths Near		0.020*		-0.012
		(0.01)		(0.02)
Num Attacks Near		-0.269		-0.209
		(0.18)		(0.18)
<u>Temporal Lags:</u>				
Gov Deaths Prev.			-0.222**	-0.219**
			(0.09)	(0.09)
Rebel Deaths Prev.			0.082*	0.068
			(0.05)	(0.05)
Civilian Deaths Prev.			0.017	0.005
			(0.02)	(0.03)
Num Attacks Prev.			0.516	0.878
			(0.37)	(0.54)
Constant	8.207***	8.241***	8.186***	8.196***
	(0.08)	(0.09)	(0.09)	(0.09)
N	550	550	550	550
R^2	0.250	0.260	0.292	0.296

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

Table A.6: Previous Year Luminosity Included

Dep Var: ln(lum)	Baseline	Spatial Lags	Temp. Lags	Both Lags
Gov Deaths	-0.262***	-0.298***	-0.211**	-0.251***
	(0.08)	(0.08)	(0.08)	(0.08)
Rebel Deaths	-0.159**	-0.096	-0.222***	-0.158**
	(0.06)	(0.06)	(0.06)	(0.06)
Civilian Deaths	0.119***	0.096***	0.119***	0.096***
	(0.03)	(0.03)	(0.03)	(0.03)
Num Attacks	-0.486	-0.398	0.046	0.095
	(0.41)	(0.42)	(0.41)	(0.43)
$\text{Ln}(\text{lum}_{t-1})$	0.580***	0.560***	0.580***	0.560***
	(0.01)	(0.01)	(0.01)	(0.01)
<u>Spatial Lags:</u>				
Gov Deaths Near		-0.172***		-0.170***
		(0.02)		(0.02)
Rebel Deaths Near		-0.019		-0.018
		(0.01)		(0.01)
Civilian Deaths Near		0.028***		0.028***
		(0.01)		(0.01)
Num Attacks Near		-0.089		-0.087
		(0.10)		(0.10)
<u>Temporal Lags:</u>				
Gov Deaths Prev.			-0.253***	-0.238***
			(0.08)	(0.08)
Rebel Deaths Prev.			0.207***	0.200***
			(0.04)	(0.04)
Civilian Deaths Prev.			0.118***	0.109***
			(0.03)	(0.03)
Num Attacks Prev.			-1.298***	-1.224***
			(0.40)	(0.40)
Constant	2.742***	2.894***	2.742***	2.890***
	(0.06)	(0.06)	(0.06)	(0.06)
N	6936	6936	6936	6936
R^2	0.410	0.423	0.415	0.428

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