Essays on Economics of Conflicts

A Thesis Presented

by

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Declaration of Authorship

I, Sze Yeung Lau, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed: _____

Date: _____

Acknowledgement:

I am grateful to Royal Holloway, University of London, not only for enriching my profession in economic science but also for waving beautiful memories throughout my study here. I am especially in gratitude to Professor Michael Spagat, who has guided me into the world of economics with countless help and support. I appreciate all the friends I met in Royal Holloway, who have brought everlasting happiness into my life.

To My Mother

Ng Oi-Lin

Abstract

Chapter 1: Conflict and Child Health: Evidence from the DRC Conflicts between 1996 and 2014

This paper uses four nationally representative household surveys to investigate the dynamics of children's health during the DRC conflicts from 1996 to 2014. I find negative effects on child HAZ scores after the First and Second Congo Wars. The ceasefire period between 2003 and 2008 significantly enhanced child nutritional performance. In contrast, the subsequent conflict in Orientale, Nord-Kivu and Sud-Kivu worsened child HAZ scores again.

Chapter 2: Conflict and Development: A Methodology by Using Outer Space Data

This paper pioneers the use of night light density data from satellite pictures to study the impacts of war on economic performance in seven countries. The results vary by conflict, with clear negative effects in Syria and Iraq. The Afghan War appears to stimulate economic development while no statistically significant effect has been found for the case of Libya, Colombia, Chad and the DRC. In general, the impacts of war on economic development are heterogeneous, conditional on the country specific characteristics.

Chapter 3: Conflict and Fertility: A Case Study by the DRC Conflicts

This paper studies the impact of conflict on fertility in the Democratic Republic of Congo by employing four nationally representative household surveys, the results estimated by women between 15 and 49 years old display a lower fertility level during the ceasefire periods. In other words, conflict boosts the fertility level, which can be explained by a risk-insurance effect. However, this result suffers from omitted variable bias. For younger women samples between 15 and 23 years old, the estimation turns out to be insignificant. Hence, it shows that the DRC conflicts has not had a significant impact on fertility.

Contents

List of Acronyms

ACLED	The Armed Conflict Location and Event Dataset
BBC	The British Broadcasting Corporation
CENTCOM	The United States Central Command
CERAC	The Conflict Analysis Resource Center in Colombia
CH4	Methane; Carbon Tetrahydride
CNN	Cable News Network
CO2	Carbon Dioxide
COSIT	Central Organization for Statistics & Information Technology
DHS	The Demographic and Health Surveys
DID	The Difference-in-Differences Estimation
DMSP	The Defence Meteorological Satellite Program
DN	Digital Number
DRC	The Democratic Republic of Congo
ELN	National Liberation Army of Colombia
EPL	People's Liberation Army of Colombia
FARC	Revolutionary Armed Forces of Colombia
FDLR	The Democratic Forces for the Liberation of Rwanda
GDP	Gross Domestic Product
GIS	Geographic Information System
HAZ	Height-for-Age Z-Score
IDMC	The Internal Displacement Monitoring Centre
IDP	Internal Displaced Persons
IDP	Internal Displaced Profiles
ISA	The International Security Assistance Force in Afghanistan
LED	Light-Emitting Diode
LNA	Libyan National Army
M23	The Congolese Revolutionary Army
MDGS	The Millennium Development Goals
MICROCON	A Micro Level Analysis of Violent Conflict
MICS	The Multiple Indicator Cluster Surveys
MNF	The Multi-National Force in Iraq
N2O	Nitrous Oxide
NATO	The North Atlantic Treaty Organization
NGO	Non-Governmental Organization
NRC	The Norwegian Refugee Council
OCHA	The United Nations Office for the Coordination of Humanitarian Affairs
OLS	Operational Line-scan System
SARAC	The System for Analysis and Register of Conflict Actions
SCPR	The Syrian Centre for Policy Research
SHT	Societe des Hydrocarbures du Tchad
TNC	The Transitional National Council in Libya
UNHCR	The Office of the United Nations High Commissioner for Refugees
UNICEF	The United Nations International Children's Emergency Fund
USAID	The United States Agency for International Development
WAZ	Weight-for-Age Z-Score
WHO	The World Health Organization
WHZ	Weight-for-Height Z-Score
WMD	Weapon of Mass Destruction
WWII	The Second World War

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1. Conflict and Child Health:

Evidence from the DRC Conflicts between 1996 and 2014

Figo Sze-Yeung Lau

Abstract

This paper applies four household surveys to analyse the children's health and nutrition status in the Democratic Republic of Congo. With the variation of the temporal and spatial treatment effects, I exploit the war impact on children's health. The results meet the initial expectation that the First and Second Congo Wars have put negative effects on child health conditions. During the ceasefire period, there were robust rebounds for child HAZ score. Even in a short-term analysis, a peace deal can considerably improve child health condition. The estimation also suggests that the subsequent conflicts among militias since 2008 have had a more detrimental impact on child health condition than the initial Great Congo Wars. In addition, under 36-months children are in particular sensitive and vulnerable by conflict treatment. The DRC has been one of the least developed countries in the world, conflict has further damaged child health condition.

Key words: conflict, health, nutrition, children, HAZ, DRC

1.1 Introduction

Improving health condition for women and children in developing world is a global target, as one of the eight Millennium Development Goals since 2000 United Nations Summit (The Millennium Development Goals Report 2012). During the past three decades, almost three quarters of Sub-Sahara countries have experienced civil conflict or political crisis (Gleditsch et al. 2002).

There has been a great deal of study focusing on the causality between conflicts and economics. However, most of the studies make use of the macro level explanations for the conflict like Collier and Hoeffler (1998) explaine the economic causes of civil war, and Alan Krueger (2007) uses economic roots to interpret the terrorism. Justino, Bruck and Verwimp (2013) introduce the in-depth research programme MICROCON, aiming to advance knowledge in the field of conflict analysis through the construction of an innovative micro level research institute. With an increasing number of local household surveys available, researchers begin to focus on using micro-level data to evaluate the impact of war on health and subsequent economic performance, such as the Cote d'Ivoire conflict (Minoiu and Shemyakina 2012)[1], the Eritrea conflict (Akresh et al. 2012)[2], Burundi Civil War (Verwimp 2012; Bundervoet et al. 2008)[3], Nigerian Civil War (Akresh et al. 2011)[4], Iraq War

[1] Miniou and Shemyakina (2012) quantified the impact of the 2002-2007 armed conflict in Cote d'Ivoire on children's height-for-age z-scores. Their results suggested that children aged 6-60 months who lived in high conflict intensity regions suffered significant health setbacks compared to those in low conflict intensity regions. Besides, they found that conflict induced economic stress, health stress, and other stress had a large and negative effect on child health in conflict-affected regions.

[2] Akresh et al. (2012) used household survey data from Eritrea to estimate the effect of exposure of the 1998-2000 Eritrea-war on child health. They concluded that war-exposed children had lower height-for-age z-scores, with similar effects for children born before or during the war.

[3] Verwimp (2012) used anthropometric data from a longitudinal survey (1998-2007) to investigate the effects of children undernutrition on the risk of mortality in Burundi. He found that undernourished children, measured by the height-for-age z-scores in 1998 had a higher probability of dying during subsequent years. Bundervoet et al. (2008) studied the effect of the civil war in Burundi on the children's health effect. The strategy also exploited the exogenous variation in the war's timing across provinces and the exposure of children's birth cohorts to the war. They obtained robust results that children exposed in the conflict provinces had 0.5 standard deviations lower height-for-age z-scores than those non-exposed children. It was concluded that the poor health status of Burundian children could lead to negative welfare effects in the long run.

[4] Akresh et al. (2011) used the variations across ethnicity and cohort during Nigerian civil war (1967 to 1970) to identify the long run effects on human health capital. As a result, the children and adolescents of all ages exposed to the war have shown decreased adult stature, and the

(Guerrero-Serdan 2009)[5], Zimbabwe Civil War (Alderman et al. 2006)[6], Kashimir conflict (Parlow 2012)[7], WWII Germany (Akbulut-Yuksel 2014)[8], and the DRC conflicts (Dagnelie et al. 2018)[9].

The nutritional status of children is an indicator of the overall health (WHO), the nutritional intake in early life is of great significance for the later life growth. Children will most likely reach their potential physical growth only when they have access to adequate food and medical care without repeated illnesses. As one of the Millennium Development Goals towards reducing extreme poverty and hunger, the United Nations has declared to reduce by half the proportion of people suffering from hunger before 2015. The level of malnutrition has remained a concern in the DRC for decades, 24 percent of children less than five years old are under-weight (MICS 2011). Thomas and Strauss (2007) conclude that health condition has a positive effect on human capital accumulation, improving productivities and population living standard. Moreover, a great deal of literature has drawn a principal conclusion that economic development and earlier childhood health condition are highly correlated, both scientifically (Victoria et al. 2008; Grantham-McGregor et al. 2007; Black et

effects are significant among the adolescent's cohorts. Furthermore, they also found a reduced life expectancy and lower income for the exposed cohort.

[5] Guerrero-Serdan (2009) used household surveys from 2003 Iraq War to analyse a causal relationship between Iraq War and nutritional outcome of children. Guerrero-Serdan used three separate datasets to constitute a panel to discover the anthropometric difference among the children from various ages and places; the results are robust from several specifications. Estimates indicated that the children growing up from high level of conflict district were 0.8 cm shorter than the children from the low level areas, besides, she also provided empirical evidence that the malnutrition in the early childhood had negative impact on later education, productivity and labour outcomes.

[6] Alderman et al. (2006) identified civil war and drought in Zimbabwe to analyse the differences in pre-school nutritional status across siblings. They applied a maternal fixed effects-instrumental variable estimator with a long term panel dataset to show that the children experienced the disasters were 3.4 cm shorter and had 0.85 years less schooling. A better pre-schooler with a higher height-for-age score were associated with more number of grades of schooling completed.

[7] Parlow (2012) used the experience of the Kashmir insurgency as an exogenous shock. Parlow used three individual datasets from the National Family Health Survey of India to analyse the effects of the Kashmir insurgency on children's height with a difference-in-differences regression. Conclusions were drawn that children who were small at birth and children with anaemic mothers were shorter for their ages. He further added that children who were more affected by the insurgency are 0.9 to 1.4 standard deviations shorter compared with children less affected by the insurgency.

[8] Akbulut-Yuksel (2014) found that exposure to destruction had long-lasting detrimental effects on the human capital formation, health, and labour market outcomes of Germans who were at school-age during WWII.

[9] Dagnelie et al. (2018) adopted an instrumental variable approach to investigate the impact of civil war in the Democratic Republic of Congo on infant mortality between 1994 and 2004. Their paper suggested that gender imbalances in infant mortality were driven by the selection induced by a higher vulnerable of boys in utero rather than by gender discrimination. Based on their outcome, I will also exploit the Second Congo War effects on the nutritional outcomes of different genders.

al. 2013)[10] and empirically (Martorell and Habicht 1986; Stein et al. 2004; Ziegler 2006; Meng and Qian 2006; Strauss and Thomas 1998; Black et al. 2016; Camacho 2008; Murdoch and Sandler 2002; Verwimp and Bundervoet 2008)[11]. This paper evaluates DRC's overall health status and attempts to propose corresponding policy to improve the living conditions for children under five years old in the DRC. Additionally, in literature it is generally accepted that the health condition has substantial influence on the economic development and well-being of the population (Bloom et al. 2001; Pritchett and Summers 1996; Bhalotra 2008). In this way, this paper also contributes to the sectors between health and economic development.

Since the collapse of Zaire state in 1997, the new-born country, the Democratic Republic of the Congo (DRC), has been involved in constant military conflicts. The country has witnessed two major interstate conflicts, the First Congo War and Second Congo War. The Second Congo War in particular triggered a devastating wave of violence and killings

[10] Victoria et al. (2008) found that undernutrition was strongly associated with shorter adult height, less schooling, reduced economic productivity and for women, lower offspring birthweight. Comparably, Grantham-McGregor et al. (2007) concluded that disadvantaged children in developing countries with early childhood stunting or absolute poverty were likely to do poorly in school and subsequently had low incomes, high fertility and provided poor care for their children, contributing to the intergenerational transmission of poverty. Black et al. (2013) stated that deficiencies of vitamin A and zinc resulted in deaths; deficiencies of iodine and iron, together with stunting, could contribute to children not reaching their development potential. In addition, mother's undernutrition contributes to foetal growth restriction, which boosted the risks of neonatal deaths. Suboptimum breastfeeding resulted in an increased risk for mortality in the first two years of life.

[11] The nutrition in the first 24 months has significant impact on the rest of life. If the growth is deterred or slow, it is not possible to catch up in the later life and can affect the cognitive ability from Martorell and Habicht (1986). Stein et al. (2004) studed the Dutch famine during World War II to evaluate the effect of prenatal exposure to the famine on body proportions at birth and found that the exposure during late pregnancy was negatively associated with child's birth weight and body proportion.

Furthermore, Metcoff (1986) proved the health condition of the mother during the pregnancy was also an important factor to affect the children's later growth. Ziegler (2006) provided evidence that infants and young children needed to intake substantially more protein than the older children. Meng and Qian (2006) found that, during the China's Great Famine, the children exposed on the food shortage led to worse adult health and socioeconomic conditions. Strauss and Thomas (1998) suggested that malnutrition in early life stage could have implications for war-exposed children's future schooling and productivity as adults.

Black et al. (2016) examined the effects of stress induced by the death of the mother's parent during pregnancy on both the short-run and the long-run outcomes of the infant. They found that acute psychological stressors during pregnancy had limited adverse consequences for the child's success in education and the labour market. However, Camacho (2008) came to evidence of 8.7 grams drop in weight as a result of a baby experiencing stress in the utero due to landmine explosions in the municipality of residence.

Besides, Murdoch and Sandler (2002) used a neoclassical growth model to empirically test the impact of civil war on steady-state income per capita at home and neighbouring countries. Verwimp and Bundervoet (2008) suggested that temporarily famine-induced migration and illness decreased growth while good harvests, more split-offs and higher initial levels of education increased it.

throughout the country, which resulted in detrimental access to the country's health services and utility supply.

The variation in the intensity of violence across the provinces and the difference in ages of children exposed to the conflict provide a quasi-natural experiment to examine a possible causality between the health outcome and the war events, where the DRC conflicts can be regarded as exogenous shocks to the household decision and the child's individual characteristic. Based on this logic, I attempt to explore a causal relationship between conflicts and child health outcomes.

I find that the First and Second Congo Wars have put negative effects on child health. During the ceasefire period, there were robust rebounds for child health. These results are consistent with other studies (Akresh et al. 2012; Guerrero-Serdan 2009; Bundervoet et al. 2009). Even in short-term analysis, a peace deal can considerably improve child health condition. In addition, the estimation suggests that the subsequent conflicts among militias since 2008 have put a more detrimental impact on child health condition than the Great Congo Wars.

The paper unfolds as follows. Section 1.2 cites a theoretical framework to support the empirical studies. Section 1.3 describes the data sources and samples. Section 1.4 presents the identification strategy and econometric frameworks. Section 1.5 highlights the empirical estimation results and interpretations. Section 1.6 discusses robustness check and potential bias. The final section draws the conclusions.

1.2 Theoretical Framework

Grossman (1972) has introduced health production function. He argues that the initial endowment of genetic heritage, early life environments, and subsequent health and nutritional inputs constitute health but form in a specific life period. Based on this theory, Cunha et al. (2006), Cunha and Heckman (2007) extend this model with multi-period skill production function, focusing on the critical period of life growth. The model displays that a critical or sensitive period of life produces a specific life skill with adamant health and nutrition investment. In our conflict context, if these skills are substitutes with later life stage development, then war impact on child development is limited even the health investment is insufficient. However, if the skills obtained in every critical life stage are complements or even have multiplier effects, the loss of the productivity in future is uncompensated. An extreme case is 'Leontief Technology' function with investment over the periods; lack of child investment will deter the child to progress into the next stage.

Formally, the model defines S_0 as initial skills endowment of the child, these skills can be influenced by in utero experiences and genetics. Investment in a child during period t as I_t, the skill produced from that investment as S_t for *t*=1, 2, 3, … So S_t contains a variety of abilities and skills in different life stage *t*.

$$S_t = f_t(I_t, S_{t-1})$$

The production function is concave in I_t, differentiable and increasing in (I_t, S_{t-1}). Therefore, the skill formation in period 1 determines substitute or complementary in different period over time. Cunha et al. (2006) conclude that earlier child investments formations are different from the later child investment, if the skills are not developed in earlier age; it is difficult to catch up and develop further.

This paper explores the conflict impact on child health under five years old covering the infancy (under 12 months of age) and early childhood periods, the critical periods for human development (Bronson 1962), especially for cognitive and non-cognitive ability development. A deteriorated health condition of children implies a productivity loss for the DRC in the future, this is another motivation for this paper.

1.3 Nutritional Indicators and Data Samples

1.3.1 Nutritional Indicators

There are multiple anthropometric indicators to measure human nutritional outcomes. In this paper, I use the z-scores, defined by the World Health Organization (WHO), to measure children's growth and malnutrition. To transform poverty, malnutrition and diseases into wealth, growth and health, the World Health Organization initiated three biological indicators to gauge the children's health condition and to assess the quality of life in the region. The three indicators are weight-for-height, height-for-age and weight-for-age z-scores.

Weight-for-height, or WHZ, is a description of acute malnutrition, which is a direct indicator of wasting caused by recent and rapid reduction in food supply, which is associated with severe starvation or disease. Hence, WHZ presents the current health condition with respect to height.

Height-for-age, or HAZ, reflects chronic malnutrition, which measures stunting due to long-term malnutrition. Stunting is a failure to reach linear growth potential as a consequence of poor health condition or malnutrition. For instance, low food availability in long term, protein deficiency or the suboptimal health condition of the pregnant mother can lead to chronic malnutrition. In addition, HAZ represents the long-term accumulated health condition; therefore, it reflects the overall socioeconomic condition of the country. Especially in developing countries in a stable environment, since height-for-age is a stock variable, reflecting current and past health investments, older children accumulate a larger deficit

during their lives, resulting in lower height-for-age z-scores compared to younger children (Martorell and Habicht 1986; Duflo 2003).

Weight-for-age, or WAZ, is an indicator for general malnutrition, which reflects the body mass relative to chronological age. WAZ is a composite, influenced by both height-for-age and weight-for-age. For example, underweight, or low WAZ score, can be attributed as the short-term weight reduction; for example, it can reflect a tall but thin child.

Generally, chronic malnutrition is significant because the earlier life stunting can remain during the subsequent life stage, and this process is not likely to recover as the conclusion from the theoretical work (Cunha et al. 2006, Cunha and Heckman 2007). Acute malnutrition can be cured with adequate nutritional intake as it is a short run effect. Besides underweight (WAZ) is a reflection of both the acute malnutrition and chronic malnutrition.

According to WHO Global Database regulation, 'the Z-score system expresses the anthropometric value as a number of standard deviations or Z-scores below or above the reference mean value'. The calculated Z-Score values with the bar of the WHO standard are accessible in all of the four household surveys applied in this paper. To investigate children's nutritional variations, I use HAZ score as the outcomes of interest in the empirical models.

1.3.2 Data and Samples

I collect quantitative input from four household surveys, conflict datasets, and international displacement reports to identify the impact of war on children's health.

1.3.2.1 MICS 2001, DHS 2007, MICS 2010 and DHS 2013

There are four household surveys in the DRC currently available, which were conducted in 2001, 2007, 2010 and 2013. Four different time points facilitate a dynamic analysis for exploring the effects of war on child growth. The household surveys cover information in detail for household living conditions across the whole country. Hence, not only am I able to interpret the influences of violent environment on children's health, but I can also pick up the reasoning variables from these surveys to figure out the mechanisms behind the truth.

The first two household surveys are both Multiple Indicator Cluster Surveys (MICS) conducted by COSIT and the Ministry of Health together with Unicef. MICS has been technically used by Unicef to monitor the situation of children and women in developing countries in order to achieve the child-related global Millennium Development Goals (MDGs). MICS investigate women between 15-49 years old and children under 5 years old, covering indicators including nutrition, sanitation, education, child health, immunisation, anthropometry and child labouring. Unicef helps developing countries to collect and disseminate the datasets, develop the methodologies and indicators to assess the development in general and the situation of children and women in particular.

MICS 2001 and MICS 2010 surveys are used in this paper. Both surveys are nationally representative and conducted from February to August 2001 and from February to April 2010 respectively. MICS 2001 covers a sample of 8704 households, of which 8622 households were interviewed. MICS 2010 selects 11490 household samples, among 11393 households' interviews were successfully held. Nutritional statuses of children are the outcomes of

interest in this paper. The interview team measures children's weight and height according to strict Unicef international guidelines (Unicef, 2006). For children's age, the interviewers ask the day, month and year of birth. Besides, based on the WHO references, MICS displays direct anthropometric indicators including the calculated Z-Scores (HAZ, WAZ, WHZ).

The next two household surveys are from Demographic and Health Survey (DHS). DHS has provided over 290 surveys to advance global understanding of health and population in developing countries and to improve health and nutrition programme. The DHS projects are funded by USAID aiming in using policy design and programme planning and monitoring. Similar to MICS, DHS household surveys are also nationally representative, collecting and disseminating data information on fertility, nutrition, maternal health, child health, family planning and illness. For anthropometric indicators, the interviewers measured children's weight and height with the same WHO standard as well as presenting the calculated Z-Scores. DHS 2007 was conducted in two phases: from January to March 2007 in capital Kinshasa and from May to August 2007 in the other provinces. Specifically, 9995 women and 4757 men aged 15 to 59 were interviewed. DHS 2013 took place from November 2013 to February 2014. During this survey, 18827 women aged 15-49 in all selected households and 8656 men aged 15-49 in half of selected households were interviewed.

Four household surveys, MICS 2001, DHS 2007, MICS 2010 and DHS 2013, contain the information for the children between 0 and 59 months old, which are the main research objectives in this paper. However, the MICS and DHS household survey has no information about the displacement of each household. Hence, I cannot identify the households as original residents or displaced migrants. This can be a potential bias for the result estimation.

1.3.2.2. ACLED

To measure the level of the military conflict in different province, I use the Armed Conflict Location & Event Dataset (ACLED), which is designed for disaggregated conflict analysis and crisis mapping. ACLED is a publicly accessible data resource from University of Sussex. The dataset records political and civil conflicts from over 50 developing countries and covers all the African countries from January 1997 and the Asian countries from 2010.

All round conflict information is attached in the datasets including the date and location of the conflict, casualty number, event type and the information sources. Specifically, the types of event include battles, civilians killed, protests, change of territories control and fatalities; the latitude and longitude are noted for geographic precision. ACLED information sources are diversely distributed, from official state agency, international media including BBC and CNN, to humanitarian agencies, research publications and the NGOs. The goal of ACLED is to present a numerical and comprehensive assessment of political, military and domestic conflicts in developing states for academic and policy analysis.

1.3.3 Preliminary Observations

Table 1.1 outlines the variables of interests for the four household surveys. The table is divided into two panels: the upper panel shows the child individual characteristics and the lower panel displays the household characteristics.

For children's characteristics, the mean HAZ score has been decreasing from MICS 2001 cohort to DHS 2013 cohort. However, the values are all negative, which indicates the DRC children have experienced a lower nutritional intakes compared with the world reference group. Children with a height-for-age Z-score below -2 are considered stunted, while children with a height-for-age Z-score below -3 are considered severely stunted.

The children in the samples are between 0 to 59 months old. As can be seen, the average age across the four surveys is around 1.9 years old or approximately 21 months old. I additionally display the percentage of each age children, almost 20 percent for each age group.

Table 1.1: Characteristics of Children and Household

VARIABLES	MICS 2001	DHS 2007	MICS 2010	DHS 2013
Child Individual Characteristics:				
Height-for-Age Z Score	-1.262	-1.617	-1.628	-1.656
	(2.061)	(2.009)	(1.865)	(1.836)
Age in Years	1.877	1.946	1.870	1.917
	(1.424)	(1.408)	(1.388)	(1.412)
Age Percentage Distribution (%):				
0	22.71	20.50	21.90	21.74
1	21.71	21.42	21.87	20.70
2	19.06	20.16	19.70	19.93
3	18.16	18.87	20.43	19.38
4	18.35	19.06	16.10	18.25
Urban Residence	0.360	0.405	0.375	0.292
	(0.480)	(0.491)	(0.484)	(0.455)
Child Gender: Female	0.501	0.513	0.498	0.504
	(0.500)	(0.500)	(0.500)	(0.500)
Household Characteristics:				
Number of Household Members	7.972	7.065	6.872	6.845
	(3.863)	(3.128)	(2.871)	(2.814)
Number of Children Under 5	2.121	2.229	1.952	2.257
	(1.022)	(1.091)	(0.906)	(0.991)
HH Head Gender: Female	0.0966	0.165	0.129	0.219
	(0.295)	(0.371)	(0.335)	(0.414)
Mother Education (%):				
No Education	27.17	23.13	22.47	21.64
Primary School	40.70	44.24	40.88	44.57
Secondary School	31.05	31.77	36.62	32.86
Non-Standard Curriculum	1.08	0.86	0.03	0.93
Household Wealth Index (%):				
Poorest	19.78	22.40	19.29	27.22
Poorer	19.04	19.06	18.56	22.84
Middle	19.37	20.44	19.90	20.31
Richer	19.54	21.51	23.11	16.99
Richest	22.27	16.61	19.14	12.63
Number of Observations:	9,646	3,264	10,520	8,059

The ratio between female children and male children is roughly one to one. In terms of the residence type, around 40 percent of the child samples are from urban areas and DHS 2013 survey has the lowest proportion of the urban residents. Another point is the household survey sample size, MICS 2001 and MICS 2010 obtain a larger number of observations than DHS 2007 and DHS 2013

The lower panel presents the household characteristics. The number of household members varied from 2001 to 2013, almost eight members in 2001 to below seven members in 2013. Averagely two children were under five years old in each family. For the gender of household head, the percentage of the female household head has promoted from 9.7 per cent in 2001 to 21.9 per cent in 2013 in the DRC, a dramatic increase across the timeline.

Education of the mothers and the household wealth are indexed variables. Therefore, I present the percentage share of each category. Mothers' education levels reflect a similar trend among the four household surveys. However, the MICS 2001 survey contains significantly more wealthy households than other survey, which may explain the higher average HAZ scores. For the instance of the richest households, 22.27 percent occupies in MICS 2001 but only 12.63 percent in DHS 2013.

1.4 Identification Strategy

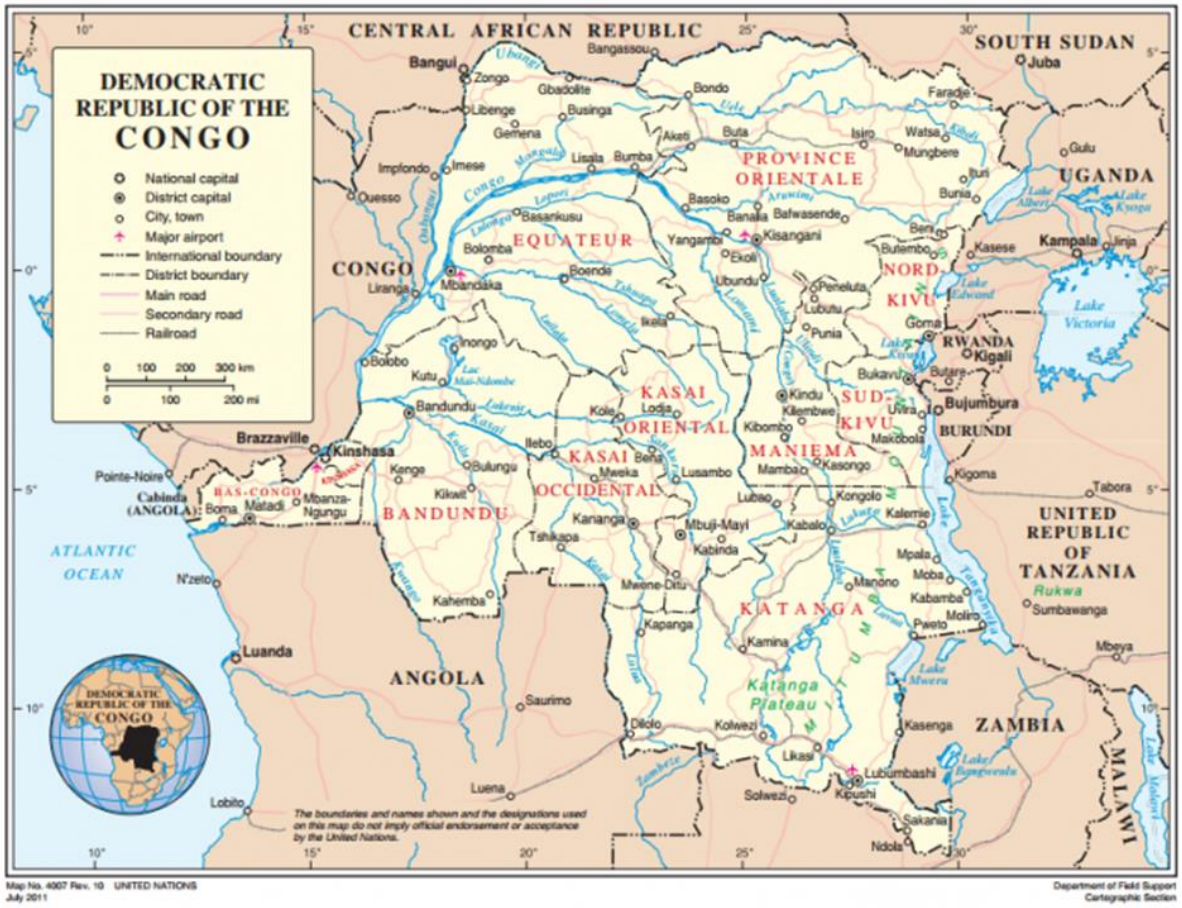
1.4.1 Conflict Background and Identification

The First Congo War commenced in 1996 and finished in 1997. Only one year after, the Second Congo War started, nine African countries and over twenty armed groups participated in this so-called “African World War”. All sides were accused of using the cover of the war to loot the country's rich economic wealth. In 2001 President Laurent Kabila was assassinated by his bodyguard, his son Joseph Kabila succeeded the president position. In 2003, Joseph Kabila called for multilateral peace talks and the Second Congo War was officially declared to an end. However, the conflict was still on going in the East DRC. Two rebel groups, the FDLR (the Democratic Forces for the Liberation of Rwanda) and M23 (the Congolese Revolutionary Army) emerged and they acted as war proxies for Rwanda. Rwanda and the Kinshasa government troops conducted tremendous military violence such as mass rapes, killings and other atrocities in the East DRC from 2008 to 2013.

Four household surveys cover the periods from 1996 to 2014, which can be categorised into three segments based on the intensity of the conflict. At first, I regard the First and Second Congo Wars as an econometrically exogenous treatment effect to the DRC household behaviours; therefore, any child who was born during the conflict period is treated by the wars. Secondly, when Joseph Kabila signed the peace agreement with the multinational leaders in 2003, the Second Congo War was officially declared to an end. The country embraced a relative peaceful environment for almost four years from 2004 to 2007. The children that were born and grew up during this period are regarded as control group as they were not directly exposed to the conflict. However, in 2008, the rebel groups triggered

another wave of armed conflicts in the East DRC. Four household surveys provide four time points across the time-line of the DRC history.

Map 1.1: the Democratic Republic of Congo (UN, No. 4007 Rev. 10, July 2011)



In this way, there are three time segments between 1996 and 2014:

From 1996 to 2003: The First Congo War (96-97) and the Second Congo War (98-03)

From 2004 to 2007: Ceasefire Period

From 2008 to 2014: Intensified East DRC Rebel Group Conflict

Therefore, the identification is based on the assumptions that the conflicts across the country had exerted an econometrically exogenous effect on children's nutritional intakes by changing household behaviours. Based on the brief history above, I emphasize the following points to support the assumptions.

1.4.1.1 Rwanda Genocide in 1994

In 1994, within three months between 500,000 and 1 million of the Tutsi minority and moderate Hutu were killed by a Hutu-Dominated regime in Rwanda. Later in 1994 when Tutsi rebels regained the power, the failed Hutu militias and over 1 million Hutu refugees fled into Zaire.

Although factors like public resentment against the corrupted and mismanaged regime had already been prevalent in Zaire at that moment, this external event triggered the collapse of the Zaire Mobutu regime and the subsequent First Congo War.

1.4.1.2 Rwanda and Uganda Invasion – The First Congo War

In 1996, Rwanda and Uganda attacked Zaire to oust dictator Mobutu. They installed Laurent Kabila as the new president and hoped to gain political and economic interest from his regime. The role of Rwanda and Uganda was external factors but they were crucial to the conflict outcome.

1.4.1.3 Kabila Dispatched the Rwanda and Uganda Troops – The Second Congo War

The Congolese people experienced around one-year ceasefire; from 1997 to 1998, largely the household would not expect additional violent conflicts in the country. However, Laurent Kabila did not provide specific benefits; instead, he ordered Rwanda and Uganda to return their troops to their home countries. The alliances broke up, in 1998, the Congolese rebel forces backed by Rwanda and Uganda attempted Kabila's forces and conquered the east. Ultimately, nine countries and twenty-five armed groups participated in the war, the Second Congo War started. Initially Rwanda and Uganda did not expect that Kabila would break the alliances even planned to manipulate the DRC government to exploit the DRC economic entities; hence, the Second Congo War was not necessarily anticipated under this inference.

1.4.1.4 Sudden Peace Deal – The Assassination of Laurent Kabila

The Second Congo War had not been ceased until Laurent Kabila was shot dead by one of his bodyguards. Instantly his son Joseph took the power and negotiated with Rwanda to withdraw the army. In 2002, Rwanda, Uganda and the DRC signed a peace deal. He formed a transitional government in June 2003. So the peace process was not expected ceased in such a process, the war was ceased suddenly. Households entered into a ceasefire period.

1.4.1.5 The All-Round Conflict

The conflicts in the DRC swept the treated regions indiscriminately. Especially because of the ethnic hatred or severe militia's violent exchanges, even schools and hospitals were not avoided being attacks. IDMC Global Report (2012, 2015) states that for the returned household to their hometowns, children found their schools destroyed and residents could not have access to medical care; particularly in Kivu regions, schools and hospitals were swept by military violence.

The factors above support an exogenous property of the DRC conflicts since 1996, so I regard the First and Second Congo Wars and the subsequent ceasefire deal have an exogenous property on child health conditions, as the households may not anticipate the war could start and cease in a sudden fashion. The militia conflict since 2008 has been continuous, I expect the increasingly fierce combats should have a significant impact on household behaviours.

1.4.2 Conflict Level Classification

There are eleven provinces in the Democratic Republic of Congo (1997-2014)[12]. Map 2 depicts a static picture for the number of conflict event from 1997 to 2015; the east part of the country witnessed the most of the military attacks.

Map 1.2: The Number of Conflict Event in the DRC (1997-2015)

There are different types of conflict based on the military target. ACLED groups the military actions like a battle between government and non-government actor, headquarter or base

[12] Since 2015 the DRC has been reclassified into 25 provinces. I use the previous classification to be consistent with the

established, non-violent transfer of territory, riots or protests, strategic development, and violence against civilians.

Among these military actions, the most harmful one to local households is the violent event directly against civilians. Table 1.2 describes the number of violence against civilian increases greatly across the four household survey years; most of the events locate in the east part of the country. I use this number of conflict event against civilians to indicate the conflict treatment effect on any child based on the province of residence and age in each household survey.

Table 1.2: The Number of Violent Conflicts against Civilians[13]

Province	MICS 2001 1997-2001	DHS 2007 2002-2007	MICS 2010 2005-2010	DHS 2013 2008-2013
Orientale	58	90	461	780
Nord-Kivu	44	146	245	669
Sud-Kivu	63	155	154	343
Katanga	37	37	29	172
Equateur	10	4	14	47
Kinshasa	19	8	10	43
Maniema	6	11	9	35
Kasai-Oriental	12	10	7	25
Kasai-Occidental	4	1	4	17
Bandundu	2	6	4	11
Bas-Congo	6	1	4	7
Total	261	469	941	2149

Table 1.2 reveals a similar trend that Nord-Kivu, Orientale and Sud-Kivu are the most violent provinces in the DRC. The table also highlights that after the Second Congo War, the number of the conflicting events have been drastically growing. The east part of the DRC experienced continuous military violence after the official ceasefire in 2003. The rebels, Rwanda army and resurgent with the DRC militaries made rampant fighting since 2008.

[13] In A Appendix, I add a conflict casualty table. Table A1.1 summarises the casualty figures by ACLED from 1998 to 2015. The majority of the fatality occurred between 1998 and 2003, reflecting the period of the Second Congo War. However, the east part of the DRC experienced continuous military violence after the official ceasefire in 2003. The rebels, Rwanda army and resurgent with the DRC militaries made rampant fighting since 2008. The casualty result is consistent to the number of conflict event result.

1.4.3 Econometric Framework

In order to acquire a precise estimation of the conflict effect on the child's health status, ideally I should observe the same child exposed in two different periods, before and after the war, as well as, to observe the same child who did not experience the war during this grow-up period while this is not feasible in reality. Furthermore, the household surveys do not particularly trace the same households to record the child's nutritional outcomes in different survey rounds.

Nevertheless, I have collected the four household surveys from the UNICEF and DHS. Four datasets address on four different points across the conflict time line. Each survey covers all the provinces in the DRC, which implies the geographical intensity of the conflict. The child's date of birth and the place of residence indicate the level of exposure to the war. Putting the information together, I can constitute a pseudo-panel to compare the health and nutritional indicators for the children born before and after the war in provinces influenced by different intensities of conflict.

Based on the geographical and temporal difference, I apply the difference-in-differences strategy with categorical treatment effects and multiple periods to investigate the conflict impacts on child nutritional status; in addition, I use the number of conflict events against civilians to classify the conflict treatment in each province of the DRC.

The four household surveys constitute a pseudo-panel including data for the periods 2001, 2007, 2010 and 2013.

$$HAZ_{ijt} = \alpha_t + \delta_j + \sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j + \boldsymbol{X_i'}\gamma \cdot + \varepsilon_{ijt}$$

Where HAZ_{ijt} is the Height-for-Age Z score for child *i* in province *j* at childbirth year *t*. The α_t represents childbirth time (both month and year) fixed effects, the δ_j denotes a set of the DRC province fixed effects. $\boldsymbol{X_i}$ is a vector of child individual and household covariates and ε_{ijt} is an idiosyncratic term. d_τ is an indicator variable, showing whether the region is treated by the conflict at household survey year τ. The treatment variable is V_j, which corresponds to the number of violent conflict events against civilians in province *j* during the household survey τ. The coefficient of interest is $\{\beta_\tau\}$, τ stands for the year (2001, 2007, 2010, and 2013) of the four household surveys. $\sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j$ indicates a separate interaction for each household year in the τ.

The previous section has stated the econometric exogeneity of the DRC wars on household behaviours. The MICS 2001 cohorts are supposed to be most severely affected because the cohort were exposed to both Congo Wars. Therefore, I expected the coefficient of interest on DHS 2007, MICS 2010 should be positive as these cohorts live during a relatively peaceful periods and ambiguous for DHS 2013 as the conflict in the DRC reignited.

All standard errors are robust, clustered at the province level to capture potential serial correction in the residual error term. One concern is that the number of clusters is relatively small (there are eleven provinces in the DRC), raising the possibility that asymptotic approximations may not be valid. As a remedy, I use the alternative wild bootstrap procedure (based on the t-statistics with the null hypothesis imposed) suggested by A. Colin Cameron, Jonah B. Gelbach and Douglas L. Miller (2008), computing the significance levels in 10,000 replications. I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using *boottest* command in Stata 14 (Roodman et al. 2016) below the coefficient of interests in the square brackets in each table.

1.5 Result Estimations

1.5.1 Four Household Surveys with Gender Differences

I start in the first three columns with Table 1.3. The coefficients of interest indicate the results from the interaction item from the specification. Column 2 controls the individual characteristics; column 3 further controls household characteristics. As the MICS 2001 cohort lived during both the First and Second Congo War, I omit this cohort as a comparison group. All the results are robust even with bootstrapping clustering standard deviation shown in the square brackets. The results meet the expectation that during the ceasefire period children from DHS 2007 cohort and MICS 2010 cohort both exhibit higher HAZ score than the MICS 2001 counterparts. The DHS 2007 cohort attained higher healthy results, around a positive differential of 0.005 standard deviation higher than the MICS 2001 cohort. MICS 2010 cohort also gains higher HAZ score, but the scale is not as large as the DHS 2007 cohort. DHS 2007 cohort grew up in a relatively peaceful period; however, older MICS 2010 cohort also lived during ceasefire but the east part of the country was exposed the militia conflict since 2008. Therefore, the results have been consistent with my hypothesis. On other hand, the coefficients in DHS 2013 cohort are negative with significance, although the scale is not big, the robust estimation indicate the DHS 2013 cohort health suffered a more damaging condition than the MICS 2001 cohort. This result also implies the militia conflicts since 2008 exert a considerably adverse effect on DRC households. Adding child and household controls hardly change the outcomes. To investigate the conflict impact on child gender differences, I add a gender indicator variable into the interaction term meanwhile omitting the 2001 female children cohort as a control group.

Table 1.3: Conflict Impact on Child HAZ Score

VARIABLES	(1) Fixed Effect	(2) Fixed Effect	(3) Fixed Effect	(4) Fixed Effect	(5) Fixed Effect	(6) Fixed Effect
Year2007×Conflict Level	0.00531*** (0.000527) [0.0230]	0.00470*** (0.000361) [0.0200]	0.00477*** (0.000709) [0.0240]	0.00522*** (0.000652) [0.0571]	0.00539*** (0.000397) [0.0541]	0.00555*** (0.000677) [0.0490]
	{-0.09197}	{-0.09536}	{-0.10519}	{-0.07369}	{-0.08007}	{-0.08907}
Year2010×Conflict Level	0.000982*** (0.00940) [0.0320]	0.000828** (0.0415) [0.0110]	0.000600* (0.0625) [0.0320]	0.000438 (0.149) [0.2302]	0.000611* (0.0917) [0.0310]	0.000379 (0.211) [0.1221]
	{-0.07639}	{-0.07595}	{-0.06844}	{-0.03722}	{-0.05004}	{-0.03810}
Year2013×Conflict Level	-0.000580** (0.0385) [0.0701]	-0.000661** (0.0361) [0.0601]	-0.000683** (0.0271) [0.0601]	-0.000817** (0.0228) [0.0661]	-0.000706** (0.0425) [0.0831]	-0.000727** (0.0329) [0.0751]
	{0.13477}	{0.18882}	{0.22071}	{0.13363}	{0.10694}	{0.12278}
Year2007×Conflict Level×Girl				0.000196 (0.808) [0.8038]	-0.00135 (0.140) [0.2943]	-0.00151* (0.0865) [0.1341]
				{-0.00666}	{0.06922}	{0.08925}
Year2010×Conflict Level×Girl				0.00109*** (0.00143) [0.2442]	0.000441*** (0.00348) [0.1471]	0.000447*** (0.00209) [0.1311]
				{-0.21242}	{-0.58050}	{-0.61694}
Year2013×Conflict Level×Girl				0.000470*** (0.00507) [0.1151]	9.02e-05 (0.261) [0.1972]	8.93e-05 (0.247) [0.1912]
				{-0.07168}	{-0.02152}	{-0.02338}

Girl		0.212***	0.215***		0.202***	0.205***
		(7.55e-08)	(6.66e-08)		(2.44e-06)	(1.93e-06)
Urban		0.406***	0.191***		0.406***	0.191***
		(2.72e-05)	(0.00826)		(2.87e-05)	(0.00882)
Constant	-1.782***	-2.297***	-2.787***	-1.783***	-2.292***	-2.784***
	(3.37e-09)	(2.61e-10)	(1.29e-10)	(3.37e-09)	(2.76e-10)	(1.21e-10)
Observations	31,427	31,427	31,427	31,427	31,427	31,427
R-squared	0.136	0.147	0.158	0.137	0.147	0.159
Province FE	YES	YES	YES	YES	YES	YES
Child Birth Month FE	YES	YES	YES	YES	YES	YES
Child Birth Year FE	YES	YES	YES	YES	YES	YES
Household Characteristics			YES			YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces I report the delta value of the Emily Oster test (Oster 2014).
Child individual controls include child gender and child residence type; household controls include gender of household head, mother's education, the number of household members, the number of children under 5 years old and household wealth.

$$HAZ_{ijt} = \alpha_t + \delta_j + \sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j + \sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j \times Girl_i + \boldsymbol{X_i'}\gamma \cdot + \varepsilon_{ijt}$$

Firstly, column 4 to column 6 shows that the DHS 2007 cohort acquired higher HAZ score and DHS 2013 cohort suffered a lower health outcome, compatible with column 1 to column 3 in the first three variables of interest. Moreover, for gender study, MICS 2010 cohort indicates that their female children obtained a robust HAZ score boost. However, when switching to the bootstrapping clustered standard errors in the square brackets, the statistical significance vanishes, and other coefficients of interest are not significant. Hence, across the DRC four household survey periods, the gender difference of the conflict impact cannot be concluded.

In sum, these results show an increasing number of conflict events against civilians result in lower child HAZ score and worsening healthy condition. In particular, the DHS 2007 cohort received better nutritional intakes thanks to the ceasefire period while the DHS 2013 cohort experienced health hardship because of their lower HAZ score. For the gender difference analysis in the DRC, Dagnelie et al. (2018) present that infant girls are less vulnerable than infant boys in terms of child mortality. However, for child HAZ score, these gender advantages are not found for the children under five years old.

1.5.2 Four Household Surveys with Age Classification

The first five years of human life is of great significance for both cognitive and non-cognitive development. Both medical and economic literature (Bronson, 1962; Dercon and Porter, 2014) has stated the critical or sensitive growth period, specifically the nutritional intakes during infancy and the first 36 months are even more crucial for subsequent growth. Based on this theoretical work, each household survey, I further classify the children into three groups, 0-1 years old (0-12 months), 2-3 years old (13-36 months) and 4-5 years old (37-59 months). Totally twelve groups are created across the four household surveys. I use an indicator variable *G* to represent which age group for any individual child. In this way, I add this indicator variable into the interaction term to explore the DRC conflict impact on different age group across the four household surveys.

$$HAZ_{ijt} = \alpha_t + \delta_j + \sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j \times G_i + \boldsymbol{X_i'}\gamma \cdot + \varepsilon_{ijt}$$

As can be inferred from the DRC conflict background, the 4-5 years old group from MICS 2001 household survey witnessed both First and Second Congo Wars. Therefore, I omit this child group as a comparison group for their intensive conflict treatment. Table 1.4 unveils the results with long columns; column (2) adds individual covariates and column (3) adds both individual and household covariates.

Firstly, I focus on the MICS 2001 cohort comparison. Actually, the 2-3 age group has an even lower HAZ score than the 4-5 age group. The 2-3 age group were born exactly at the outbreak moment of the Second Congo War, which would result in their deficient status. In

column three, the HAZ score for 2-3 age group is 0.00653 standard deviations lower than the 4-5 age group. However, for 0-1 age group, no robust estimation is found.

Secondly, for the DHS 2007 cohorts, the older 4-5 age group do not show a higher HAZ score, probably because when they were born, the Second Congo War was still on going until they grew to three years old. The robust estimation can be found for the 2-3 age group, they were born and grew up in the ceasefire period. With positive coefficient, we can state that the peace deal did benefit child health condition. I still found strong statistical significance for the 0-1 age group; however, the bootstrapping clustering standard error denies this result.

Thirdly, the MICS 2010 cohort displays a rather moderate result, 4-5 age group and 2-3 age group do not show a better nutritional result than the control group. The surprising part is the 0-1 age group, they show a higher HAZ score, when the east DRC militia conflict commenced in 2008.

Lastly, I found the same pattern result for the DHS 2013 cohort. All three age groups display a deteriorated HAZ score comparing with the control group. In terms of the scale, oldest group suffered the most as they were treated by the most violent period since 2008; the other junior groups also received scarce nutrition.

Since the First Congo War broke out in 1996, the country has been involved in continuous violence. I assume the 4-5 age group in MICS 2001 cohort should be most vulnerable children as a comparison group. I obtain a positive coefficient from both 0-1 and 2-3 groups in the DHS 2007 cohort, when the new president signed peace deal. This result further verify that a peaceful environment can drastically improve child nutritional intakes. However, the subsequent conflicts by militias, especially the rampant violent events against civilians further damage children's health status according to the results from the DHS 2013 cohorts.

Table 1.4: Conflict Impact on Child HAZ Score with Cohort Classifications

VARIABLES	(1) Fixed Effects	(2) Fixed Effects	(3) Fixed Effects
Year2001×Conflict Level×0-1 Age Group	-0.000129	-0.00212	-0.000731
	(0.974)	(0.570)	(0.851)
	[0.9770]	[0.5806]	[0.8569]
	{-0.00022}	{-0.00392}	{-0.00149}
Year2001×Conflict Level×2-3 Age Group	-0.00600***	-0.00757***	-0.00653***
	(0.00755)	(0.000193)	(0.00187)
	[0.0781]	[0.0060]	[0.0100]
	{-0.04600}	{-0.05845}	{-0.05773}
Year2007×Conflict Level×0-1 Age Group	0.00959***	0.00882***	0.00934***
	(0.00313)	(0.00325)	(0.00384)
	[0.0951]	[0.1341]	[0.1061]
	{-0.67051}	{-1.02028}	{-0.088939}
Year2007×Conflict Level×2-3 Age Group	0.00448***	0.00361**	0.00379**
	(0.00997)	(0.0203)	(0.0167)
	[0.0250]	[0.0330]	[0.0190]
	{-0.10474}	{-0.10485}	{-0.11668}
Year2007×Conflict Level×4-5 Age Group	0.000541	-0.000343	-0.000295
	(0.488)	(0.636)	(0.713)
	[0.5796]	[0.6787]	[0.7177]
	{-0.00675}	{0.00497}	{0.00465}
Year2010×Conflict Level×0-1 Age Group	0.00163***	0.00135**	0.00121**
	(0.00345)	(0.0245)	(0.0210)
	[0.0140]	[0.0110]	[0.0150]
	{0.41596}	{0.25804}	{0.22049}
Year2010×Conflict Level×2-3 Age Group	-0.000145	-0.000394*	-0.000542*
	(0.581)	(0.0976)	(0.0567)
	[0.4825]	[0.1121]	[0.0741]
	{0.00846}	{0.02721}	{0.4322}
Year2010×Conflict Level×4-5 Age Group	0.000666**	0.000403	0.000224
	(0.0358)	(0.129)	(0.367)
	[0.1431]	[0.1832]	[0.3764]
	{0.03743}	{-0.02697}	{-0.01748}
Year2013×Conflict Level×0-1 Age Group	-0.000298	-0.000498*	-0.000499*
	(0.194)	(0.0787)	(0.0747)
	[0.1351]	[0.0551]	[0.0761]
	{-0.01791}	{0.03017}	{-0.03301}
Year2013×Conflict Level×2-3 Age Group	-0.000164	-0.000320*	-0.000316*
	(0.305)	(0.0969)	(0.0863)
	[0.3644]	[0.0480]	[0.0721]
	{0.02331}	{0.05703}	{0.06129}

Year2013×Conflict Level×4-5 Age Group	-0.00131**	-0.00141**	-0.00137**
	(0.0101)	(0.0116)	(0.0113)
	[0.0430]	[0.0470]	[0.0761]
	{0.15669}	{0.19645}	{0.20206}
Girl		0.211***	0.213***
		(6.87e-08)	(6.06e-08)
Urban		0.409***	0.193***
		(2.87e-05)	(0.00779)
Constant	-1.778***	-2.294***	-2.781***
	(4.06e-09)	(2.26e-10)	(1.54e-10)
Observations	31,427	31,427	31,427
R-squared	0.141	0.151	0.163
Province FE	YES	YES	YES
Child Birth Month FE	YES	YES	YES
Child Birth Year FE	YES	YES	YES
Household Characteristics			YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces I report the delta value of the Emily Oster test (Oster 2014).
Child individual controls include child gender and child residence type; household controls include gender of household head, mother's education, the number of household members, the number of children under 5 years old and household wealth.

1.5.3 Individual Household Survey Investigation-A Short Term Analysis

In this part, I use each individual household survey to gauge the conflict impact on child HAZ score in a rather short-term analysis. Analogue to previous sections, I create an indicator variable for classifying child age and a dummy variable for child gender to interact the level of conflict for a categorical treatment effect. For each household survey, I omit 4-5 age group children as control group.

$$HAZ_{ijt} = \alpha_t + \delta_j + \beta_1 \cdot (Conflict\ Level \times Group)_{jt} + \beta_2 \cdot (Conflict\ Level \times Group \times Girl)_{jt} + \boldsymbol{X_i'}\gamma + \varepsilon_{ijt}$$

Initially, the first two columns present the MICS 2001 cohort outcomes, the first column contains individual covariates and the second column contains both individual and household covariates. The result is consistent with Table 1.5. In particular, the 2-3 age group shows a lower HAZ score than the 4-5 age comparison group, around 0.0057 standard deviation differences by the conflict impact. 0-1 aged group receives a similar nutritional intake to the comparison group. Besides, gender differences are not found by statistical significance.

Secondly, for DHS 2007 cohort the omitted 4-5 age group was born between 2002 and 2003, when the Second Congo was on going. At the first sight, the estimation reflects a strong HAZ score bounce for the 2-3 age group. These children were born and grew up during the temporary ceasefire period; a better nutritional treatment is expected. However, no statistical significance is found for the 0-1 age group, which signals the ceasefire period was ending and the militias' conflict had started to distort household nutritional intakes. In addition, the female children from the 0-1 age group suffered a decreasing HAZ score in comparison with the male children in the comparison group.

Table 1.5: Conflict Impact on Child HAZ Score by Individual Household Survey Investigation

VARIABLES	(1) MICS2001	(2) MICS2001	(3) DHS2007	(4) DHS2007	(5) MICS2010	(6) MICS2010	(7) DHS2013	(8) DHS2013
Conflict Level×0-1 Age Group	-0.00142	-0.00120	-0.000654	-0.000468	-0.00100***	-0.000986***	-0.000320	-0.000338
	(0.758)	(0.803)	(0.734)	(0.810)	(0.00794)	(0.00770)	(0.161)	(0.101)
	[0.8081]	[0.8448]	[0.7938]	[0.8318]	[0.1051]	[0.0811]	[0.1021]	[0.0981]
	{-0.00248}	{-0.00218}	{-0.00515}	{-0.00406}	{-0.01654}	{-0.01914}	{-0.01267}	{-0.01454}
Conflict Level×2-3 Age Group	-0.00572*	-0.00575*	0.00213***	0.00214**	-0.000796**	-0.000786**	-0.000194	-0.000249*
	(0.0513)	(0.0550)	(0.00715)	(0.0151)	(0.0260)	(0.0177)	(0.104)	(0.0504)
	[0.0671]	[0.0771]	[0.0400]	[0.0531]	[0.2072]	[0.1892]	[0.2272]	[0.1331]
	{-0.85643}	{-0.88436}	{-0.06433}	{-0.07046}	{0.02132}	{0.02459}	{0.03227}	{0.04684}
Conflict Level×0-1 Age Group×Girl	-0.00116	-0.00104	-0.00315*	-0.00321*	0.000669**	0.000748***	0.000101	6.86e-05
	(0.599)	(0.664)	(0.0748)	(0.0513)	(0.0105)	(0.00376)	(0.631)	(0.695)
	[0.6496]	[0.7317]	[0.0591]	[0.0531]	[0.0521]	[0.0350]	[0.6246]	[0.7387]
	{-0.00393}	{-0.00366}	{-0.03859}	{-0.04282}	{0.02566}	{0.03428}	{0.00593}	{0.00437}
Conflict Level×2-3 Age Group×Girl	0.00243	0.00250	-0.000723	-0.000678	0.000544***	0.000589***	0.000275	0.000304
	(0.280)	(0.268)	(0.578)	(0.614)	(0.000154)	(7.10e-05)	(0.159)	(0.127)
	[0.3083]	[0.2983]	[0.6827]	[0.6987]	[0.0881]	[0.0941]	[0.2262]	[0.1371]
	{0.19815}	{0.21576}	{0.12356}	{0.12148}	{0.06067}	{-0.07472}	{-0.19064}	{-0.21224}
Middle Cohort	0.152	0.152	-0.149	-0.144	-0.198	-0.194	-0.180	-0.212
	(0.303)	(0.292)	(0.168)	(0.182)	(0.208)	(0.185)	(0.267)	(0.193)
Young Cohort	0.419	0.411	0.396**	0.414**	-0.511**	-0.519**	-0.346	-0.406
	(0.121)	(0.116)	(0.0448)	(0.0250)	(0.0455)	(0.0343)	(0.420)	(0.355)
Girl	0.122***	0.132***	0.240***	0.244***	0.235***	0.223***	0.227***	0.231***
	(0.00810)	(0.00518)	(0.00449)	(0.00366)	(8.35e-06)	(4.14e-06)	(8.85e-06)	(7.55e-06)

Urban	0.477***	0.220**	0.537***	0.277**	0.121***	-0.191***	0.379***	0.00720
	(0.000220)	(0.0402)	(0.000794)	(0.0459)	(5.18e-07)	(0.000733)	(0.000553)	(0.912)
Constant	-2.470***	-2.799***	-2.358***	-2.796***	-2.092***	-2.701***	-1.830***	-2.370***
	(5.51e-09)	(6.67e-10)	(1.24e-07)	(3.26e-07)	(2.83e-10)	(3.84e-10)	(3.91e-08)	(9.39e-08)
Observations	9,584	9,584	3,264	3,264	10,520	10,520	8,059	8,059
R-squared	0.224	0.231	0.169	0.182	0.137	0.157	0.192	0.206
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Child Birth Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Child Birth Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Household Characteristics		YES		YES		YES		YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces I report the delta value of the Emily Oster test (Oster 2014) generated using psacalc command in Stata 14.
Child individual controls include child gender and child residence type; household controls include gender of household head, mother's education, the number of household members, the number of children under 5 years old and household wealth.

Thirdly, in terms of the MICS 2010 cohort estimation, the omitted 4-5 age group was born between 2004 and 2005, so the comparison group was less treated by the conflict than the other groups and a worsening HAZ score is anticipated. The results display HAZ score reduction in both 0-1 age group and 2-3 age group. However, based on the bootstrapping clustering estimation, the statistical robustness was stripped in the 2-3 age group. Largely, the 2-3 age group also grew up in the ceasefire period; they should receive similar nutritional provision to the comparison group. It is thereby reasonable for these children had no significant difference. The 0-1 group was indeed exposed to the new conflict since 2008 or even earlier, a HAZ score reduction is expected. Turning to the gender difference analysis, I find girls performed better from both 2-3 and 0-1 age groups, a resilience of the girls' healthy condition from peace to conflict.

Finally, for DHS 2013 cohort, in the previous section I have realised that these children have been severely affected by the new DRC militia conflict, no more actual function from the ceasefire contract. The whole groups were living in a new conflict era. The only significant estimation is the 0-1 age cohort; their HAZ score was reduced. Although the coefficient scale is not large, the outcome implied the child health condition in the DRC has not been improved since the new conflict. Further, no gender difference is significant.

These estimations reveal that even in short term the conflict can have a negative impact on child health condition. This consistent result also demonstrates the previous long-term analysis does not suffer from strong intervening effects with long time gaps. Each individual survey covers five to six years' period, violence activities can dramatically affect child nutritional condition in the DRC either from conflict to ceasefire (DHS 2007 cohort) or from ceasefire to conflict period (MICS 2010 cohort). Besides, I find girls obtain a better health condition in the MICS 2010 survey. From ceasefire period to conflict period, this result suggests a resilient characteristic for female children.

1.6. Robustness Check and Potential Bias

1.6.1 Selection Bias

One potential thread to identification is that the children with severe conflict exposure may have already suffered strong level of mortality, which produced survival biases for the analysis of conflict effects on child health. To address this argument, I specifically choose the number of children under five years old to investigate the variations of the household size. With the same econometric framework, we find the results in the table below.

Table 1.6: Conflict Impact on the Number of Children U-5 in Household

VARIABLES	(1) Children U-5	(2) Children U-5
Year2007×Conflict Level	-5.06e-05	-1.89e-05
	(0.920)	(0.972)
	[0.9439]	[0.9600]
Year2010×Conflict Level	0.000372	0.000311
	(0.156)	(0.208)
	[0.0120]	[0.0240]
Year2013×Conflict Level	0.000122*	0.000115*
	(0.0691)	(0.0962)
	[0.0450]	[0.0711]
Constant	1.075***	1.129***
	(0)	(4.89e-09)
Observations	47,072	47,072
R-squared	0.015	0.034
Province FE	YES	YES
Household Survey Year FE	YES	YES
Household Characteristics		YES

Note:
Standard errors are clustered at Province level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Household characteristics include gender of household head, mother's education, the number of household members, and household wealth.

In Table 1.6, the results do not reveal that the Congo War has significantly reduced the number of children for the DHS 2007. In fact, both MICS 2010 and DHS 2007 cohorts

deliver positive results with statistical robustness. The number of children has been growing in contrast with the MICS 2001 cohort, which rules out the concerns of the survival bias.

1.6.2 Unobserved Endogenous Household Characteristics

Omitted variable bias has been a common concern to almost all of the quasi-natural experimental estimations in economics. For instance, the conflict literature shows that conflict may in particular target wealthy household (Serneels and Verpoorten 2015). Econometricians attempted to rule out this problem by including observed controls. However, in many studies, observed controls are not a complete proxy for the entire real omitted variable. Especially for child health condition, socioeconomic status plays a major role as well. To explore this validity of the real omitted factors, I specifically use Emily Oster's test to assess the endogenous nature of conflict.

To explore the sensitivity of treatment effects to the inclusion of observed controls, Oster (2016) concludes that if a coefficient is stable after inclusion of the observed controls, this is taken as a sign that omitted variable bias is limited. For all the estimations of interest in this paper, I have applied Oster test on the variables of interest, the results are displayed in braces under the coefficient.

Based on the Oster (2016), I calculate the value of *delta* for which the true effect equals zero, given an assumption on R squared max. In other words,

Delta=1 means controls and omitted variables are equally important determinates.

Delta<1 means controls are more important.

Delta>1 means omitted variables are more important.

As can be seen, from all of the delta values in Oster test, there is no any value larger than one. I specifically compare the variations of the test values after adding household covariates, however, the values inside braces do not change significantly and still less than 1. Therefore, the results of interest do not suffer the omitted variable bias.

1.6.3 Aggregation at Provincial Level

Provinces in the DRC are large. For example, the size of Orientale is more than 500,000 square kilometre; Katanga is approaching to 500,000 square kilometre; Equateur is larger than 400,000 square kilometre. These sizes are equivalent to major European countries like Germany (357,386), the UK (242,495) and Spain (505,990). In terms of econometric specifications, if large geographical entities were distinguished by affected and non-affected within a particular cohort, this would contribute to measurement error and attenuation bias in the estimation, as well as risking that confounding factors cannot be isolated.

For this issue, I tried to classify the DRC into district level or even into household level to avoid the attenuation bias. However, MICS household survey does not have a uniform classification standard like DHS household surveys and did not provide the information or document for this classification. I cannot constitute a consistent data samples across the four household surveys. However, I use the number of conflict against civilians of each province in each household survey to have a more accurate war treatment measurement on each child to minimise the error effect.

Moreover, only eleven provinces (1996-2015) in the DRC results in the problem of few clusters in the estimation, which leads to ‘overfitting’ in the OLS regression. Downward biased clustering-robust variance matric estimate and over-rejection (too narrow confidence interval) emerge (Cameron and Miller, 2014). To correct this issue, I use wild cluster

bootstrap method to correct the standard errors, which are all stated in the squared brackets in the tables.

1.6.4 Displacement and Refugees

The disadvantage of the MICS and DHS household survey is lack of information about the displacement of each household. The DHS Survey asked the household how many years they lived in the region, but did not ask their previous location. Therefore, I cannot identify the households as original residents or displaced migrants. Because of the war, it is highly likely that people were displaced from their initial settlement.

The First and Second Congo Wars have triggered tremendous internal and external displacement across the DRC; numerous documents have raised the disastrous issues of humilities because of the movement (Kandala et al. 2014). Based on the Global IDP (Internal Displaced Persons) Report[14] from Norwegian Refugee Council, there are 2,045,000 IDPs in Sep 2001, 1,075,297 in Feb 2007, 1,706,591 in Nov 2010 and 2,963,700 May 2014, the corresponding years of our four household surveys taken. (Data sources are from UN OCHA). Meanwhile most of the displacement occurred in the East part of the country, and over half of them concentrated in the provinces of Nord and Sud Kivu. The figures clearly describe the dynamics between the conflict level and the displacement,

The first factor affecting my result is the placement of the refugees. In fact, most of the DRC refugees did not live in the UN camps in the conflict regions. According to IDMC Global Overview 2014, in December 2013, 2 per cent of IDPs were living with host families and 28

[14] IDMC is a global monitor and analyst for internal displacement worldwide. IDMC is part of the Norwegian Refugee Council (NRC) and has been endorsed by United Nations General Assembly resolutions. The internal displacement is separated as the conflict-induced and the natural disaster-induced. To the date of this paper, the datasets for the DRC displacement are still not available after request. However, IDMC generates an Internal Displacement Profile (IDP) for the DRC based on IDP database. The IDP provides figures and tables containing the displacement number at the province level from February 2000 to December2010.

per cent in informal sites and camps. IDPs may only be displaced for a few days or weeks at a time, but others have been living in protracted displacements for years. Nord Kivu IDPs have generally been displaced longer, but Sud Kivu IDPs much shorter (IDMC, 2015). The host families would accept the refugees as being considered as cheap labour supply. Therefore, the conflict impacts on household living condition are from other dimensions.

Secondly, the destinations of the IDPs are crucial for my identification. By IDMC 2015, Displacement mapping displays that IDPs often choose their place of refuge based on family links and ethnic ties to their host community. This fact reflects the tribal nature of the conflict; people went to another village nearby to avoid the militia's conflict and returned. For instance, in Masisi and Uvira, 60 per cent said that 'about half' or 'more than half' of the people from their home villages fled to the same location. Even in macro context, the DRC displacement peaked in 2003 (3.4 million) but returns outnumbered new displacements in the east in 2007, when the peace deal signed. These results also implied that the majority of the East DRC displacement would be within the province although the cross-province and international displacement has been remaining high.

However, IDMC has not uploaded a detailed dataset for the DRC internal displacement to the date I write this paper. To address this significant mechanism, including the displacement variable into the identification strategy will be the principal element to identify the issues for future research.

1.7 Conclusions

This paper applies four household surveys to analyse the children's health and nutrition status in the Democratic Republic of Congo. With the variation of the temporal and spatial treatment effects, I exploit the war impact on children's health and the results meet the initial expectation.

Firstly, I combined the four household surveys and concluded that child HAZ score significantly improved during the ceasefire period. The long-run panel also implies the subsequent 2008 conflict in east in fact had an even worse health impact on children than the First and Second Congo Wars. However, I did not find a child gender difference.

Secondly, I classify the children into three groups and I conclude that the 2-3 age group was in particular sensitive and vulnerable to conflict, consistent with Dercon and Porter (2014). These result also suggests that children grew up in the ceasefire period obtained a higher HAZ score.

Thirdly, I use each individual household survey to investigate the short-term effect of war on child heath. The effects were swift, especially I can compare the two cohort, one lived in the conflict periods one, the other did not witness conflict. The untreated children have higher HAZ score even within five-year period. For gender effects, girls were shown a slower catch up from war to peace periods but girls turned out to be more resilient from peace to war periods.

However, the estimation may suffer the endogenous factor of displacement as there is no data resource to incorporate into the whole estimation. In summary, the international community should further look into the situation of the Democratic Republic of Congo. The results from this paper imply that the country is running at a relatively healthy path, but the recent rebel

violence is damaging the conflict regions. The overall living standard in the DRC is still low; the international community should assist the DRC government for real life improvement and help to eliminate the long-term conflict within the country.

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A Appendix

Table A1: Conflict Casualty from 1998 to 2015 in the DRC

Province	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Sum
Bandundu	0	0	21	1	0	27	0	0	10	0	6	0	0	3	3	8	2	1	82
Bas-Congo	73	310	0	1	14	0	0	0	13	134	27	6	0	4	0	7	0	4	593
Equateur	0	1899	286	129	1	0	0	9	0	0	0	312	171	2	7	17	25	26	2884
Kasai-Occidental	0	0	100	4	0	2	0	5	0	0	0	54	2	2	3	11	3	2	188
Kasai-Oriental	0	900	170	35	2	82	21	19	0	40	0	19	18	39	21	5	6	7	1384
Katanga	754	844	31	39	177	1	30	40	2	12	0	0	8	30	38	486	123	93	2708
Kinshasa	422	1	104	26	5	254	2	16	79	0	0	4	2	58	1	123	24	456	1577
Maniema	179	28	10	63	97	252	0	12	0	7	0	1	0	14	0	119	43	3	828
Nord-Kivu	865	408	63	280	275	228	201	207	67	146	144	1136	398	197	707	939	674	772	**7707**
Orientale	164	2179	735	1235	2715	2467	73	89	196	29	2075	3583	705	112	182	179	131	273	**17122**
Sud-Kivu	985	1075	171	597	2856	95	98	220	45	21	16	1986	269	156	503	82	204	107	**9486**
Sum	3442	7644	1691	2410	6142	3408	425	617	412	389	2268	7101	1573	617	1465	1976	1235	1744	44559

Data Source: ACLED

2. Conflict and Development:

A Methodology by Using Outer Space Data

Figo Sze-Yeung Lau

Abstract

The impact of conflict on output growth could well be an integral part of the economic development process, yet it has proven difficult to analyse this issue. This paper pioneers the use of night light density data from satellite pictures to study the impacts of war on economic growth. The results are heterogeneous with year and regional fixed effects. Afghanistan has been a war-based economy, the war civilian boosting the service sector of the economy by civilian activities of millions of solders and personnel staff. Negative impacts are obtained from Syria and Iraq case studies. The war destroyed physical capital as well as human capital, investment collapsed especially for the urban areas. Libya is an oil based economy, the energy sector dominates the economy crowding out other sectors; the damage caused by the conflict to other business activities hardly affected the output. Moreover, the Libyan government subsidises electricity to its citizens and continued to do so during the war. Long-term conflict in Colombia and the poor infrastructure in Chad and the DRC explain the insignificant results of them. The results suggest that, in general, the impact of war on economic development depends on the country-specific characteristics such as initial economic endowment, conflict duration, political stability, natural resource management and conflict geographic locations within the country.

Key Words: Conflict, Economic Growth, Night Light, ArcGIS

2.1 Introduction

The impact of conflict on economic growth has been an integral part of economic study. Although it is generally accepted a strong negative correlation between conflict and development, there are heterogeneous mechanisms to interpret the relationship. Neoclassical growth theory concludes that an economy can recover quickly and converge into a steady state (Solow, 1956), in particular focusing on physical destructions. However, alternative schools predict the recovery process can be prolonged and the country can be even trapped into low-level income equilibrium. This school concentrates on human capital (Barro and Sala-i-Martin 2004) and poverty traps (Sachs 2005). A large body of literatures applies cross sectional data. Nevertheless, there is no consensus about the war impact on economic development. Different studies have obtained the different results, some countries experienced rapid recovery with a swift catch-up effect[15], some struggled into a slow convergence even into poverty trap[16], and some countries witnessed an in-variation of economic growth[17] by the conflict treatment (Organski and Kugler 1997, Kugler and Arbetman 1989 and Flores and Nooruddin 2009).

[15] There is evidence that economy can experience robust growth immediately after the end of a civil war. Collier and Hoeffler (2004) investigated 34 post-conflict cases between 1974 and 1997 and found first two post-conflict four-year periods had a positive coefficient but robust at only 10% level. Chen et al. (2008) found positive post-conflict growth effects significantly at 5% level. Elbadawi et al. (2008) used 39 post-conflict episodes and concluded that the first five years witness substantial economic growth but the subsequent five years see economic decelerations. Bleaney and Dimico (2011) found that only the more severe conflicts have a significant negative growth effect. Post-conflict recovery of output has been enhanced by aid flows.

[16] Some economists found ambiguous results from conflict effects on the output growth. Wheeler (1980) examined sixty episodes from 1816 to 1970 and he found no effects on aggregate output, there were statistically significant effects on individual conflict, some were positive, some were negative and some no effects. Barro and Lee (1994) investigated the determinants of economic growth from 1965 to 1985 with large cross sections. However, they found war effect is not a significant variable. Later Collier (1999) used the same methods to study the economic consequences of war and concluded that protracted wars had been associated with higher growth. Koubi (2005) studied the consequences of interstate wars for economic growth in a large cross section during the period 1960-1989 and found that post-war economic performance was positively related to the severity and the duration of war.

[17] The other literature provides further insights of post-war recoveries. Rasler and Thompson (1985) investigated both global and interstate wars and concluded that global war have more important but transitory effects on growth than interstate wars. This argument corresponds to the geographic spread hypothesis of Imai and Weinstein (2000) that wide-spread wars involve larger economic costs than wars fought in small, concentrated regions. In the empirical section, the conflicts with larger scales are expected with higher economic recoveries.

This paper employs nightlight density data from satellite pictures to explore the causal effect of conflict on output growth. Satellite nightlight data are useful proxies for economic activity at temporal and geographic scales for which traditional data are of poor quality or unavailable at subnational level. For any country, nightlight data can play a crucial proponent in analysing growth at sub- and supranational levels, where income data at a detailed spatial level are unavailable (Henderson et al. 2012). For countries with low-quality national accounts data, like sub-Sahara Africa, nightlight growth provides an alternative estimation for national account variations.

Nightlight data allow me to investigate recent civil or interstate wars all over the world. From 1992 to 2013, the twenty years long panel endows the paper with an unparalleled opportunity to explore the impact of conflict on economic growth from beginning of the war, during the war to post-war period. Global satellite pictures are able to capture any regions in the Earth, which enable this paper to identify nightlight growth variations at sub-national level.

Therefore, to exhibit the war impact on the economy, I take advantage of the temporal and geographic variations of the conflict with region and year fixed effects. Specifically I study Afghanistan War, Chad Civil War, Colombia Civil War, Iraq War, the Democratic Republic of Cong Wars, Libya Civil War and Syria Civil War, seven modern conflicts in total. Different conflict in different country possesses different characteristics of the economy. These heterogeneities give paths for different interpretations on these seven country-specific conflict impacts.

However, the results do not directly show that the conflicts exert a negative impact on the regions as generally supposed to. There are negative effects on Syrian and Iraqi economies, but there are also positive effects on Afghanistan economy; no statistically significant effects are found on Libya, Chad, Colombia, and the DRC economies. The country's initial

economic endowment, historical environment, political body, and conflict geographic locations jointly contribute to these results.

The remainder of this paper is structured as follows. Section 2.2 discusses previous literature and Section 2.3 provides an overview of the theoretical frameworks between conflict and economic development. Section 2.4 details the nightlight data and other data applied in this paper. Section 2.5 explains identification strategy and econometric specification. The Section 2.6 presents the seven country's estimation interpretations with robustness check. Section 2.7 summarises the whole paper.

2.2 Literature Reviews

2.2.1 Conflict Effects on Economy

2.2.1.1 A Single Equilibrium V.S. Multiple Equilibria

A closely related literature is from Bove et al. (2017), which generalises the main studies of civil war impact on economic development. They find that the occurrence of a civil war has heterogeneous effects on the level of GDP by using case-study, large-N panel data estimation and synthetic control approaches, consistent to the results obtained in this chapter. Case studies can take account of country specific history but are a sample of one and may make it unrepresentative of other cases. Large-N studies can be generalised but ignore the country specific heterogeneity by, for instance, imposing common coefficient. Comparing these results with a panel data analysis, the authors find that the incidence of civil wars has almost on significant effects on the GDP level. Yet, by relaxing the homogeneity restrictions, panel data also reveals a variety of positive and negative impact of conflict on development. In this paper, I apply both case study approach and large-N method by pooling all the countries together to provide a panoramic picture of the impact of conflict on economic development.

Davis and Weinstein (2002) investigate the World War II bombing in Japan. However, they find that temporary shock, even if frightening magnitude appears to have little long-run impact on the spatial structure of the Japanese economy. Brakman et al. (2004), who applied the same specification to study the strategic bombing of German cities during World War II to analyse its impact on post-war German city growth, obtain similar findings. West Germany shows a consistent result to Japan, that large, temporary shocks have at most a temporary impact on city growth, a tendency towards mean reversion. However, East Germany

witnessed a permanent impact on relative city size. The subsequent paper by Miguel and Roland (2011) acquire a parallel estimation from the Vietnam War, the most intense bombing campaign in military history. Nevertheless, US bombing do not have negative impacts on local poverty rates, consumption levels, infrastructure, literacy, or population density. In other words, Vietnam War does not generate poverty trap in Vietnam. These papers clearly indicate conflicts do not necessary exert a permanent negative impact on economic growth. There could be a sudden decline for the development by the conflict shock, but a temporary deviation from the mean value would return to the mean value subsequently; empirical literature usually acquires multiple equilibria result.

There is no consensus agreed on the conflict impact on the path for the economy by a single equilibrium or multiple equilibria. Therefore, an evidence based empirical study is the core for this paper.

2.2.1.2 Synthetic Control Methods

Synthetic control methods use a counter-factual approach and compare the variations of the real per capita GDP for regions affected by a conflict with the evolution of an artificial control group. For instance, the seminal paper from Abadie and Gardeazabal (2003) presents a negative impact of the terrorist conflict in the Basque County in Spain. They pioneer creating a weighted average of other Spanish regions as a “synthetic” Basque County without terrorism, against which they can compare the actual Basque County with terrorism. To a large extent, synthetic control method seems to be the most promising approach, the subsequent papers like Hsiao et al. (2012) and Abadie et al (2015) all apply this methodology. However, the choice of the reference regions and the size of weights have been inspected. Like Hsian et al. (2012), they aim to study Hong Kong economic development

after returning to China in 1997. To synthesize a HK without returning to China, they use a number of countries like the US, Japan and Korea with specific weight to cancel the confounding factors.

By contrast, nightlight methods can apply at sub-national level within the country, where standard GDP measures are not available; meanwhile, the nightlight growth automatically subtracts the confounding factors as the high correlation between nightlight growth and income growth.

2.2.1.3 Phoenix Factor

Another thing to expect from estimations is “Phoenix Factor”; the country critically suffered from conflict destruction may experience a surge of output growth in the post-war period.

Neo-classical economic growth modelled by Robert Solow (1956) hold that, through the physical destruction of resources by the conflict, the economy would experience a surge rate of output growth after the conflict ended, which is named the “Phoenix Factor”. The typical examples are the post-World War II economic recovery of Germany, Italy, and Japan benefiting from advanced technology and reserved human capitals. The papers by Organski and Kugler (1977, 1980) document the existence of the “Phoenix Factor” by studying the two world wars. They combined the technological innovation-adoption and the direct resources destination channel of the neoclassical theory. They find that nations suffered serious damage to their industrial capacity during the war rebuild afterwards. Rebuilding typically demanded for higher investment, which enhanced the growth rate of output by itself. In addition, the nations after the conflict exposure are likely to found a more technologically advanced fundamental.

However, the specific cases from the seven conflicts in this chapter are different from the cases from Japan and Germany after the Second World War. Firstly, Japan and Germany had been the most industrialised and technological-advanced countries in the world before the World War, which lay the advanced foundation for their economic miracle after the defeats. All seven countries in this chapter are all developing; some of them have been the least wealthy countries in the world for decades. Both physical and human capitals are insufficient. Secondly, Marshall Plan injected huge capital to the jeopardised countries promoting them into a fast track into a higher equilibrium. Germany joined the European Steel and Coal Union in 1951, which symbolised the German economy taking off again. However, no large-scale investment assistance or technical support will be provided like Japan or Germany case. Therefore, it is difficult to observe a robust "Phoenix Effect". Thirdly, after the World War, both Japan and Germany entered into a new period with no civil conflict and relative external environment. By contrast, the civil conflict was still lingering by militias or insurgents after the war officially declared ended. A peaceful and political stable state can boost economic development; however, the countries this paper are not endowed.

Therefore, from the channels of capital foundation, investment, and political entity, I cannot conclude that a "Phoenix Factor" will appear from the estimations.

2.2.2 Night Light as a Proxy for Economic Growth

High-resolution data on light density measured by satellites have been widely applied in the current economic researches. Nightlight data can be collected primarily from the DMSP-OLS (the Defence Meteorological Satellite Program) sensor, which offers normal 1-kilometre resolution and are now easy to access and process. Henderson et al. (2012) demonstrate that nightlight growth is a good proxy for income growth. In an annual panel of countries from

1992 to 2008, and the corresponding long difference, these authors estimate a light-GDP elasticity of 0.28 to 0.32 for a global sample as well as a sample of low and middle-income countries, with no evidence of nonlinearity or asymmetry between increases and decreases in lights. Especially in both samples, the lights explain about 20% of the variation in Log GDP net of country and year fixed effects. In the same year, Michalopoulos and Papaioannou (2012) rely on night light to find the relationship between previous colonial ethnic institutions and current African economic development; Storeygard (2012) uses the night light data to figure out oil price and transport cost impacts on urban growth in Sub-Sahara region, specifically with the spatial distance analysis.

In their earlier paper in 2011, Henderson et al. introduced a bright idea of using nightlight data to measure economic growth. They propose there are two obstacles. The first one is the relationship between economic activity and the true amount of light emanating from the earth's surface is not constant across time and space, light is a by-product of consumption and production activity. The second one is that the satellites may imperfectly measure true light because sunlight, moonlight and cloud cover contamination all differ across the globe. Nevertheless, they advocate great advantages for using light growth as a GDP growth proxy. The principal strength is that nightlight data are available for regions for which standard GDP. Light top codding is less of a problem in poorer countries, and especially in sub-Sahara Africa, where no pixels are top-codded.

The recent paper by Proville et al. (2017) uses a parallelized spatial analytics platform to process the 21-year totality of the longest-running time series of nightlight data to review the global, long-term relationships between night-time lights and a series of socio-economic indicators. They conclude that nightlight data has the most significant correlations with electricity consumption, CO2 emission, and GDP, followed by population, CH4 emissions,

N2O emissions, poverty (inverse) and F-gas emissions. Further, areas lightened by electricity consumption show that while a basic linear regression provides a good statistical fit. Hence, in this chapter, I integrate electricity consumption to interpret the estimation results. Donaldson and Storeygard (2016) outline general applications of satellite data in economics including night-lights, climate and weather, topography, agricultural land use, urban land use, building types, natural resources and pollution monitoring. They state that using nightlight as a proxy for economic activity is under the assumption that lighting is a normal good.

Subsequently, based on the theoretical framework between nightlight growth and income growth, an increasing number of literatures have used nightlights as a proxy for economic activities. Within five geographic units for which no alternative data sources is available such at cities (Storeygard 2016), ethnic homelands (Michalopoulos and Papaioannou 2013, 2014), subnational administrative units (Hodler and Raschky, 2014), larger uniform grid squares (Henderson et al. 2016), nature features like river (Bleakley and Lin 2012) and even North Korea (Lee 2016).

This paper principally uses the night light intensity data to evaluate the conflict effects on economic growth. I apply the sub-national data to study Afghanistan War, Libya Civil War, Syria Civil War, Chad Civil War, Colombia Conflict, Iraq War, and the DRC War, where the provincial or sub-national GDP level data are not available. In addition, the estimation covers a long period from the pre-war condition to the post-war period, which enables me to analyse the conflict effects in a dynamic perspective. I expect this pioneering work would unfold the mechanisms of impact of conflict on output.

2.3 Theoretical Mechanisms

There is a variety of routes for conflict to influence economic development. Costs and benefits of war on subsequent economic growth have been extensively investigated. To construct a theoretical framework for empirical result explanations, I rely on two seminal papers from Humphreys (2003) and Koubi (2005) to summarise the impacts of conflict on economic development.

2.3.1 Conflict can lead to destruction of physical capital and reduced investment in physical capital.

Conflict can bring violence to remove physical capitals like bridges, buildings, communications and energy sector infrastructure. For countries depending on natural resources export, the destruction of energy sector physical capital would bring tremendous effects on the economy. In addition, loss of physical capital could lower standard of living, which may not be easily identified by GDP measure. Night light methodology, to a large extent, can capture the electricity variations by the conflict, a better indicator to gauge living standard at sub-national level.

Conflict can bring uncertainty and be likely to induce capital flight. A surge in military spending would crowd out the investment in other sectors; to finance the warfare, government would issue bonds, accumulated deficits is likely to reduce investment levels. Humphreys (2003) argued that the magnitude depends on how severe the war is. On the other hand, Paul Collier contended that capital flight depends on the length and duration after the war ends.

2.3.2 Conflict can lead to human capital loss and reduced investment in human capital

When a country was plunged into conflict, human capital would flee through migration. Especially for well-educated people, they have more routes to quit a country. Moreover, a large number of human capital losses occurred through deteriorations in health, for instance, the spread of diseases such as malaria and tuberculosis, and severe shortage of food supply.

War can shrink investment in human capital because schools close or are destroyed; typically teachers and students often join armies and rebellions. In under-developed countries, schooling level has already very low. In this case, conflict slows the rate of growth in human capital rather than causing declines. The large displacement and mass civilian fatality is likely to alter local economic activity.

2.3.3 Conflict can cause population loss

Population size turns down as a consequence of battle death. In fact, more deaths tend to occur because of famine, disease and the destruction of health services. This also affects labours in production through distortions of labour markets. However, the impact of population loss on economic development is ambiguous. A neoclassical growth model contends that population loss can have positive impact on economic growth. Young (2005) concludes that a reduced population would enhance the future per capita consumption possibilities because a lower population growth is strong enough to counteract the human capital loss. The impact of population loss remains ambiguous conditional on the country-specific factors.

2.3.4 Conflict can reshape political structures and public policies

It is stated in Imai and Weinstein (2000) that conflict, especially civil war, undermines the legitimacy of the state, threatening the country's institutions, the security of property rights and the rule of law. Political economy models indicate that internal conflicts could affect the aggregate domestic economy by worsening the government fiscal balances. Civil war is a cause of poor macroeconomic policy: high inflation distorted foreign exchange markets and large budget deficits.

Especially a large body of literature has attempted to explore the war effects on economic output combining a number of different variables. Olson (1982) concludes that the relationship between war and subsequent economic performance must be conditional on the effects of war on political structures and distributional coalition.

2.3.5 Conflict can revise total factor productivity

Technological innovation is a by-product from conflicts as there has been a belief that conflict induces technological innovation that can benefit the whole society in general. In economic views, the promotion from military technological innovation derives primarily from discoveries and production processes rather than from the use of the new military technology. In this way, increased demand for military equipment would come up with investment in new technology and enhanced productivity.

Conflict can disrupt production and market transactions. The conflicts between different regions give rise to block freedom of movement. Trade requires trust and social institution. Conflict may jeopardise the norms and alter the level of regulation of trade and production.

In this paper, I empirically explore modern war effects on economic performance as well as to test the theoretical framework.

2.4 Data and Sample

2.4.1 US National Geophysical Data Center

Nightlight density data are collected by the US National Geophysical Data Center. These data are open for public and are available from 1992 to 2013, 21 years. The Earth Observation Group takes photos 14 times per day, capturing human activities, lightning, gas flare and the aurora at night. A six-bit number (0 to 63) calculated for every 30-second area. Hence, there is an annual composite picture for the night light for putting one year's the pictures together. Each 30-arcsecond pixel in each satellite-year contains a digital number (DN), an integer between 0 and 63, inclusive that represents an average of lights in all nights after sunlight, moon lights and clouds have been eliminated algorithmically, leaving human activities.

In terms of nightlight intensity data, one measurement error is the difference between the true light amount and what record from the satellites. Another measurement error includes variations from the relationship between GDP growth and growth of light emanation, due to variation in the mix of sectors that are growing. For a specific example, the data panel runs over 21 year's period from 1992 to 2013, technology improvement like notably the advent of solar power and LED lighting could generate spurious correlations in the data. Alternatively, the increased production of steel and software both represent GDP growth, but former leads to a larger increase in visible light than the latter. To analyse this issue, Henderson et al. (2012) develop a statistical model to combine data on changes in night-lights with data on measured income growth. They assume that measurement error in GDP growth is uncorrelated with the measurement error that occurs when the change in lights is used to measure growth (Rao 1992). Although there are many potential sources of error in using lights growth to measure income growth, none of them suggests that this assumption is in

appropriate. Furthermore, the model could be adjusted to allow for such correlation such as combining two problematic measures can produce a composite with smaller measurement error than either of them.

Annual variations in GDP are correlated with variations in DN, with an elasticity of approximately 0.3 for a global sample as well as a sample of low and middle-income countries. For countries with low-quality national accounts data, like sub-Sahara Africa, night light growth provides an alternative estimation for national account. All seven countries to be studies in this chapter belong to low or middle income countries.

Hence, annual nightlight growth is the variable of interest rather than nightlight density data. I use the logarithm of average nightlight density plus 0.01 as dependent variable. The logarithmic transformation is applicable as I use all observations and I may account some extreme value. Besides, a zero level of nightlight density can be observed either because there is population scarcity in the area without electricity supply or because the satellite could not capture the some areas in the planet[18].

Hence, Satellite night-lights data are a useful proxy for economic activity at temporal and geographic scales for which traditional data are of poor quality or are unavailable. For all countries, lights data can play a key role in analysing growth at sub- and supranational levels, where income data at a detailed spatial level are unavailable. (Henderson et al. 2012). I investigate seven country's conflict impact on economic growth, Afghanistan, Chad, Colombia, The Democratic Republic of Congo, Iraq, Libya, and Syria from 1992 to 2013 via the satellite pictures as displayed in Map 2.1.

[18] Hodler and Raschkey (2014): 1. Adding just a small constant before taking the logarithm ensures that the coefficients remain close to (semi-) elasticity. 2. Doing so can be justified on the grounds that absence of night light and certainly not absence of economic activity. 3. In particular, men-made nightlight in these regions may have been below the detection limit of the satellites sensors or "wrongly" identified as ephemeral lights or background noise. 4. Henderson et al. (2012) find that "there are remarkably few pixels with values 1 or 2".

Map 2.1: Seven Country's Frames for Administrative Classification

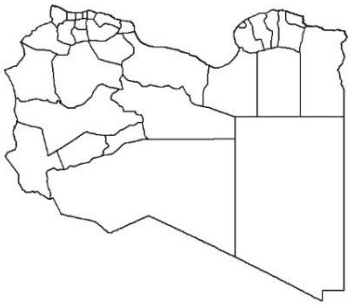
Afghanistan at District Level (328 Districts)

Chad at Department Level (55 Departments)

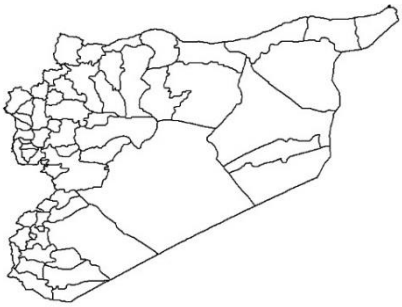
Colombia at Department Level (32 Departments)

DRC at District Level (150 Districts)

Iraq at District Level (102 Districts)



Libya at Municipality Level (32 Municipalities)



Syria at District Level (60 Districts)

2.4.2 DIVA-GIS

The conflict event and casualty datasets are based on the provincial and county level. To implement the identification strategy, I need to classify the countries into province level, county level or other sub-national levels. DIVA-GIS is a free computer program for mapping and geographic data analysis (a geographic information system (GIS). With DIVA-GIS you can make maps of the world, or of a very small area, using, for example, state boundaries, rivers, a satellite image, and the locations of sites where an animal species was observed. From administrative areas or national boundaries, the data provides country outlines and administrative subdivisions for all countries; the level of subdivision varies between countries. From DIVA-GIS, I categorise the seven countries into the following levels as indicated in Picture 1

2.4.3 ACLED

To measure the level of the military conflict in different province, I use the Armed Conflict Location & Event Dataset (ACLED), which is designed for disaggregated conflict analysis and crisis mapping. ACLED is a publicly accessible data resource from University of Sussex. The dataset records political and civil conflicts over 50 developing countries and covers all the African countries from January 1997 and the Asian countries from 2010.

All round conflict information are attached in the datasets like on the date and location of the conflict, casualty number, event type and the information sources. Specifically, types of event include battles, civilians killed and protests, change of territories control and fatalities; the latitude and longitude are noted for geographic precision. ACLED information sources are diversely distributed, from official state agency, international media like BBC and CNN, to

humanitarian agencies, research publications and the NGOs. The goal of ACLED is to present a numerical and comprehensive assessment of political, military and domestic conflicts in developing states for academic and policy analysis.

For instance, the ACLED Libya datasets, it records specific conflict casualty and events since 1997. These fatalities and event information grant me a research opportunity to differentiate the municipalities of the Libya into high conflict level and low conflict level.

2.4.4 i-Casualty

The website of i-Casualty records the conflict level of Afghanistan War. This is an independent website created in May 2003 by Michael White, a software engineer from Stone Mountain, Georgia, to track casualties in the Afghanistan War and Iraq War.

The website compiles information on casualties incurred by the Multi-National Force (MNF) in Iraq and the International Security Assistance Force (ISA) in Afghanistan using news reports and press releases from the U.S. Department of Defence, CENTCOM, the MNF, and the British Ministry of Defence. The project has grown in scope since its conception, and now also provides fatality counts for contractors, Iraqi security forces (since January 2005), and Iraqi civilians (since March 2005).

2.4.5 Syrian Revolution Martyr Database

For Syrian War, the casualty dataset is from the website of Syrian Revolution Martyr Database. This website collects the conflict casualty information from Damascus Centre for Human Rights Studies (http://dchrs.org/) and Violations Documentation Center in Syria

(http://vdc-sy.net/en/). This conflict fatality information enables me to classify the provinces of Syria into high conflict intensity provinces and low conflict intensity provinces.

2.4.6 Iraq Body Count

As ACLED does contain information about Iraq conflict casualty information, I rely on Iraq Body Count to classify the conflict level of Iraq. However, the paper from Guerrero Serdan (2009) has already classified Iraq into no-conflict, low-conflict, medium-conflict and high-conflict regions. I cite this classification directly to explore the casual effects of conflict on Iraqi output growth.

2.4.7 Database of the Armed Conflict in Colombia from CERAC

The Conflict Analysis Resource Center (CERAC) makes accessible its Database of the Armed Conflict in Colombia[19], and the glossary with the definition of each variable included in the database.

The database of CERAC is composed by information reported by publicly accessible sources (press, international organizations, nongovernmental organizations, research centres etc). The database team of CERAC monitors these sources and compiles, selects, codes the information, and add it to the System for Analysis and Register of Conflict Actions (SARAC). Finally, the data is processes to offer the users (academics, students, the public) the possibility to analyse the general dynamic of the conflict in Colombia.

[19] Accessible to download from Prof Michael Spagat's research link: http://personal.rhul.ac.uk/uhte/014/Mike%20Spagat's%20Conflict%20Data%20Page.htm

2.5 Identification Strategy and Econometric Specification

This paper assumes war put an exogenous impact on economic growth of each country. Nightlight growth is regarded as a proxy for income growth. To explore the geographic variations across the conflict timeline, I apply a difference-in-differences specification with multiple periods to investigate the conflict effects on economic growth via nightlight growth dynamics. Night light data are available from 1992 to 2013; based on the country-specific conflict events, the panel is likely to cover the entire war era from pre-war period, on-going period to post-war period. With the non-parametric regression, the difference-in-differences model is estimated with fixed effects:

$$Log(NightLight + 0.01)_{jt} = \alpha_t + \delta_j + \sum_{t \in 92:13} \beta_t \times d_t \times Conflict_j + \varepsilon_{jt}$$

$Log(NightLight + 0.01)_{jt}$ is the outcome of interest as defined in the previous section, representing nightlight intensity growth across province *j* at year *t*. d_t is an indicator variable, showing whether the region is treated by the conflict at year *t*. $Conflict_j$ is a dummy variable[20], reflecting whether the subnational region *j* like province, county or department is exposed with conflict. Subscript t indicates the year and subscript j represents the

[20] Appendix presents the conflict intensity classification for Afghanistan War, Chad Civil War, Colombia Civil War, the DRC Conflicts, Iraq War, Libya Civil War and Syria Civil War. For each table, I obtain the conflict intensity information based on either casualty figure or the number of conflict in each sub-national unit. The tables illustrate the selection criterion and conflict level intervals in Afghanistan, Chad, Colombia, the DRC, Iraq, Libya and Syria.

subnational region. For instance, $NightLight_{jt}$ is the mean value of nightlight density at the region *j* at year *t*.

$\{\beta_t\}_{t\in 92:13}$ is the coefficient of interest, representing the difference-in-difference (DID) estimator, which measures the conflict effects on nightlight growth.

To present a dynamic variation of the conflict treatment effects on the economy, I treat year 1992 as a reference group to compare with the subsequent nightlight growth variations.

α_j are province fixed effects and δ_t are year fixed effects. ε_{jt} is a random, idiosyncratic error term. The data obtained from night light picture are strongly balanced panel data, so all the regressions are applied with fixed effects.

A test of difference-in-differences assumption is that β_t is equal to zero before the conflict. Moreover, this during or post treatment coefficient may not identical. For instance, the effect of conflict could accumulate over time, so the absolute coefficient value increases.

In the example of the Syrian Civil War, the War begins in 2001. So the coefficients of years before 2001 are assumed to be zero. The coefficients during the war treatment years should be significantly different from zero and negative if there were harmful impacts of the civil war.

Furthermore, in the specification above, I divide the nightlight density value by the size of the region to obtain a nightlight density within a unit area. I use this framework as a robustness check as well as to eliminate the possible confounding factor of the region's size.

$$Log(\frac{NightLight}{Area} + 0.01)_{jt} = \alpha_t + \delta_j + \sum_{t\in 92:13} \beta_t \times d_t \times Conflict_j + \varepsilon_{jt}$$

In this paper, all standard errors are robust, clustered at the regional level to allow for an arbitrary variance-covariance matrix capturing potential serial correlation in the residual error term (Wooldridge 2002). For the issue of the fewer cluster numbers, I further report score wild cluster bootstrap p-values (Kline et al. 2012) generated using *boottest* command in Stata 14 (Roodman et al. 2016). In order to capture the omitted variable bias such as the conflict is more likely to target areas with more resources to loot, I apply Oster test (2016) to filter endogenous bias.

2.6 Result Estimation and Interpretation with Robustness Check

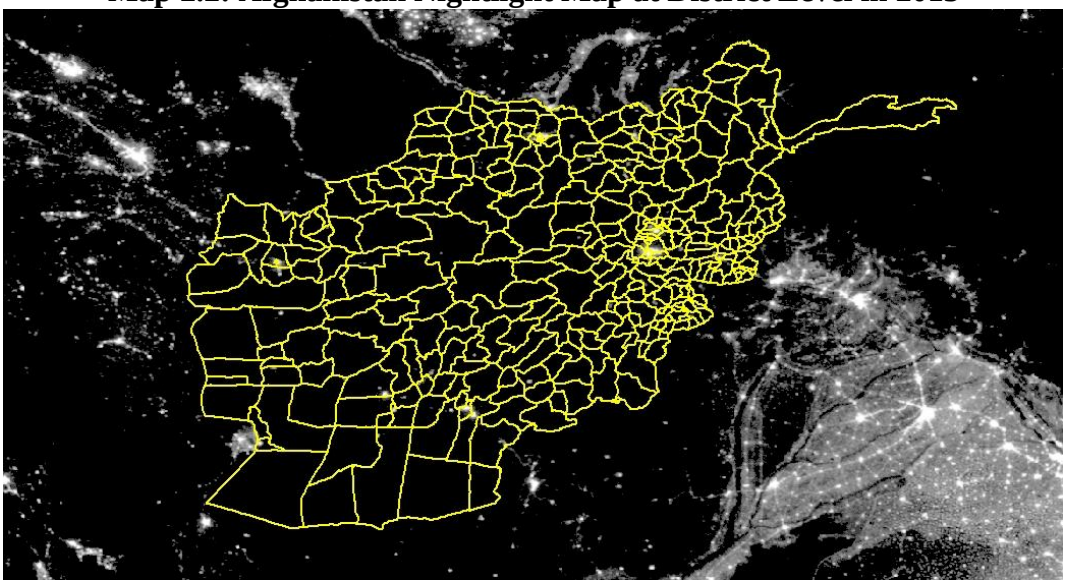
War can influence the economic development through a variety of routes; this section interprets the estimations by combing country-specific characteristics including conflict background, economic endowment, energy (electricity) supply, and public policies. The estimation covers periods from 1992 to 2013, twenty-one years in total with taking 1992 nightlight growth as a reference group; countries range from Afghanistan, Chad, Colombia, the DRC, Iraq, Libya to Syria, I attempt to interpret the impact of war on economic growth for each case independently.

2.6.1 Afghanistan War (2001-Present)

Conflict background

In 2001, following the 911 attacks on the United States, the US-led coalition forces began to invade Afghanistan, and then international Afghanistan war began to topple the Taliban militia. From 2002 to 2008, US defeated the Taliban and installed new government for the Afghan state. In September 2005, Afghanistan held the first parliamentary elections in more than 30 years. However, since 2009 the conflict had been intensified between the US troops and the Taliban insurgents. Especially in 2010, the number of civilians killed was even higher than in 2001. Foreign coalition forces decided to hand over the security responsibilities to Afghan authority. In December 2014, the US and NATO troops withdrew from Afghanistan. Nevertheless, the civilian casualties and the insurgent attacks still climbed high; the violence still happens in Afghanistan.

Map 2.2: Afghanistan Nightlight Map at District Level in 2013



Afghanistan War officially commenced in 2001, when the conflict started to treat the economy. Therefore, the coefficients before 2001 capture the economic growth in the pre-war period; after 2001, the estimations display the conflict effects on economic output.

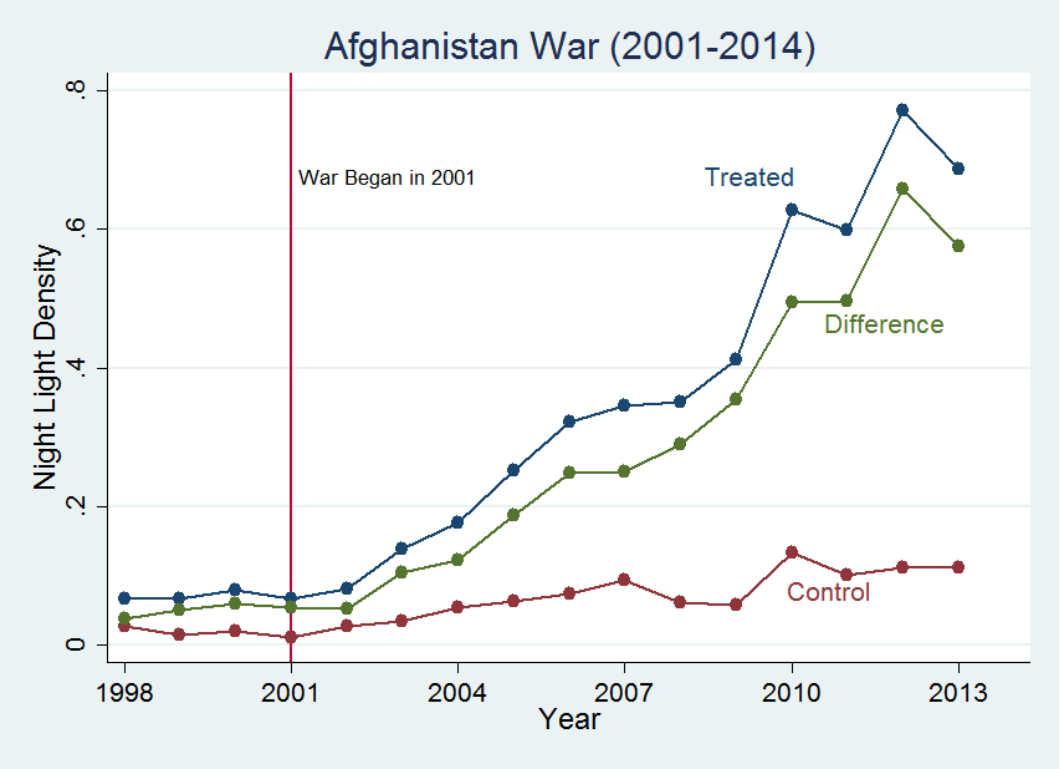
Identification and Trend Analysis

Figure 2.1 displays the nightlight density variations between control and treated groups. The graph clearly shows that a divergence between treated regions and control regions. Since the war broke out in 2001, in fact the high conflict regions experienced higher output growth, as the night light density grew much faster than control regions. One reason would be the military violent field in Afghanistan like Kandahar and Helmand is generally urban, which was equipped with better infrastructure than the rural areas. Another reason would be the war brought additional economic activities, which delighted the war regions at night.

Result Interpretation

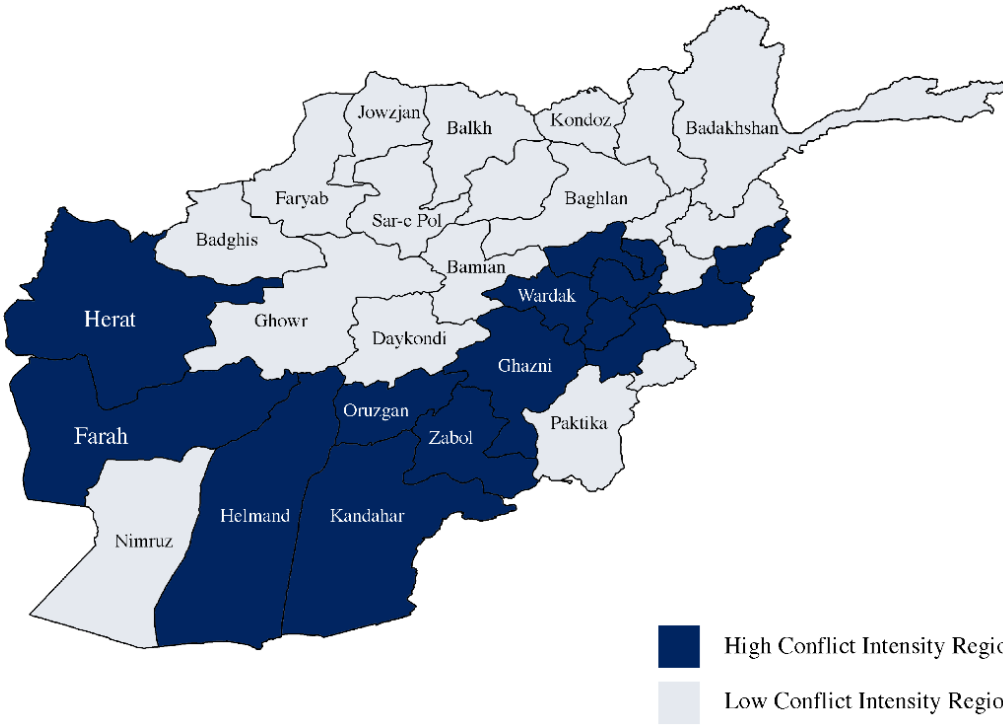
I use the nightlight growth in 1992 as the baseline year in the difference-in-differences specification; however, the results are beyond the theoretical prediction.

Figure 2.1: Afghanistan Trend Analysis by Control and Treated Provinces



In Table 2.1, initially the nightlight growth in actuality has been decreasing from 1993 to 1996 in comparison with the 1992 group. However, since the war broke out in 2001 the significant and positive values from 2003 to 2013 indicate that the nightlight growth experienced a robust enhancement; the scale of the coefficients has been increasingly growing. In other words, the conflict actually boosted the Afghan economy. For instance, the coefficient in 2003 can be interpreted that the nightlight growth in high conflict intensity regions is 0.775 percentage points higher than that of low conflict intensity regions. Hence, the War has brightened the high conflict intensity regions. Column (2) with nightlight growth per unit area verifies the positive impact of war on economic growth. Below the coefficients, applying bootstrapping clustering standard errors does not change the statistical significance; Oster test in the braces demonstrate the identification does not suffer from the omitted variable bias. The positive effects of war on Afghanistan economy implies the 'blessing of the War', the specific economic conditions in Afghanistan contribute to the mechanisms of this positive impact results.

Map 2.3: Afghanistan Conflict Level Classification at District Level



First, in Figure 2.2, I outline the Afghanistan GDP condition from World Bank datasets from 2001. Previously Afghanistan is one of the least developed countries in the world, as consequences of decades of conflicts and lack of investment. However, the figure describes a strong growth mode from 2001 to 2012, and then a slight drop to 2014. Therefore, although the 911 event in 2001 triggered the US-led troop to invade Afghanistan, the economy situation across the country actually has been improved throughout the country. By calculation, the Afghan economy experienced a 9.2% growth rate of GDP from 2003 to 2012, but the economy began to decelerate from 2012. This fact has been considerably consistent with the estimation from my night light identification, a strong economic growth took off in 2001 but slipped down after 2012.

Table 2.1: Afghanistan War Impact on Economic Growth

VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	-0.118** (0.0227) [0.0190]	-0.248*** (0.00858) [0.0040]
	{0.01560}	{0.01732}
Conflict×1994	-0.156** (0.0419) [0.0340]	-0.247* (0.0680) [0.0571]
	{0.01971}	{0.01641}
Conflict×1995	-0.228*** (0.00234) [0.0010]	-0.418*** (0.000919) [0.0020]
	{0.03189}	{0.03083}
Conflict×1996	-0.163** (0.0204) [0.0220]	-0.302** (0.0208) [0.0260]
	{0.02384}	{0.02371}
Conflict×1997	-0.0276 (0.632) [0.6266]	-0.0507 (0.652) [0.6697]
	{0.00405}	{0.00405}
Conflict×1998	0.0901 (0.136) [0.1261]	0.146 (0.232) [0.2442]
	{-0.01685}	{-0.01567}
Conflict×1999	0.102 (0.151) [0.1612]	0.0911 (0.478) [0.4785]
	{-0.01772}	{-0.00840}
Conflict×2000	0.0626 (0.457) [0.4805]	-0.00287 (0.986) [0.9870]
	{-0.01336}	{0.00035}
Conflict×2001	0.0831 (0.289) [0.2853]	0.0479 (0.743) [0.7347]
	{-0.01467}	{-0.00459}
Conflict×2002	0.105 (0.258) [0.2372]	0.101 (0.557) [0.5425]
	{-0.02895}	{-0.01585}
Conflict×2003	0.256** (0.0255) [0.0250]	0.295 (0.146) [0.1361]
	{-0.29336}	{-0.25129}
Conflict×2004	0.221* (0.0793) [0.0791]	0.313 (0.160) [0.1552]
	{0.35055}	{0.15013}

Conflict×2005	0.486***	0.801***
	(0.000958)	(0.00208)
	[0.0020]	[0.0020]
	{0.10958}	{0.08207}
Conflict×2006	0.442***	0.740***
	(0.00304)	(0.00462)
	[0.0020]	[0.0040]
	{0.10760}	{0.08636}
Conflict×2007	0.228	0.263
	(0.136)	(0.312)
	[0.1181]	[0.3293]
	{0.05347}	{0.03354}
Conflict×2008	0.287**	0.438*
	(0.0439)	(0.0743)
	[0.0460]	[0.0611]
	{0.13530}	{0.10174}
Conflict×2009	0.457***	0.714***
	(0.00245)	(0.00619)
	[0.0010]	[0.0040]
	{0.12173}	{0.09187}
Conflict×2010	0.539***	0.838***
	(0.00333)	(0.00554)
	[0.0030]	[0.0080]
	{0.05817}	{0.05152}
Conflict×2011	0.701***	1.121***
	(6.26e-05)	(0.000139)
	[0.0000]	[0.0000]
	{0.07433}	{0.06285}
Conflict×2012	0.775***	1.129***
	(2.64e-05)	(0.000181)
	[0.0000]	[0.0000]
	{0.07705}	{0.06405}
Conflict×2013	0.737***	1.144***
	(4.34e-05)	(0.000128)
	[0.0000]	[0.0000]
	{0.08926}	{0.07936}
Constant	-4.248***	-3.953***
	(0)	(0)
Observations	7,216	7,216
R-squared	0.254	0.230
Number of Districts	328	328
District FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at district level (328 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

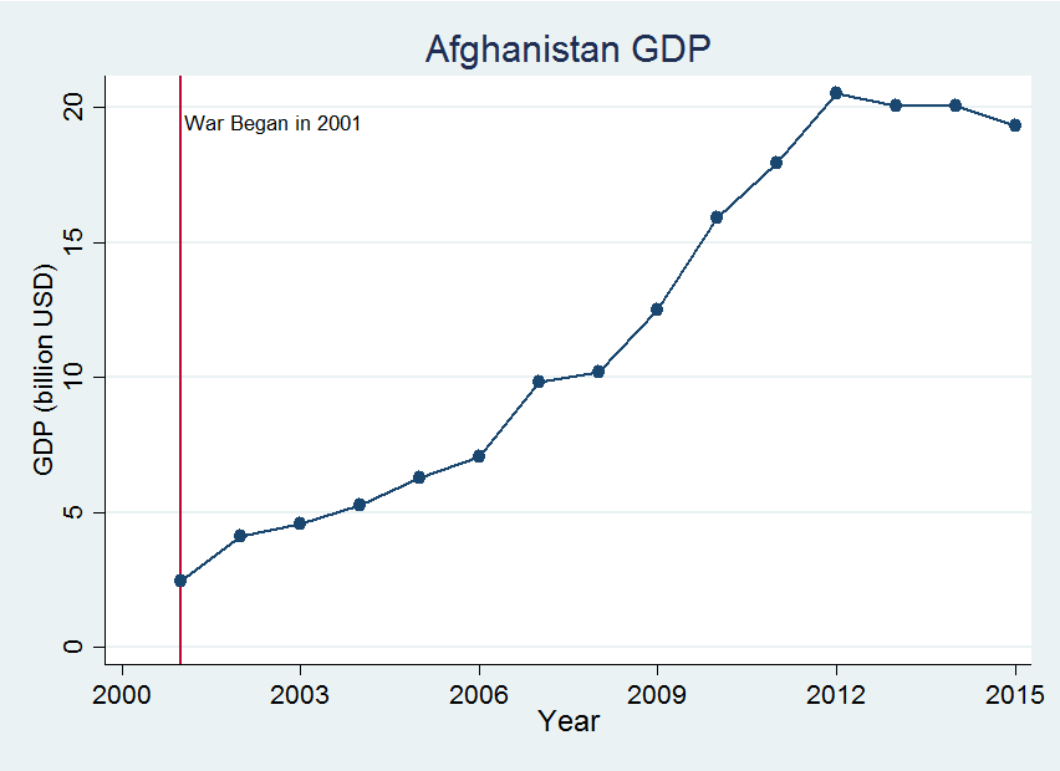
Second, I suggest that Afghanistan is a war based economy. Afghanistan War has brought by rotation over 5.2 million solders, with 2.5 million from the US along for over 13 years. To assist the civilian various activities, there have been more than 60 United Nation affiliates and multiple international organisations. Besides, there are over 100,000 contractors from the US, 3000 NGOs. 50 countries send intelligence personnel, diplomats, as well as US multinational corporations like Halliburton and Bechtel send personnel staff in Afghanistan. Large foreign military and civilian continents, all these individuals rocket the demand for service sectors in the Afghanistan.

Third, a booming service sector is the core for Afghan economic development. Afghanistan used to be an agrarian based economy, 60% population acquired the livelihood from agricultural activities. However, based on the Afghanistan Statistical Yearbook, after the Afghanistan War in 2001, service sector generates more than half of the GDP for the foreign armies and other personnel, agriculture and industry sectors make increasingly less occupations. The economy witnessed a transformation from the agriculture economy to a service sector based economy, or a war based economy. The vigorous growth is parallel to the night light density results, activities from foreign soldiers and staffs ignite the night light intensity. So the economy slowed down in 2012, when the rapid troops withdrew and war budgets shrank, the night light estimation also turns out to be insignificant in 2013. In sum, the service sector is the main engine for the Afghan economy from the 2002 invasion, when out night light estimation start to be significant.

Fourth, the agriculture sector does not include the output value of opium. UNDC (The United Nations Disarmed Commission) estimated that Afghanistan provides 6000 ton of this produce, making up 90% of the supply with a market value of $61.2 billion. It is documented that the amount of money has been taken by the Afghan corrupted staffs and well-connected

foreign personnel, but it is also reported that Afghan farmers also receive around $3 billion annually. This illegal transaction also promoted consumption capacities of Afghan civilians, consistent with the nightlight estimations.

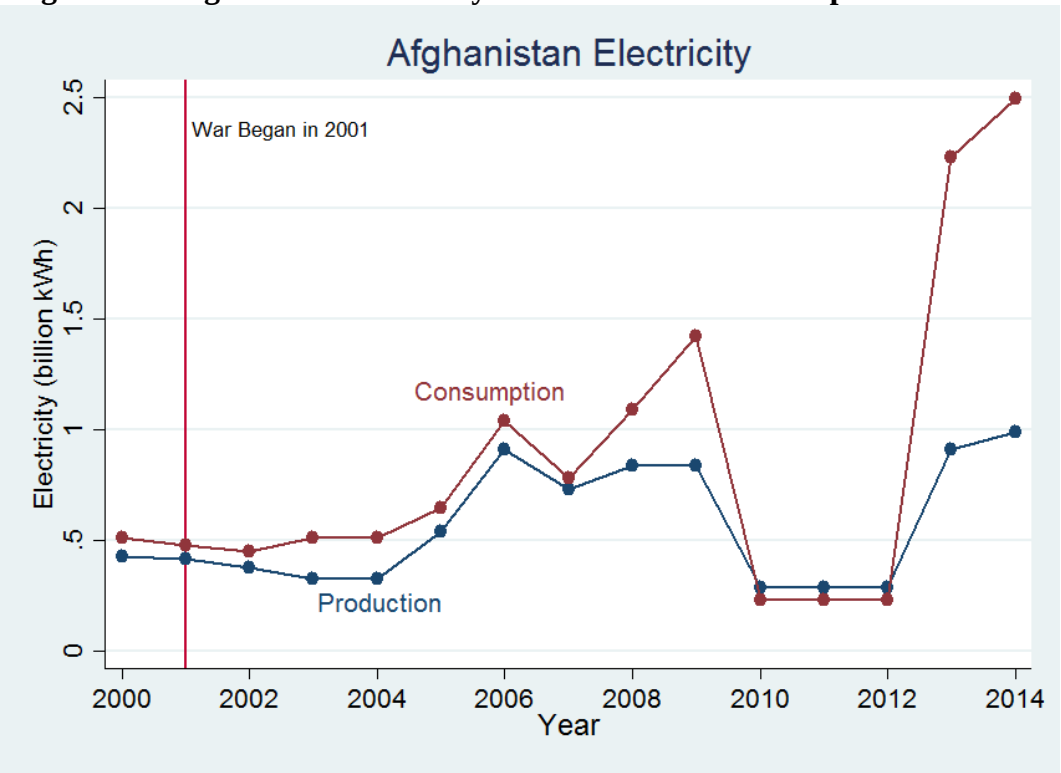
Figure 2.2: Afghanistan GDP from 2000



Night Light Map 2.2 displays a vast region of Afghanistan lacks of electricity supply. For Afghan electricity in Figure 2.3, the production and consumption lines share similar trend: there is no upward trend but there is also no downward trend. Especially for the electricity consumption, there is a general growing trend but with fluctuations, in other words, the war did not drag down utility consumption significantly. The conflicts are still on going now. Afghanistan has great economic potential for development, especially in natural resources like petroleum and lithium, agricultural products like pomegranates, grapes and apricots. A strong economic recovery is expected when the country can avoid civil war.

Afghanistan presents a positive impact of conflict during the war and after the coalition troops withdrew from the country. However, main factors like physical and human capital, technology, political stability and external investment have been damaged by the war. It is not a “Phoenix Factor”. The consumption from the coalition forces and the personnel made up the major economic growth. When the people returned to their home countries in 2012, the Afghan GDP figure began to go down straightforwardly. In other words, this model is not sustainable for Afghan economic development.

Figure 2.3: Afghanistan Electricity Production and Consumption from 2000

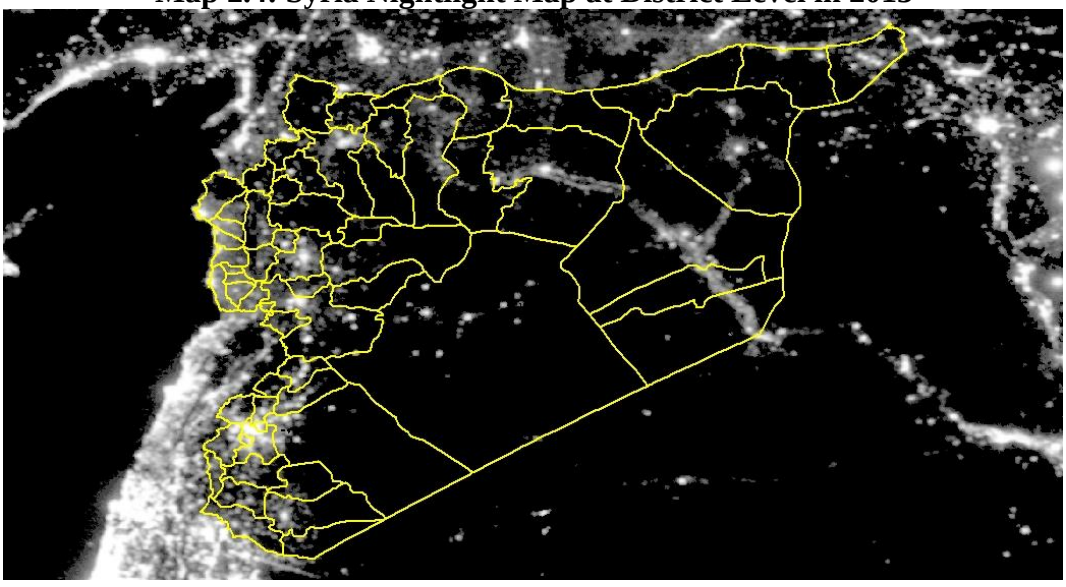


2.6.2 Syria Civil War (2011-Present)

Conflict Background

The uprising of the Arab Spring in 2011 stimulated the demand for democracy of the Syrian people. However, in March, security forces shoot dead protestors in South city of Deraa, which stirred the nation-wide violent unrest wave over the subsequent month, Syria Civil War commenced. At first, President Bashar Assad announced conciliatory measures to please the protestors. However, in July, as the mass demonstration on Hama province, he sent troop to restore the order at the cost of civilian lives. In July 2012, Free Syria Army seized Aleppo in the north. In November 2012, National Coalition was formed in Qatar as recognised as "legitimate representative" by US, UK, France, Turkey and Gulf states. From 2013, the Islamist group gradually played a bigger role in the conflict.

Map 2.4: Syria Nightlight Map at District Level in 2013



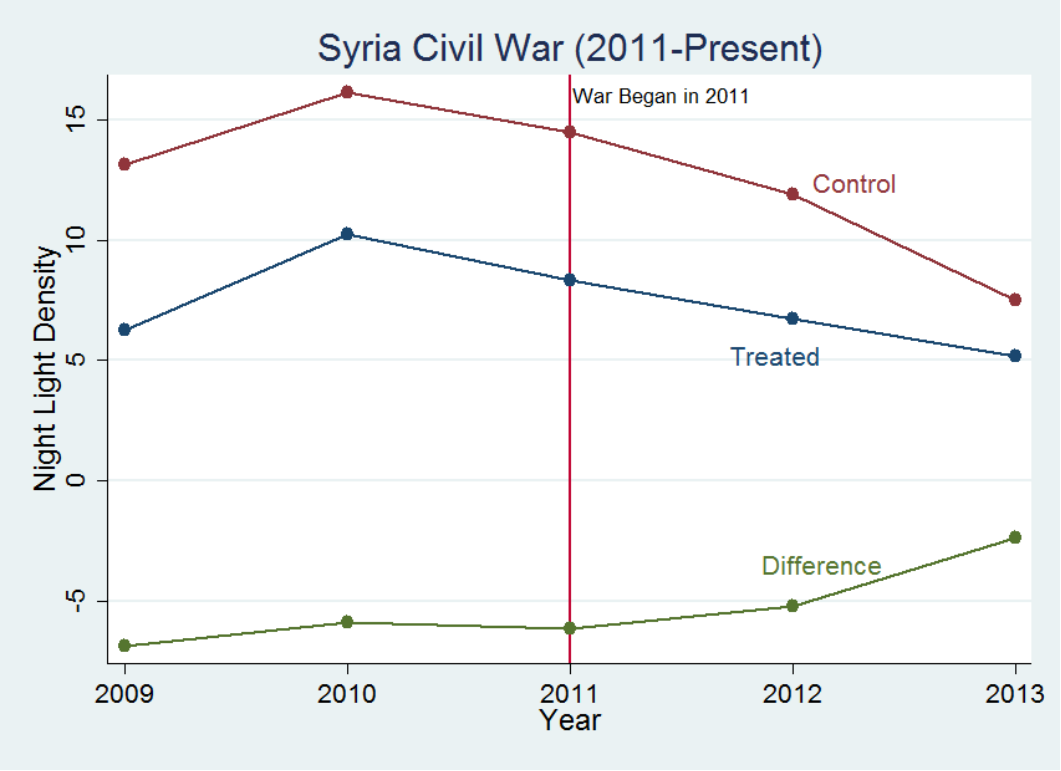
The panel covered the period from 1992 to 2013; currently Syria War is still on going as a global spot. The treated years in this panel are 2011, 2012 and 2013, so there is a long panel for pre-war period. From the night light Map 2.4, the west part of the country is much more

developed and brightening than the rest of the country, especially the major cities like Damascus and Aleppo located here, the severe military actions has destroyed these historical areas, I expect significant effects on night light.

Identification and Trend Analysis

In Figure 2.4, both treated and control regions have witnessed a declining nightlight since 2010. But the treated regions declined rather faster than the control regions from 2011, when Syria War commenced. The graph implies that Syrian War has exerted negative effects over this country's economy, but the effects on provinces exposed to high conflict are much stronger even with only two years treatment. Damascus and Aleppo have been severely damaged by heavy bombings and raid, this graph consistently displays the result.

Figure 2.4: Syria Trend Analysis by Control and Treated Provinces



Result Interpretation

From 1993 to 2012, column (1) of Table 2.2 does not display any significant value, which indicates a parallel trend in the pre-war period. However, the coefficient turns out to be negative in 2013, when Syria had experienced two years of fierce violence. Additionally, the absolute value implies night light growth in the high conflict regions in 2013 is 0.469 percentage point lower, implying the conflict becomes severe and exerts serious impacts on Syrian economy. The second column describes a consistent result that Syrian War has reduced the nightlight growth in the high conflict intensity regions compared with the regions with less conflict exposures. Besides, using the methods of bootstrapping clustering standard errors does not change the result and no omitted variable bias is found by Oster test.

Map 2.5: Syria Conflict Level Classification at District Level

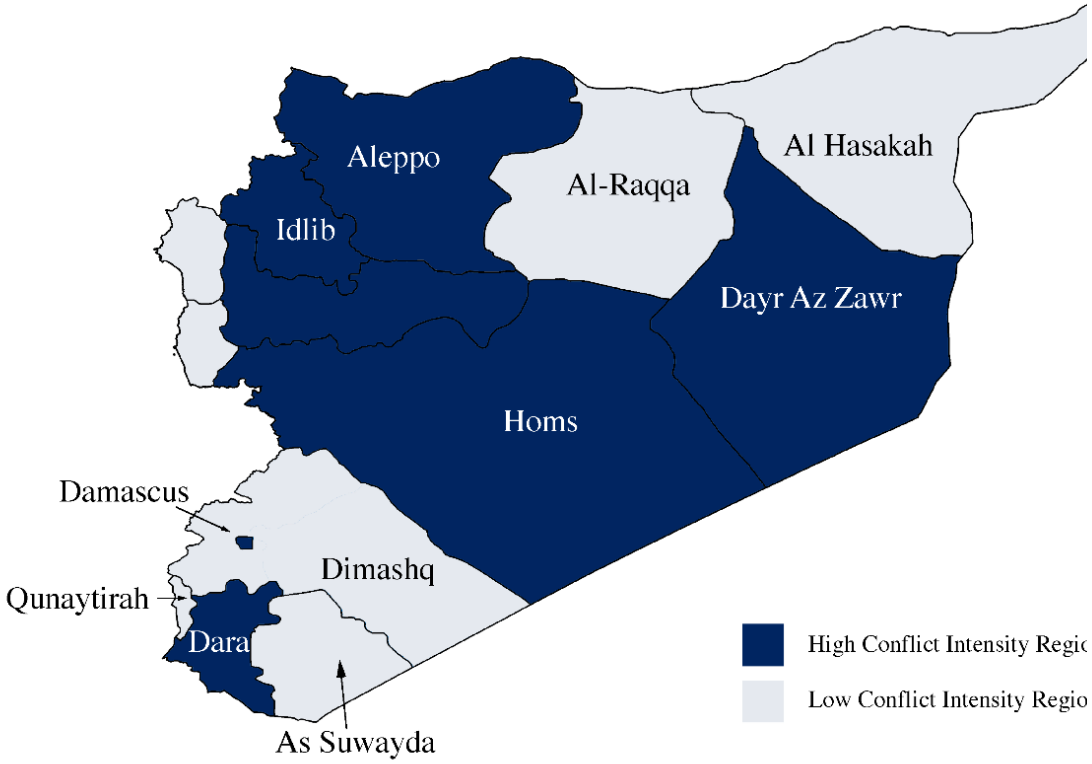


Table 2.2: Syria War Impact on Economic Growth

VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	0.150** (0.0185) [0.0070]	0.149** (0.0201) [0.0080]
	{-0.10380}	{-0.10269}
Conflict×1994	0.229** (0.0293) [0.0280]	0.230** (0.0303) [0.0290]
	{-0.59614}	{-0.60670}
Conflict×1995	0.183* (0.0937) [0.0811]	0.181* (0.0996) [0.1021]
	{-3.09416}	{-3.24302}
Conflict×1996	0.215* (0.0606) [0.0701]	0.214* (0.0657) [0.0631]
	{3.61883}	{3.49351}
Conflict×1997	0.213* (0.0607) [0.0511]	0.213* (0.0634) [0.0811]
	{-0.34404}	{-0.34630}
Conflict×1998	0.216* (0.0834) [0.0711]	0.215* (0.0877) [0.0821]
	{-0.57955}	{-0.58221}
Conflict×1999	0.218 (0.112) [0.0991]	0.215 (0.118) [0.0901]
	{-5.97116}	{-6.08204}
Conflict×2000	0.206 (0.102) [0.0921]	0.204 (0.108) [0.0991]
	{-1.24508}	{-1.24153}
Conflict×2001	0.150 (0.273) [0.2663]	0.148 (0.283) [0.2863]
	{5.07846}	{4.72970}
Conflict×2002	0.104 (0.479) [0.4665]	0.103 (0.489) [0.5025]
	{-0.68717}	{-0.68516}
Conflict×2003	0.134 (0.368) [0.3534]	0.132 (0.378) [0.3694]
	{1.29638}	{1.25489}
Conflict×2004	0.0920 (0.556) [0.5495]	0.0894 (0.570) [0.5786]
	{0.22603}	{0.21878}

Conflict×2005	0.0823	0.0801
	(0.559)	(0.572)
	[0.5626]	[0.5816]
	{-33.42177}	{-65.50784}
Conflict×2006	0.111	0.108
	(0.459)	(0.474)
	[0.4575]	[0.4615]
	{0.15342}	{0.14888}
Conflict×2007	0.131	0.128
	(0.398)	(0.412)
	[0.4054]	[0.3834]
	{0.15483}	{0.15060}
Conflict×2008	0.117	0.114
	(0.445)	(0.460)
	[0.4735]	[0.4715]
	{0.31948}	{0.31087}
Conflict×2009	0.147	0.142
	(0.307)	(0.322)
	[0.3073]	[0.3163]
	{0.98020}	{0.92450}
Conflict×2010	0.126	0.121
	(0.439)	(0.460)
	[0.4314]	[0.4414]
	{0.07810}	{0.07391}
Conflict×2011	0.128	0.123
	(0.448)	(0.467)
	[0.4334]	[0.4575]
	{0.13990}	{0.13333}
Conflict×2012	-0.0324	-0.0363
	(0.851)	(0.833)
	[0.8478]	[0.8238]
	{-1.22865}	{-1.45962}
Conflict×2013	-0.469**	-0.474**
	(0.0139)	(0.0130)
	[0.0180]	[0.0130]
	{0.21263}	{0.21004}
Constant	1.099***	3.085***
	(0)	(0)
Observations	1,320	1,320
R-squared	0.613	0.613
Number of Provinces	60	60
Province FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at province level (60 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

As a matter of fact, Damascus and Aleppo are the main conflict areas, the capital and the second biggest city respectively. These regions have been under severe attacks by government army, rebel groups and other militias. To a large extent, the impact of Syria War on economic development can be interpreted by the theoretical framework like physical destruction and human capital loss. The subsequent part attempts to explain the results through goods markets, labour markets and energy supply.

First, Figure 2.5 describe GDP until 2008 due to the data limitation. But *Syria Overview from World Bank* states Syria GDP has plummeted since 2010. GDP in 2015 dropped 57 per cent more than that in 2010, especially there were more than 20 per cent GDP real growth contraction between 2012 and 2013. All GDP components collapsed, especially for international trade, exports plunged 55.5 per cent from 2012 to 2013 and imports fell almost 47 per cent. The significant estimation in 2012 describes this sharp economic tumble. In terms of electricity supply, IMF documents that various groups have used tactical water and power cuts to reduce service provision to targeted population areas. The violence therefore damaged the electricity utility, reflecting on the nightlight growth results. The graph in Figure 2.6 also captures the trend for electricity production and consumption has been exogenously disrupted since the Arabic Spring movement.

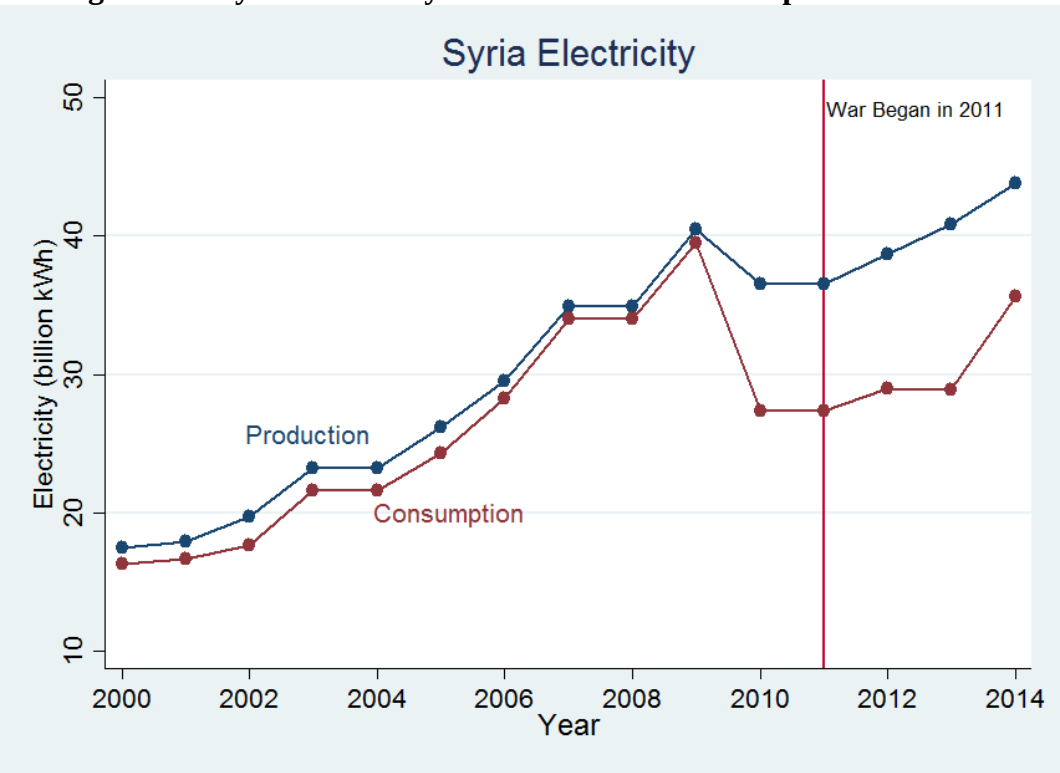
Second, Syrian War has resulted in a tremendous outflow of refugees, half of the Syrian population have been forcibly displaced until 2016, the United Nations High Commissioner for Refugees (UNHCR) estimates. In 2015, 4.8 million people have left the country, accounting for 22 per cent of the whole population; 6.6 million refugees have been internally displaced in the country. Additionally, the Syrian Centre for Policy Research (SCPR) estimated death toll at 470,000 in 2016. The huge amount of labour force outflow and

population loss considerably reduced economic activities across the country, thus the electricity production and consumption plunged.

Figure 2.5: Syria GDP from 2000

Third, oil occupies about 50 per cent of Syrian exports and 30 per cent of the government revenue in 2010. However, revenue from oil exports dropped from 4.7 billion US dollar in 2011 to 0.14 billion US dollar in 2015. Besides, many oil fields have been dominated by ISIS, outside government control. The accumulated current account deficit made up 19 per cent of GDP in 2014, which made it unlikely to make investment for public infrastructure. Public revenue plummet contributes to the darker night light from my estimations.

Figure 2.6: Syria Electricity Production and Consumption from 2000



2.6.3 Iraq War (2003-2011)

Conflict Background

From 1991 to 2002, US and UK destroyed Iraq's nuclear, chemical and biological weapon programmes and disabled Iraq's air defense networks. President George W. Bush asserted that Iraqi possession of WMD threatened the security of US and its allies and accused of Saddam of supporting al-Qaeda. In March 2003, US-led military forces invaded Iraq and Saddam Hussein was captured in December 2003. However, insurgency intensified such as suicide attacked the UN headquarters in Baghdad and Shia festivals etc. The coalition army dismantled the dictatorship and installed democracy for the people in Iraq; the first government and parliament vote held in Iraq in December 2005. However, the conflict started among Shia, Sunni and Kurdish ethnicities about the political power distribution. Especially between Shias and Sunnis, as well as the insurgency against US and coalition forces, the major warfare and conflict casualties occurred between 2004 and 2007. In December 2011, the US army pulled out of Iraq. This paper treated year between 2003 and 2011 as war period. The nightlight data panel spread from 1992 to 2013. I take the conflict classification results from Guerrero Serdan (2009).

Identification and Trend Analysis

In Iraq, the regions with conflict in fact experienced better electricity infrastructure as the indicated in Figure 2.7. Although low conflict regions have been lower than the high conflict regions, both high and low conflict regions share a similar growth path. Thereby the difference remains stable, from this graph, I do not expect a dramatic estimation from the night light methods, and it seems that the variations caused by the conflict are limited.

Map 2.6: Iraq Nightlight Map at District Level in 2013

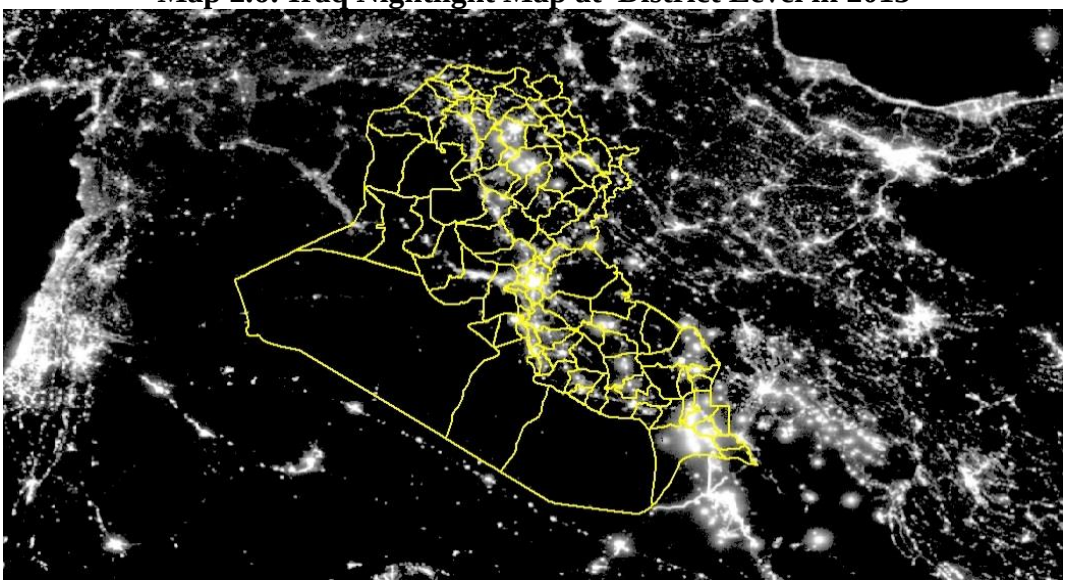
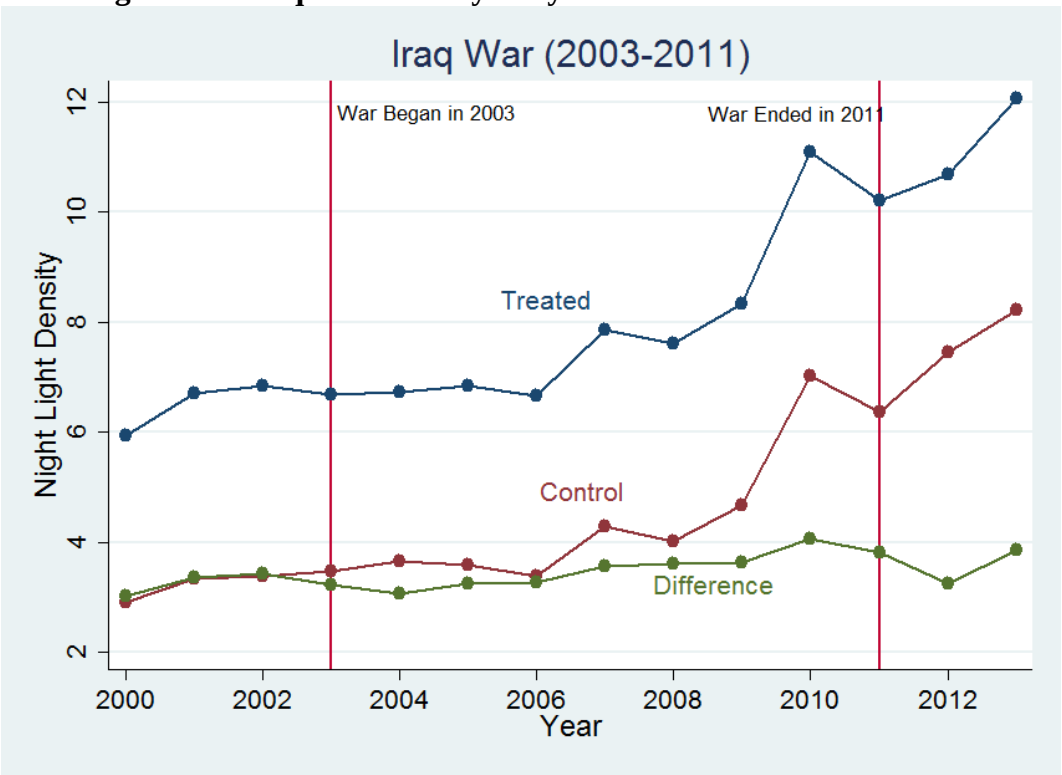


Figure 2.7: Iraq Trend Analysis by Control and Treated Districts



Result Interpretation

In Table 2.3, the first column shows Iraq has experienced a slower nightlight growth since 1998; the scale of the reduction has been increasing after the coalition forces invaded the country in 2003 particularly from 2010 to 2013. From the Iraq military record, in 2012 Sunni Muslims stage mass rallies across Iraq over months because Shia-dominated government marginalising Sunnis. My identification shows that the high conflict regions suffered much more nightlight growth loss than low conflict regions. War has put an adverse effect on output growth, especially Iraq experienced a steady economic growth from 2009 to 2011 as indicated in both GDP and electricity graphs. This sudden conflict event with large scale interrupted the growth path.

Map 2.7: Iraq Conflict Level Classification at District Level

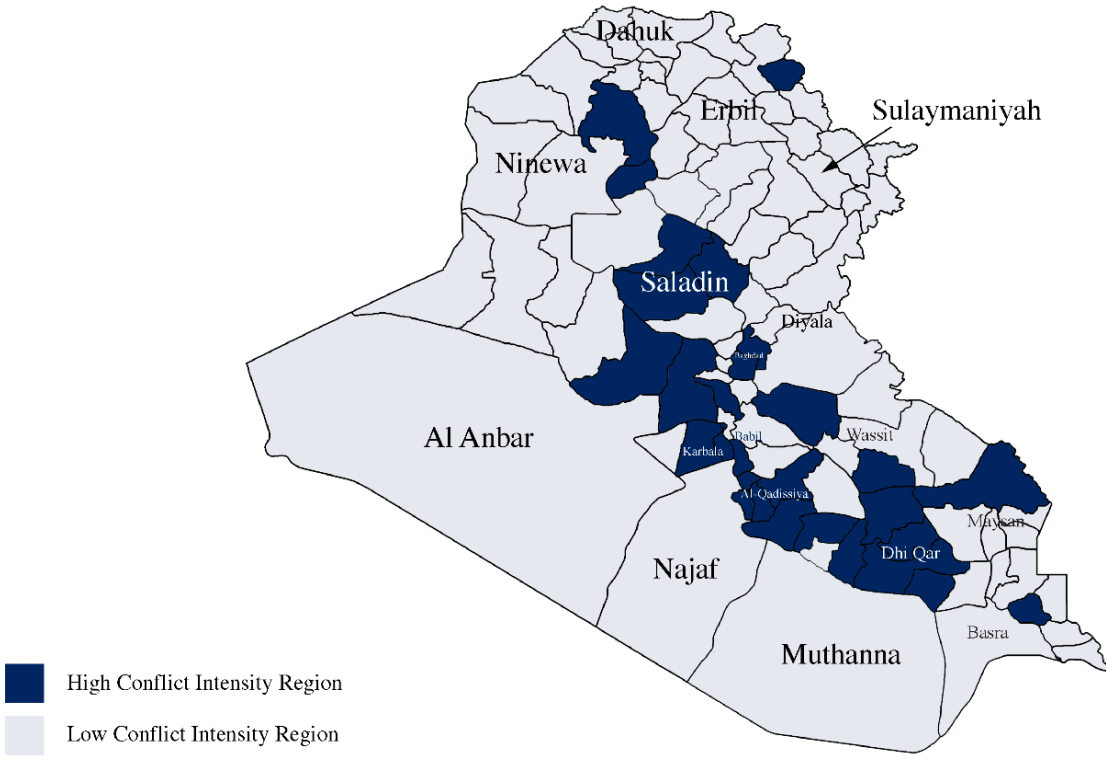


Table 2.3: Iraq War Impact on Economic Growth

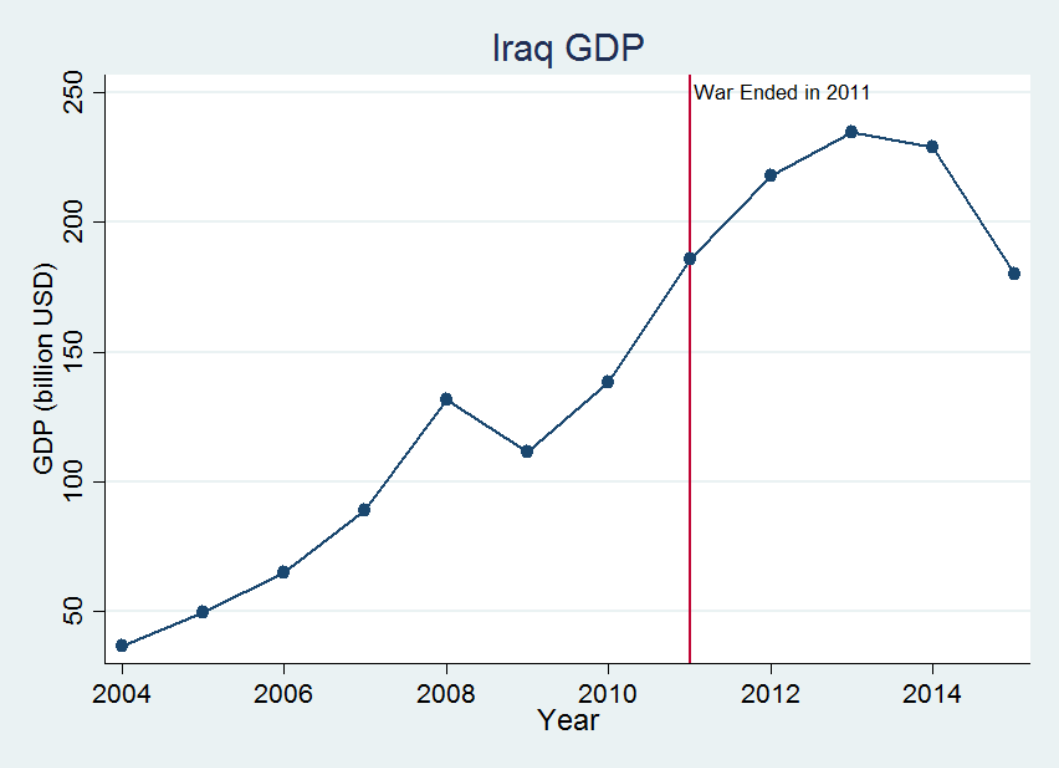
VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	0.146** (0.0240) [0.0160]	0.231* (0.0763) [0.0290]
	{-2.30414}	{-1.13448}
Conflict×1994	0.128 (0.146) [0.1522]	0.262 (0.116) [0.1181]
	{-0.23329}	{-0.28648}
Conflict×1995	-0.150 (0.135) [0.1311]	-0.0954 (0.586) [0.7387]
	{-0.45873}	{-0.24808}
Conflict×1996	-0.108 (0.282) [0.3053]	-0.0379 (0.827) [0.8789]
	{-1.57462}	{-3.37626}
Conflict×1997	-0.135 (0.235) [0.2523]	-0.0910 (0.609) [0.6827]
	{0.11259}	{0.05426}
Conflict×1998	-0.355*** (0.00595) [0.0030]	-0.315 (0.109) [0.0951]
	{0.36040}	{0.23015}
Conflict×1999	-0.282* (0.0700) [0.0851]	-0.249 (0.277) [0.3313]
	{0.33231}	{0.21326}
Conflict×2000	-0.261 (0.111) [0.1241]	-0.222 (0.355) [0.4444]
	{0.52768}	{0.31848}
Conflict×2001	-0.255* (0.0774) [0.0781]	-0.221 (0.304) [0.2663]
	{1.43096}	{0.82553}
Conflict×2002	-0.306* (0.0605) [0.0631]	-0.277 (0.245) [-1.1433]
	{3.46597}	{2.02482}
Conflict×2003	-0.374** (0.0248) [0.0210]	-0.347 (0.153) [0.1532]
	{-6.72521}	{-5.85981}
Conflict×2004	-0.465** (0.0115) [0.0080]	-0.439* (0.0910) [0.0791]
	{-1.58486}	{-1.15062}

Conflict×2005	-0.504***	-0.477*
	(0.00547)	(0.0647)
	[0.0020]	[0.0561]
	{-1.26973}	{-0.91764}
Conflict×2006	-0.441**	-0.414
	(0.0167)	(0.110)
	[0.0150]	[0.1001]
	{-2.37206}	{-1.75518}
Conflict×2007	-0.470**	-0.442
	(0.0230)	(0.120)
	[0.0170]	[0.1111]
	{-0.61232}	{-0.43355}
Conflict×2008	-0.398*	-0.370
	(0.0611)	(0.201)
	[0.0631]	[0.2132]
	{-0.82460}	{-0.58233}
Conflict×2009	-0.462**	-0.436
	(0.0194)	(0.111)
	[0.0090]	[0.1051]
	{-0.59616}	{-0.42540}
Conflict×2010	-0.558***	-0.529*
	(0.00935)	(0.0697)
	[0.0060]	[0.0631]
	{-0.30588}	{-0.21751}
Conflict×2011	-0.577***	-0.547*
	(0.00790)	(0.0630)
	[0.0130]	[0.0581]
	{-0.35508}	{-0.25301}
Conflict×2012	-0.737***	-0.705**
	(0.00240)	(0.0277)
	[0.0020]	[0.0160]
	{-0.39436}	{-0.28302}
Conflict×2013	-0.618**	-0.583*
	(0.0122)	(0.0725)
	[0.0090]	[0.0611]
	{-0.25914}	{-0.18318}
Constant	0.308***	1.798***
	(6.81e-06)	(0)
Observations	2,244	2,244
R-squared	0.530	0.456
Number of Districts	102	102
District FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at district level (102 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

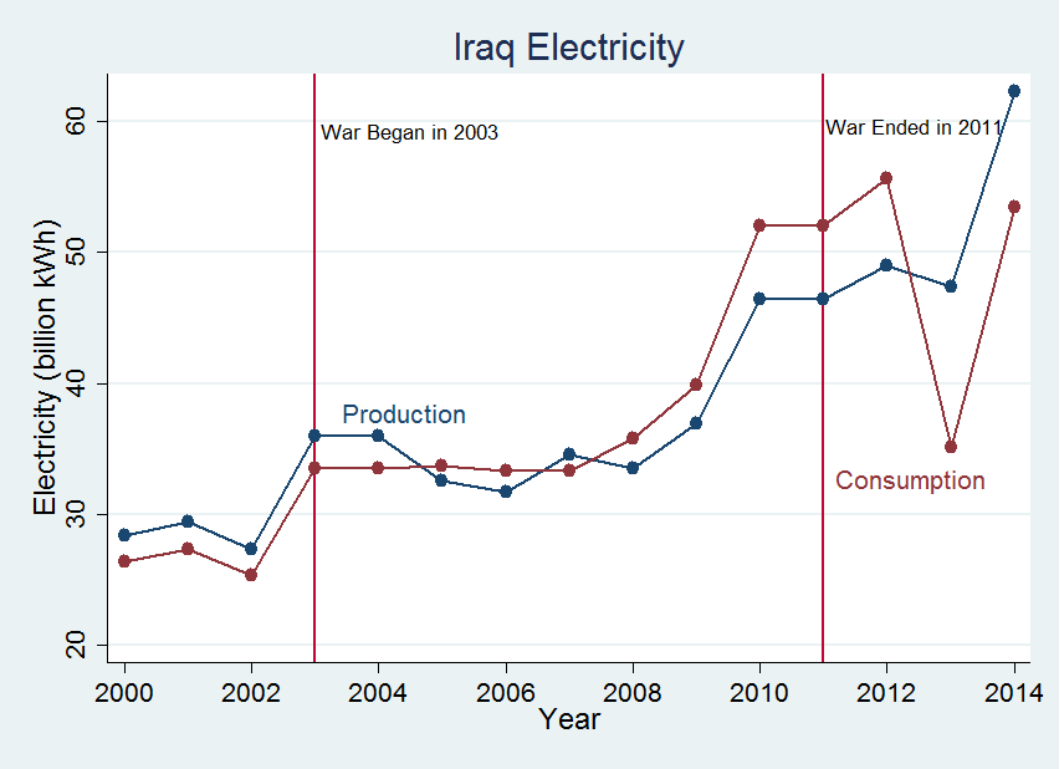
In the second column for robustness check, although some estimation turns out to be insignificant, the coefficients from 2010 to 2013 remain negative with robust estimation. Below the coefficients, results are consistent with cluster bootstrapping and Oster test.

Figure 2.8: Iraq GDP from 1990



Therefore, the results exhibit that Iraq War has exerted considerable negative impact on economic growth with high conflict regions. World Bank GDP data (Figure 2.8) from Iraq starts from 2004 because of the war break, it is indicated a strong growth trajectory until 2013. In 2011, the output level reached the higher level (equivalent to the GDP level in 1990), which implies a drastic conflict impact on Iraq economy. In terms of electricity production, in Figure 2.9 the graph line shows a stable trend from 2000 to 2009, and a big jump from 2009 to 2010. The civil war was most intensified between 2004 and 2007. Electricity consumption displays a similar picture to the production. However, from 2012 to 2013, there is a substantial decline between 2012 and 2013, from 55.66 billion kWh to 35.12 billion kWh.

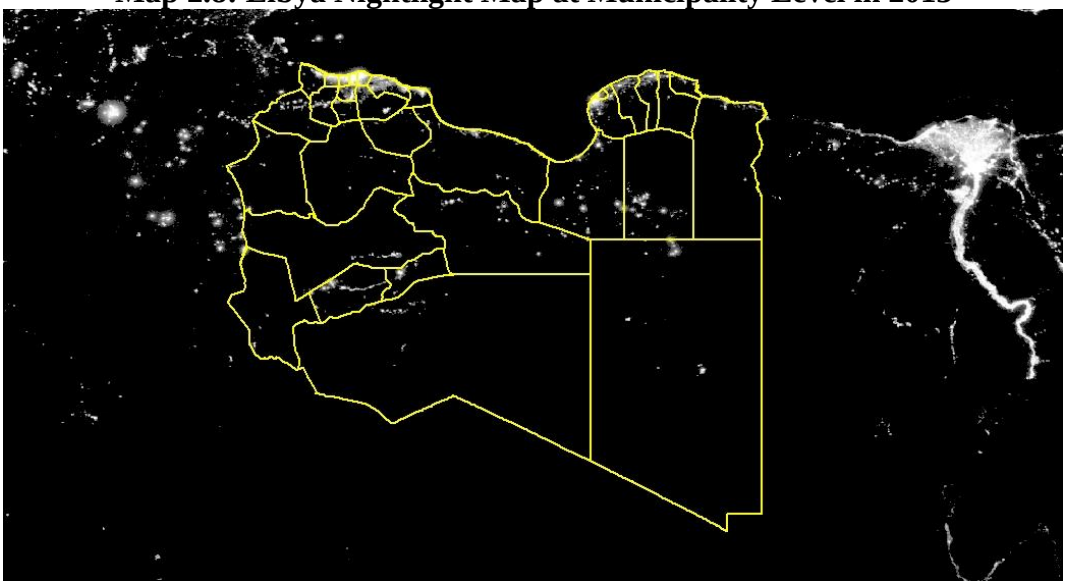
Figure 2.9: Iraq Electricity Production and Consumption from 2000



2.6.4 Libya Civil War (2011-Present)

Conflict Background

Map 2.8: Libya Nightlight Map at Municipality Level in 2013

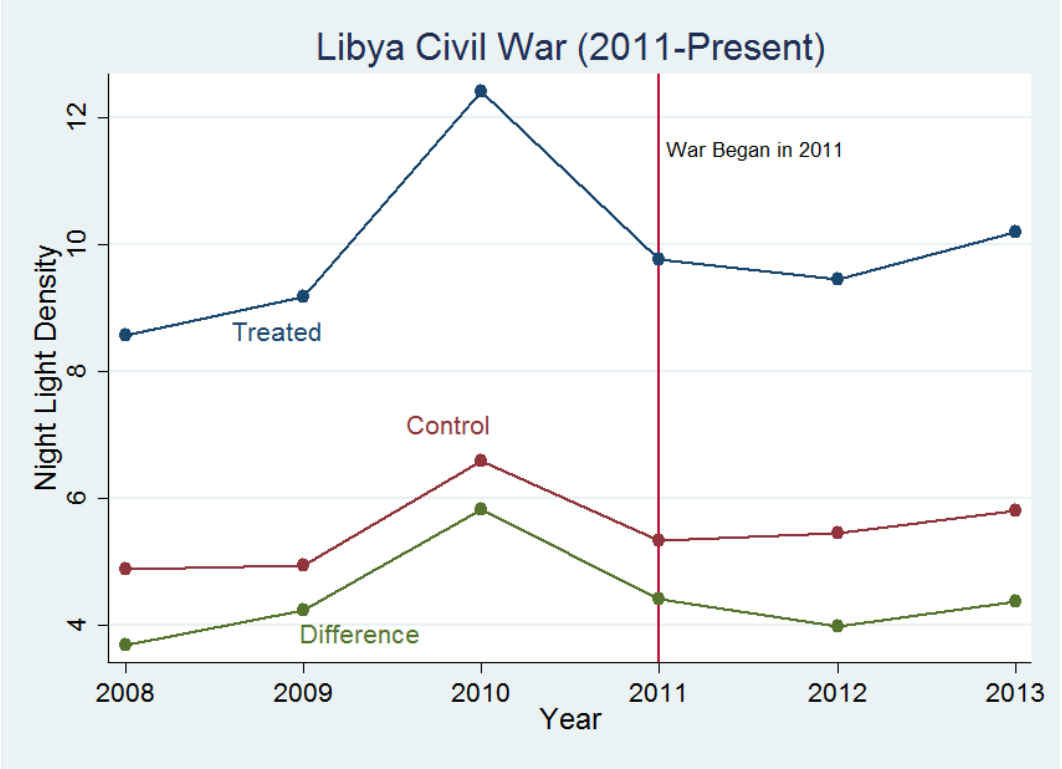


In 2011 with the pro-democracy movement of Arab Spring, an increasing power of anti-Gaddafi was emerging, especially inspired by revolts in other Arab countries like Egypt and Tunisia. In February, Libyan military attacked protesters by security forces and even military jets. In March, the Transitional National Council (TNC), a group of rebel leaders, declared as the representative of Libya and was recognised as the legitimate government body by the USA. Later in this year, Qaddafi was captured and killed by the rebels. However, the ending era of Qaddafi did not bring peace and prosper into Libya. The clash between former rebel forces pushed the country into civil war. In addition, the rise of Islamic State extremist militia seizes control of the country east triggered the conflict with Libyan National Army. In this paper, I focus on the civil war beginning in 2011. Therefore, 2011, 2012 and 2013 are identified as the treated periods.

Identification and Trend Analysis:

Libyan Crisis began in 2011, because of the data limited, there are only two years effects on the night light variations. In Figure 2.10, there is a slight decline in treated regions from 2011 to 2012 but bounced back in the following year. In the control regions, night light density has been growing. The difference between treated regions and control regions is marginal. This result does not meet my expectation that conflict reduces the economic output in the high conflict regions. One interpretation is that Libya has already supplied sufficient level of electricity across the country; a conflict could not exert immediate effects on the utility. Although the treated region began to rally of the electricity usage, I cannot predict a robust estimation based on this figure.

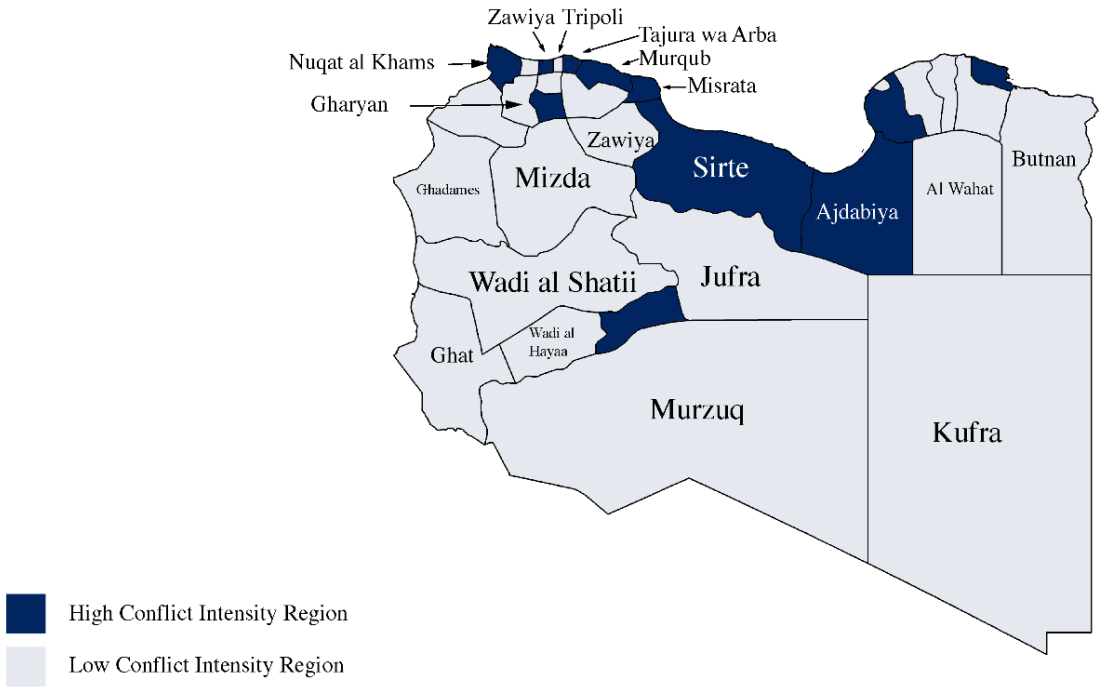
Figure 2.10: Libya Trend Analysis by Control and Treated Municipalities



Result Interpretations

The panel covers from 1992 to 2013 and the civil war commences in 2011. The default assumption is that the effects of years from 1992 to 2010 should not be significant, if the civil war put an impact on economic output, 2011, 2012 and 2013-year effect should be significant.

Map 2.9: Libya Conflict Level Classification at Municipality Level



Neither of the columns in Table 2.4 presents a robust estimation; Libya Civil War did not shape the night light growth during the first three years of the conflict. For Libyan economy, apart from the authoritarian regime, the economic structure and public policy on electricity can be the key factors to interpret the mechanisms behind the results.

Table 2.4: Libya War Impact on Economic Growth

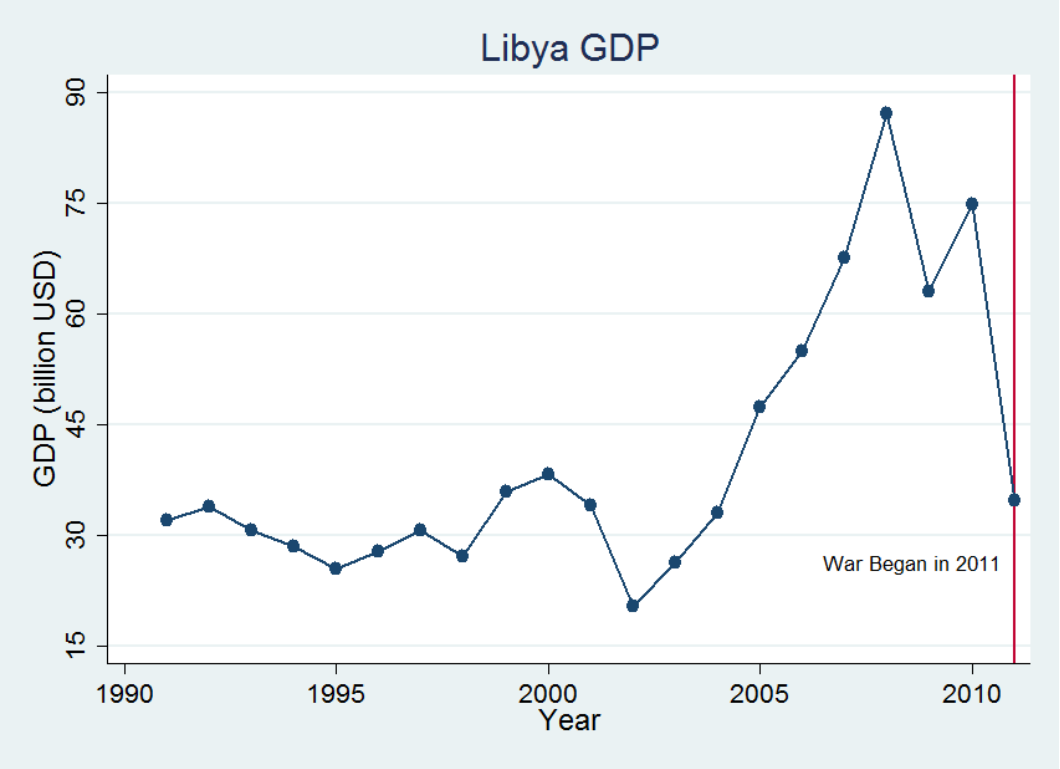
VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	-0.0270 (0.453) [0.4575]	-0.0268 (0.426) [0.3774]
	{0.05570}	{0.04991}
Conflict×1994	0.121 (0.142) [0.1632]	0.0707 (0.274) [0.2603]
	{-0.21854}	{-0.12068}
Conflict×1995	0.0288 (0.659) [0.6857]	0.0206 (0.705) [0.7077]
	{-0.09421}	{-0.06111}
Conflict×1996	0.0304 (0.635) [0.6537]	0.0336 (0.535) [0.5425]
	{-0.12280}	{-0.12084}
Conflict×1997	0.0634 (0.487) [0.4735]	0.0176 (0.834) [0.8438]
	{-0.10503}	{-0.02736}
Conflict×1998	-0.0344 (0.690) [0.7197]	-0.0709 (0.378) [0.3614]
	{0.05512}	{0.10564}
Conflict×1999	-0.0141 (0.892) [0.8999]	-0.0396 (0.684) [0.6617]
	{0.03105}	{0.08086}
Conflict×2000	0.00271 (0.980) [0.9770]	-0.00926 (0.925) [0.9369]
	{-0.01026}	{0.03215}
Conflict×2001	-0.00212 (0.986) [0.7107]	-0.000241 (0.998) [0.9990]
	{0.01118}	{0.00115}
Conflict×2002	0.0412 (0.732) [0.8629]	0.0384 (0.733) [0.7247]
	{-0.22905}	{-0.19537}
Conflict×2003	-0.0218 (0.853) [0.8629]	0.00140 (0.990) [0.9910]
	{1.88897}	{-0.05505}
Conflict×2004	-0.0229 (0.866) [0.8468]	0.0247 (0.851) [0.8589]
	{-0.08876}	{0.09592}

Conflict×2005	-0.0544	-0.0222
	(0.672)	(0.858)
	[0.6857]	[0.8799]
	{-0.85407}	{-0.41742}
Conflict×2006	-0.0682	-0.0143
	(0.642)	(0.922)
	[0.6326]	[0.9169]
	{-0.23302}	{-0.04827 }
Conflict×2007	-0.0579	0.00791
	(0.720)	(0.960)
	[0.7427]	[0.9550]
	{-0.11966}	{0.01581}
Conflict×2008	-0.0624	-0.00155
	(0.695)	(0.992)
	[0.7137]	[0.9900]
	{-0.15135}	{-0.00365}
Conflict×2009	0.0624	0.103
	(0.736)	(0.570)
	[0.7207]	[0.5936]
	{0.17334}	{0.26921}
Conflict×2010	-0.0149	0.0923
	(0.931)	(0.603)
	[0.9399]	[0.5856]
	{-0.01427}	{0.08294}
Conflict×2011	0.00633	0.0536
	(0.974)	(0.774)
	[0.9690]	[0.7508]
	{0.01406}	{0.11171}
Conflict×2012	-0.0717	-0.0207
	(0.679)	(0.904)
	[0.6827]	[0.9129]
	{-0.14873}	{-0.04073}
Conflict×2013	-0.0127	0.0358
	(0.952)	(0.860)
	[0.9690]	[0.8539]
	{-0.02328}	{0.06173}
Constant	-0.194***	-0.284***
	(0.00413)	(4.35e-05)
Observations	704	704
R-squared	0.692	0.669
Number of Municipalities	32	32
Municipality FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at municipality level (32 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

First, Libyan oil reserves were discovered in 1959 and the country has been heavily relied on oil exportation for revenue. In 1977, Qaddafi restricted private ownership and commerce in Libya under his regime. A strong energy sector crowds out other business activities. Therefore, largely, the civil war could not affect economic activity dramatically in Libya, as there are hardly other economic activities.

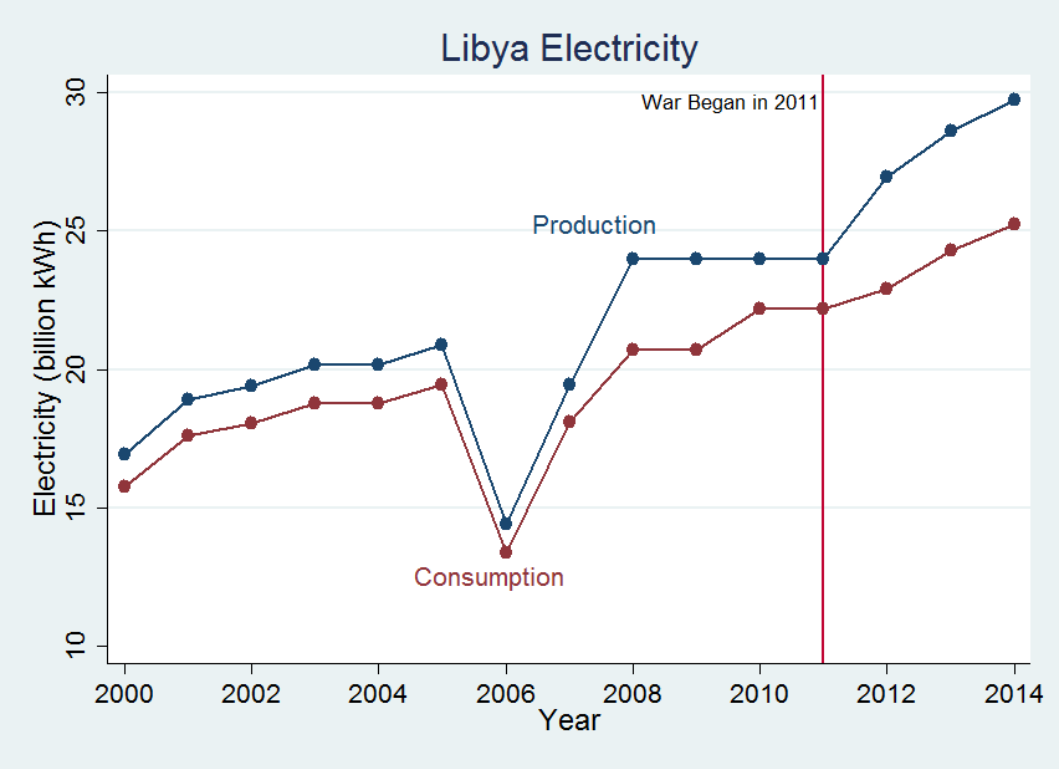
Figure 2.11: Libya GDP from 1990



Secondly, currently half of the population are under 30 years old. Oil sectors are unable to provide enough employment, which is also one of the causes of the conflict between Islamists and Nationalist in Libya. Meanwhile the east oil export terminal were controlled by Islamic State and later taken by Libyan National Army (LNA). War did not worsen the economic condition in high conflict regions compared with that in the low conflict regions subsidy in the country.

World Bank provides Libya GDP data until 2011. However, as indicated in Figure 2.11 between 2008 and 2011, there is a sharp decline, it is indicated that to a large extent, the civil conflict has put a negative effect on the economy. This displays that the GDP started to decline after 2013; however, no satellite data are available after 2013 to investigate the subsequent effects on the economy. In Figure 2.12, from 2008 to 2013, Libya electricity production and consumption remained constant until 2011 and witnessed a steady increase after 2011. It seems that the civil war did not exert an adverse effect on electricity. Therefore, as can be seen from the night light Map 2.8, Libya is visibly brighter than Afghanistan, reflecting Libyan better economic endowments than the other economies in this paper.

Figure 2.12: Libya Electricity Production and Consumption from 2000

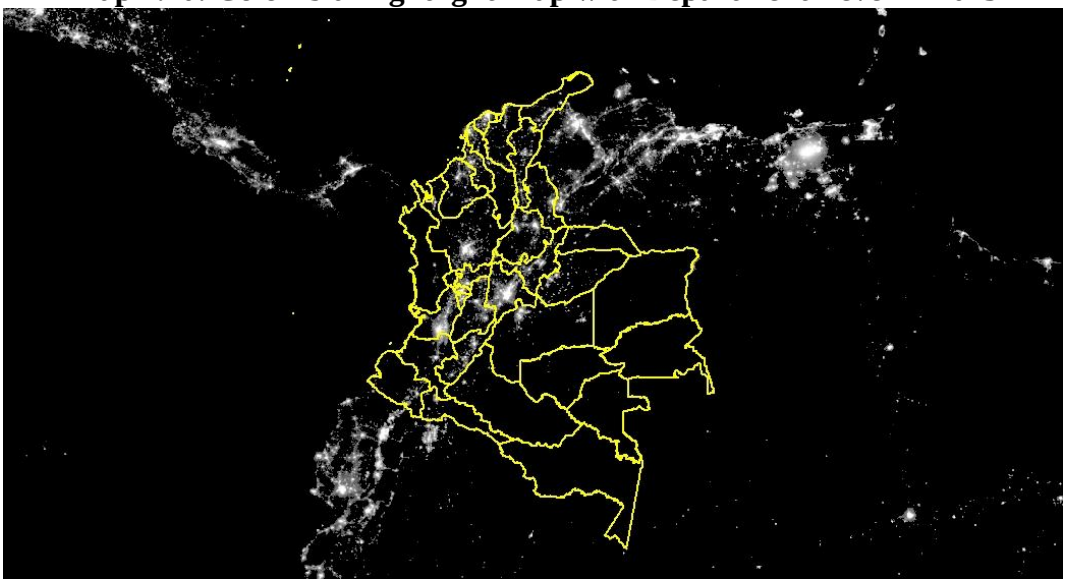


2.6.5 Colombia Conflict (1964-Present)

Conflict Background

In the middle of 1960s, with the founding of Revolutionary Armed Forces of Colombia (FARC), National Liberation Army (ELN) and People's Liberation Army (EPL), Colombia was plunged into civil war and anti-drug war until the present. From 1998 to 2002, Conservative President Andres Pastrana attempted to end the conflict with peace talks and granting safe havens. His successor, the independent candidate Alvaro Uribe promised to crack down hard on rebel groups. Although his economic austerity plan and political reforms were denied by voters on referendum, his fighting against rebels acquired successes from

Map 2.10: Colombia Nightlight Map with Department Level in 2013



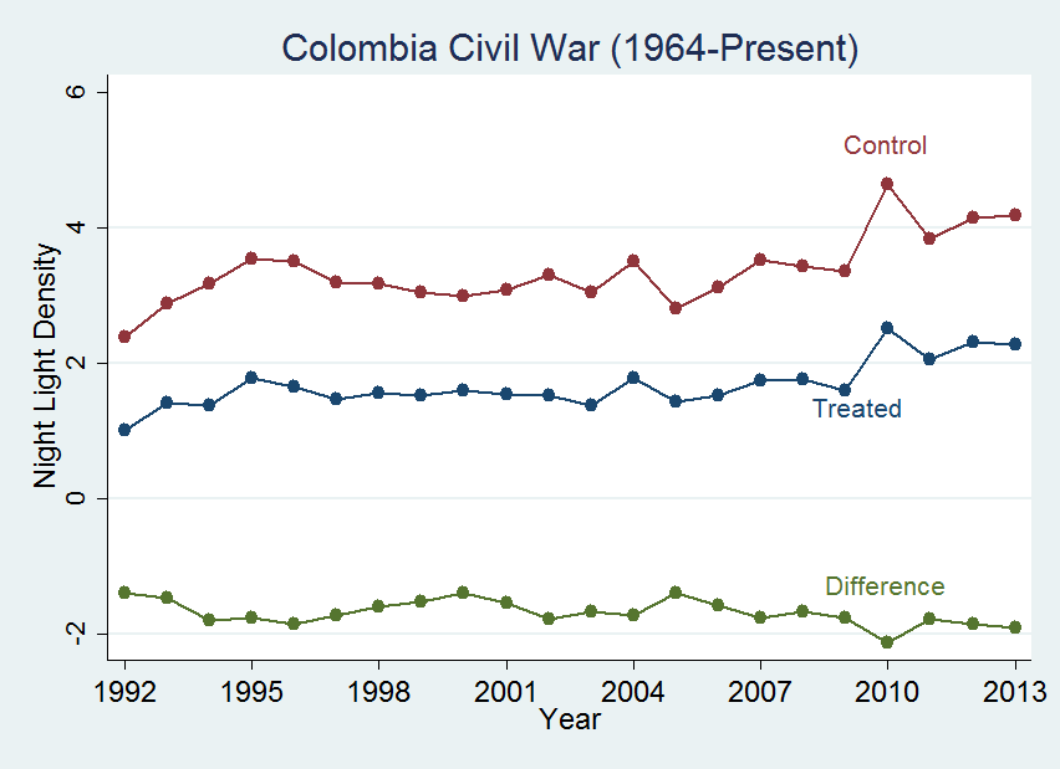
2002 to 2008. In 2012, formal peace talks held in Havana between Colombia government and FARC, FARC announced ceasefire for two months. The conflict between government and left-rebels are still on going now. My panel is from 1992 to 2013, so the entire period was under conflict treatment to some extent. The on-going conflict in Colombia provides an

opportunity to study the long-term conflict impact on economic development by analysing night light variations across the country.

Identification and Trend Analysis

In Table 2.13, both control and treated regions exhibit considerably consistent trend from the 1990s. Control regions are more economic advanced, night light densities are higher. The half a century Colombia conflict has marginal effects for the economy in 1990s as the rebel groups are shrinking and the economy has adapted to the environment. It is hardly to expect a robust estimations, the graphs shows the conflict has little impact on the output growth.

Figure 2.13: Colombia Trend Analysis by Control and Treated Departments



Result Interpretation

Neither of the columns in Table 2.5 displays any value statistically significant from 1992 to 2013. Colombia conflict does not have a considerable effect on nightlight growth. First, the half a century conflict cannot have generate marginal impact on the economy. As majority of civilians have displaced to the secure regions; meanwhile, with the diminishing power of the rebel group, the government is able to concentrate more on the economic development. Second, the insurgents usually fought with government army in rural area, the night light variation has been constrained. The robustness check confirmed this estimation.

Map 2. 11: Colombia Conflict Level Classification at Department Level

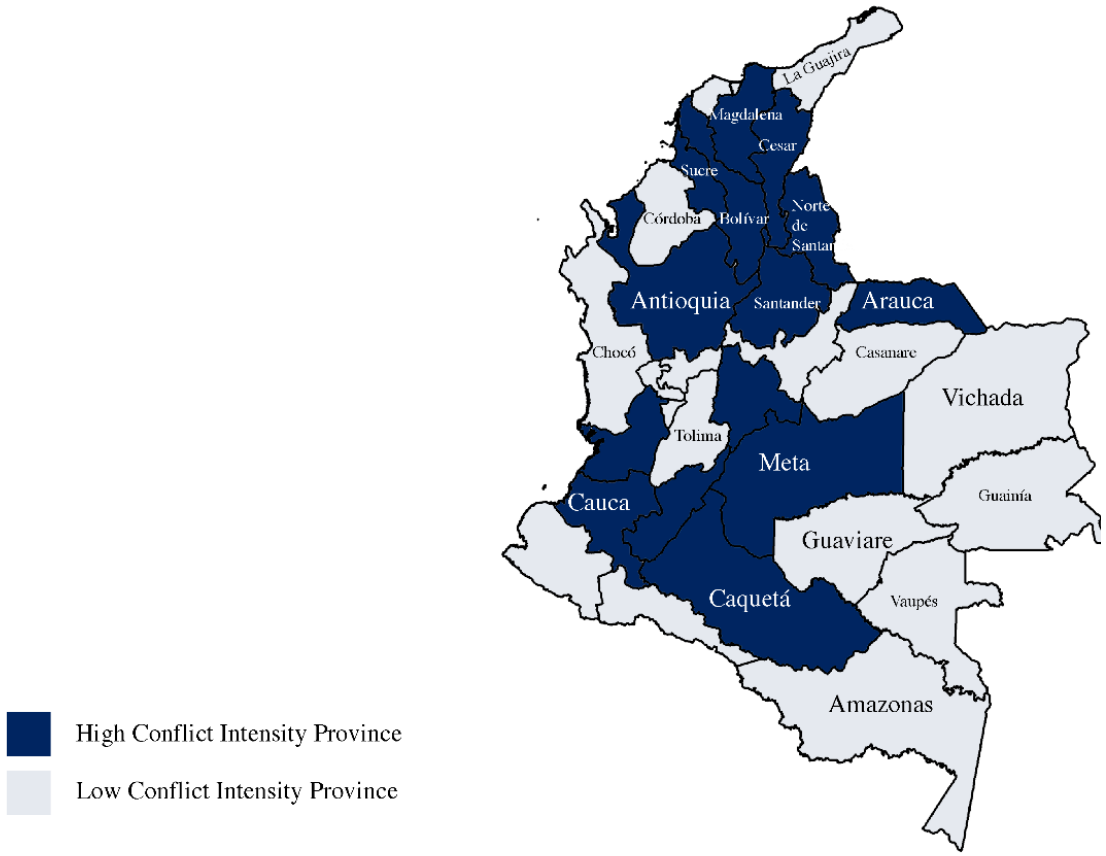


Table 2.5: Colombia War Impact on Economic Growth

VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	0.188* (0.0647) [0.0691]	0.137* (0.0902) [0.0891]
	{-0.36408}	{-0.28829}
Conflict×1994	0.156* (0.0561) [0.0501]	0.122** (0.0452) [0.0490]
	{-0.27460}	{-0.23195}
Conflict×1995	0.255** (0.0228) [0.0190]	0.210** (0.0308) [0.0220]
	{-3.86388}	{-5.71584}
Conflict×1996	0.248** (0.0341) [0.0310]	0.196** (0.0415) [0.0430]
	{-1.58591}	{-1.48319}
Conflict×1997	0.161 (0.215) [0.2222]	0.108 (0.295) [0.2823]
	{-0.51611}	{-0.36607}
Conflict×1998	0.214 (0.107) [0.1021]	0.156 (0.139) [0.1341]
	{-1.08840}	{-0.91049}
Conflict×1999	0.213 (0.104) [0.0871]	0.165 (0.107) [0.1071]
	{-0.81083}	{-0.65689}
Conflict×2000	0.235* (0.0983) [0.0981]	0.190 (0.101) [0.0891]
	{-1.51048}	{-1.24547}
Conflict×2001	0.185 (0.182) [0.1672]	0.148 (0.196) [0.2072]
	{-0.98344}	{-0.77709}
Conflict×2002	0.131 (0.352) [0.3534]	0.0945 (0.400) [0.3784]
	{-0.68935}	{-0.48746}
Conflict×2003	0.108 (0.424) [0.4294]	0.0585 (0.576) [0.5906]
	{-0.26486}	{-0.14605}
Conflict×2004	0.221 (0.121) [0.1141]	0.187 (0.108) [0.1061]
	{3.06351}	{2.69554}

Conflict×2005	0.192	0.144
	(0.170)	(0.184)
	[0.1712]	[0.1762]
	{-0.57221}	{-0.43809}
Conflict×2006	0.205	0.161
	(0.152)	(0.159)
	[0.1281]	[0.1542]
	{-1.08954}	{-0.88615}
Conflict×2007	0.233	0.213*
	(0.118)	(0.0920)
	[0.1091]	[0.0791]
	{2.23933}	{2.21571}
Conflict×2008	0.233	0.217*
	(0.115)	(0.0863)
	[0.1041]	[0.0721]
	{2.91733}	{2.92964}
Conflict×2009	0.239	0.184
	(0.135)	(0.129)
	[0.1201]	[0.1101]
	{-3.51704}	{-2.77340}
Conflict×2010	0.300*	0.305**
	(0.0835)	(0.0477)
	[0.0851]	[0.0531]
	{0.38523}	{0.39018}
Conflict×2011	0.292*	0.263*
	(0.0979)	(0.0710)
	[0.0901]	[0.0841]
	{0.82484}	{0.75263}
Conflict×2012	0.270	0.256
	(0.149)	(0.116)
	[0.1371]	[0.1081]
	{0.46361}	{0.43910}
Conflict×2013	0.297	0.280*
	(0.108)	(0.0762)
	[0.1101]	[0.0791]
	{0.52618}	{0.49538}
Constant	-0.814***	-1.061***
	(0)	(0)
Observations	704	704
R-squared	0.672	0.654
Number of Departments	32	32
Department FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at department level (32 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

The long-term civil war among government military and Maoist rebels has not prevented the economic development for Colombia. From 1990s to 2000s, the economy grew with a low rate and but took off quickly in the middle of 2000s, benefiting from market economy, but peaking in 2013 at Figure 2.14. Colombia is a country with rich natural resources, oil, precious stones and agricultural products. The on-going conflict between government and FARC does not exert a tremendous effect overall nation.

In terms of electricity, production and consumption graphs reveal a similar trend in Figure 2.15. There have been a few of fluctuations; however, there is a slight up-tendency for production and a relative stability for consumption. The feature of Colombian energy industry is green efficiency factor, especially almost 70% electricity are from hydroelectric generation.

Figure 2.14: Colombia GDP from 1990

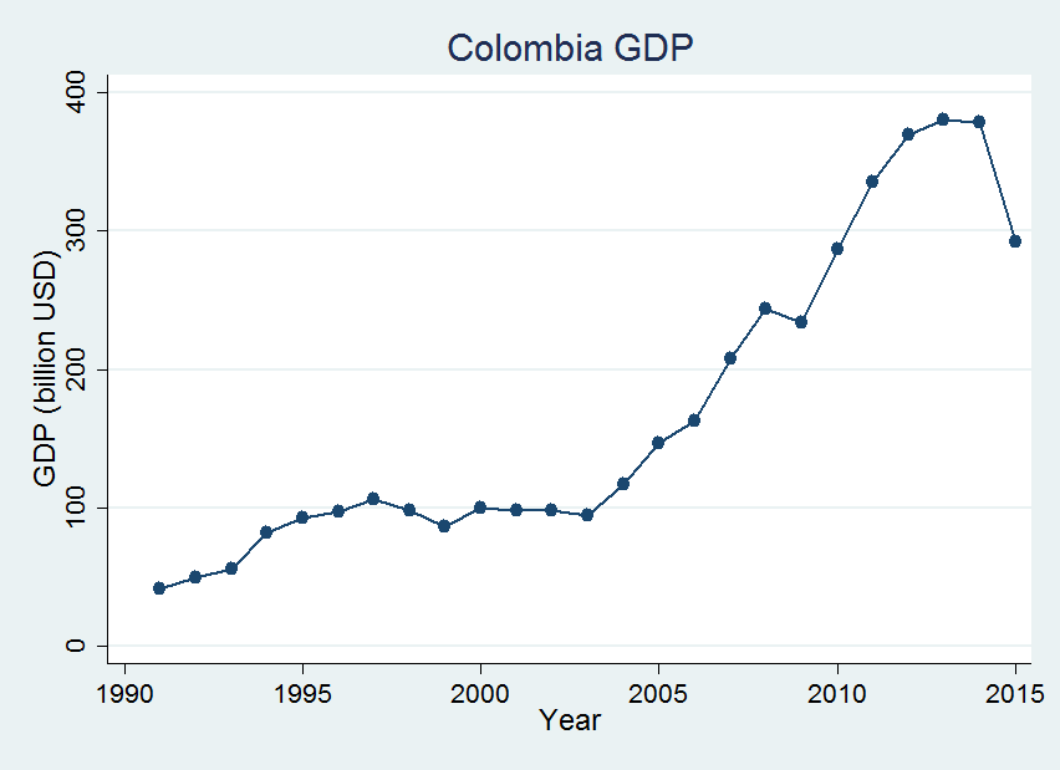
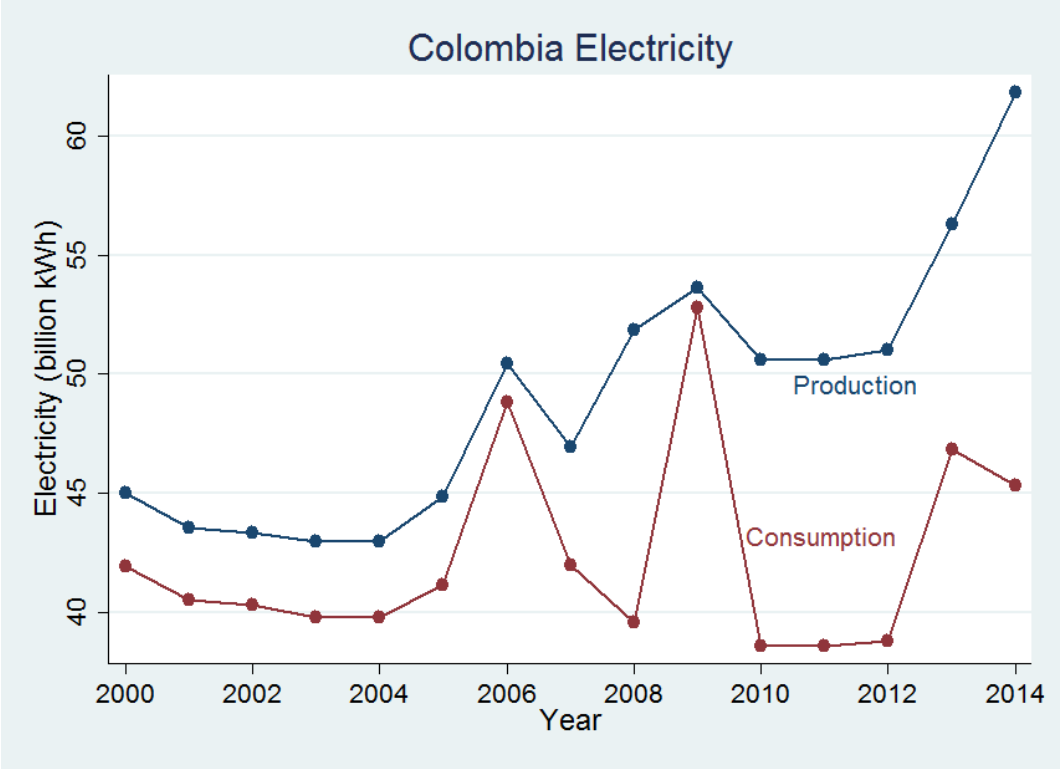


Figure 2.15: Colombia Electricity Production and Consumption from 2000



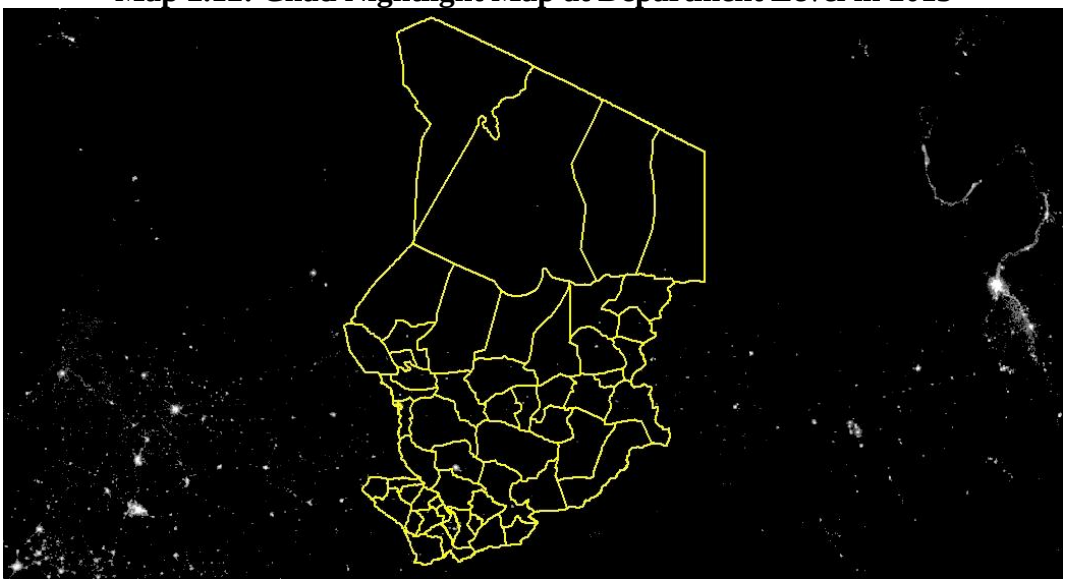
2.6.6 Chad Civil War (2005-2010)

Conflict Background

From 1998 to 2001, Chad experienced three years of civil war as the former Defence Minister triggered military rebellion against the government. Although there was a ceasefair deal in January 2002, the battle continued. Meanwhile the fighting in Sudan Darfur region draw thousands of Sudanese refugees to arrive in Chad in 2004. In 2006, Sudan backed rebels' attempted military coups to oust President Deby, hundreds of people were killed in the capital. Since December 2006, the three military parties among Chad government, Sudanese government and Chad rebel group heated up. In April 2010, Chad-Sudan border reopened 7 years after the Darfur conflict. In this section, I treated 2005 as the year of conflict commence, as the rebel attacked the town of Adre in December 2005. Therefore, from 2005 to 2010 will be identified as the treated period.

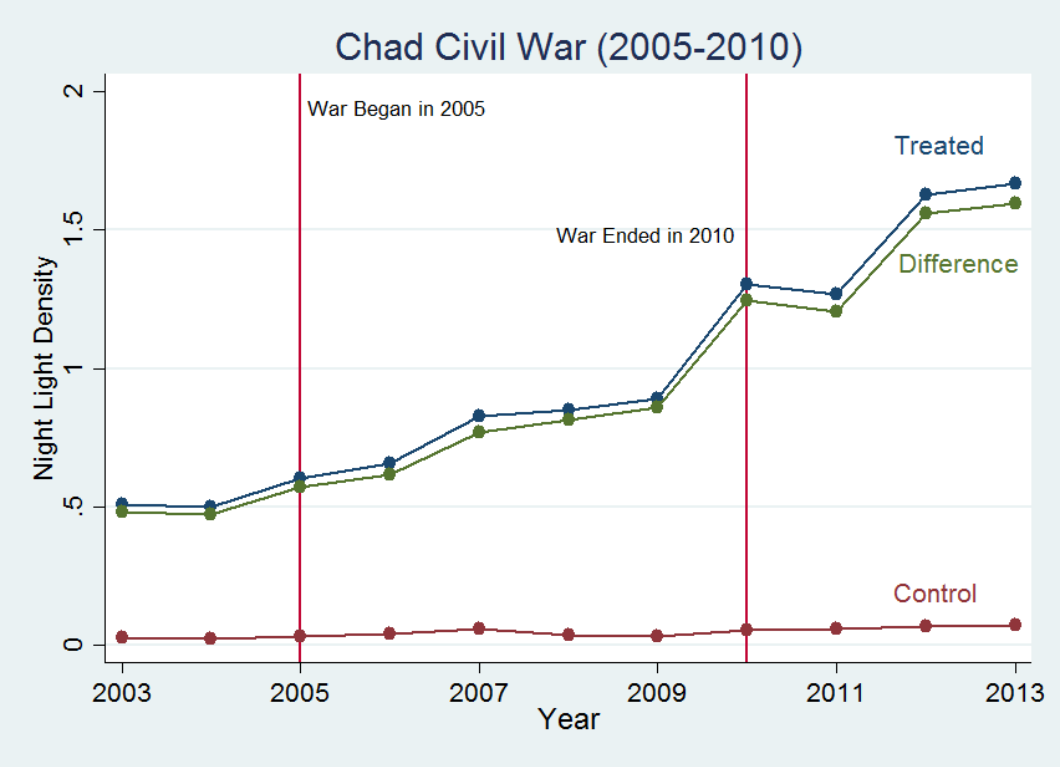
Identification and Trend Analysis

Map 2.12: Chad Nightlight Map at Department Level in 2013



Like the nightlight Map 2.12, Figure 2.16 displays that the control regions almost received no electricity supply; meanwhile there is not tendency for the utility development. The war treated regions actually experienced economic growth after the civil war, the political coup focused on the capital regions, the urban and relatively rich regions.

Figure 2.16: Chad Trend Analysis by control and treated provinces

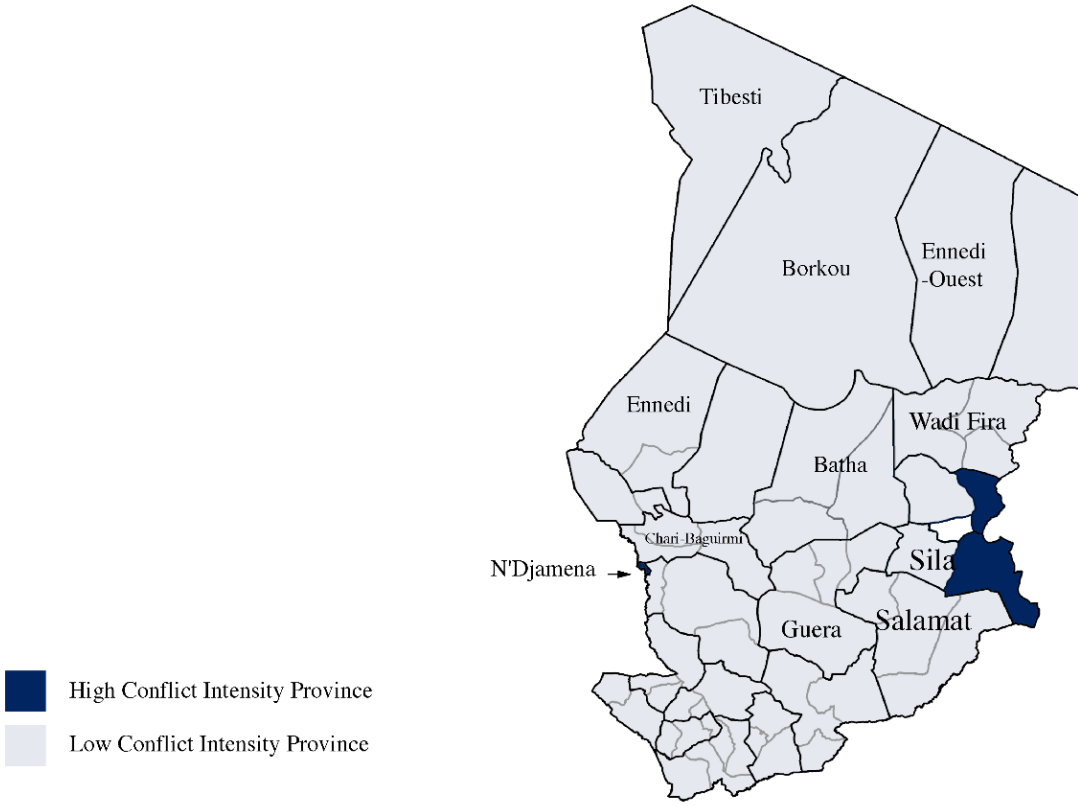


Result Interpretation

From both columns in Table 2.6, I do not find robust estimations, although the coefficients are all negative. The hypothesis that Chad War exerted a significant effect on Chadian economy is rejected. The reasons are multifaceted. First of all, the electricity production and consumption for Chadian household has been considerably low since the panel starts, which indicates that even the conflict jeopardised the economic activities, the marginal effects on

nightlight growth is negligible, meanwhile the electricity has not been developed during the period. Secondly, Chad Civil War mainly focused on the capital

Map 2.13: Chad Conflict Classification at Department Level



N’Djamena and the east border with Sudan, these regional conflicts did not create nation-wide effect on household behaviours. Besides, other regions did not receive electricity supply. Thirdly, the civil war duration was relatively short, and fewer fatal battles across the warfare, which also released the effects on economic activities. From the GDP graph, it is clearly indicated a growing path during the civil war period, which also implied that the electricity sector at least were not affected in both conflict and peace regions.

Table 2.6: Chad War Impact on Economic Growth

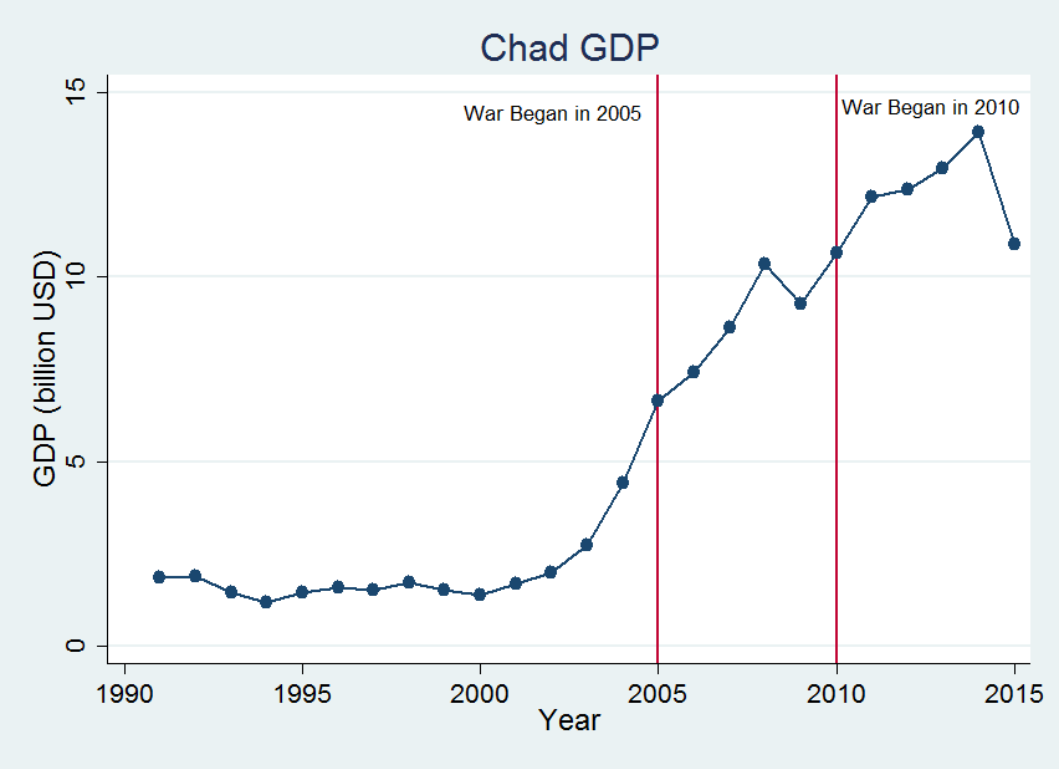
VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	-0.00301 (0.942) [0.9449]	-0.0512 (0.420) [0.4314]
	{0.00206}	{0.03350}
Conflict×1994	-0.0128 (0.790) [0.7487]	-0.0481 (0.503) [0.6486]
	{0.00685}	{0.02241}
Conflict×1995	-0.0462 (0.527) [0.5826]	-0.140 (0.198) [0.2212]
	{0.04404}	{0.15171}
Conflict×1996	-0.104 (0.225) [0.2072]	-0.215* (0.0955) [0.0981]
	{0.10329}	{0.27028}
Conflict×1997	-0.113* (0.0651) [0.0711]	-0.195* (0.0542) [0.0490]
	{0.07929}	{0.14129}
Conflict×1998	-0.0997* (0.0850) [0.0871]	-0.185* (0.0507) [0.0501]
	{0.07763}	{0.14927}
Conflict×1999	-0.141** (0.0405) [0.0400]	-0.276** (0.0132) [0.0110]
	{0.13544}	{0.37931}
Conflict×2000	-0.158* (0.0595) [0.0601]	-0.333*** (0.00714) [0.0050]
	{0.20329}	{0.82027}
Conflict×2001	-0.305*** (0.00289) [0.0020]	-0.539*** (0.000403) [0.0010]
	{0.69651}	{-1.62299}
Conflict×2002	-0.245** (0.0294) [0.0360]	-0.421*** (0.00865) [0.0090]
	{0.58453}	{-3.18144}
Conflict×2003	-0.227* (0.0683) [0.0450]	-0.386** (0.0237) [0.0140]
	{0.42307}	{2.65424}
Conflict×2004	0.0848 (0.656) [0.6767]	-0.0740 (0.744) [0.7578]
	{0.10981}	{-0.05340}

Conflict×2005	-0.242*	-0.444**
	(0.0919)	(0.0271)
	[0.0711]	[0.0190]
	{1.37746}	{-0.77716}
Conflict×2006	-0.0184	-0.160
	(0.911)	(0.446)
	[0.9169]	[0.4945]
	{-0.05105}	{-0.16314}
Conflict×2007	-0.0541	-0.206
	(0.749)	(0.316)
	[0.7588]	[0.3754]
	{-0.08970}	{-0.19334}
Conflict×2008	0.101	-0.0933
	(0.574)	(0.663)
	[0.6046]	[0.6757]
	{0.08392}	{-0.04726}
Conflict×2009	0.0875	-0.0865
	(0.663)	(0.705)
	[0.6577]	[0.7287]
	{0.05953}	{-0.03760}
Conflict×2010	0.132	-0.0874
	(0.613)	(0.769)
	[0.6186]	[0.7778]
	{0.03329}	{-0.01604}
Conflict×2011	-0.155	-0.435
	(0.519)	(0.123)
	[0.5365]	[0.1251]
	{-0.04292}	{-0.08162}
Conflict×2012	-0.141	-0.332
	(0.535)	(0.212)
	[0.5516]	[0.2182]
	{-0.05068}	{-0.08241}
Conflict×2013	-0.190	-0.440
	(0.427)	(0.115)
	[0.4254]	[0.1201]
	{-0.05421}	{-0.08759}
Constant	-4.392***	-4.311***
	(0)	(0)
Observations	1,210	1,210
R-squared	0.287	0.236
Number of Departments	55	55
Department FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at department level (55 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

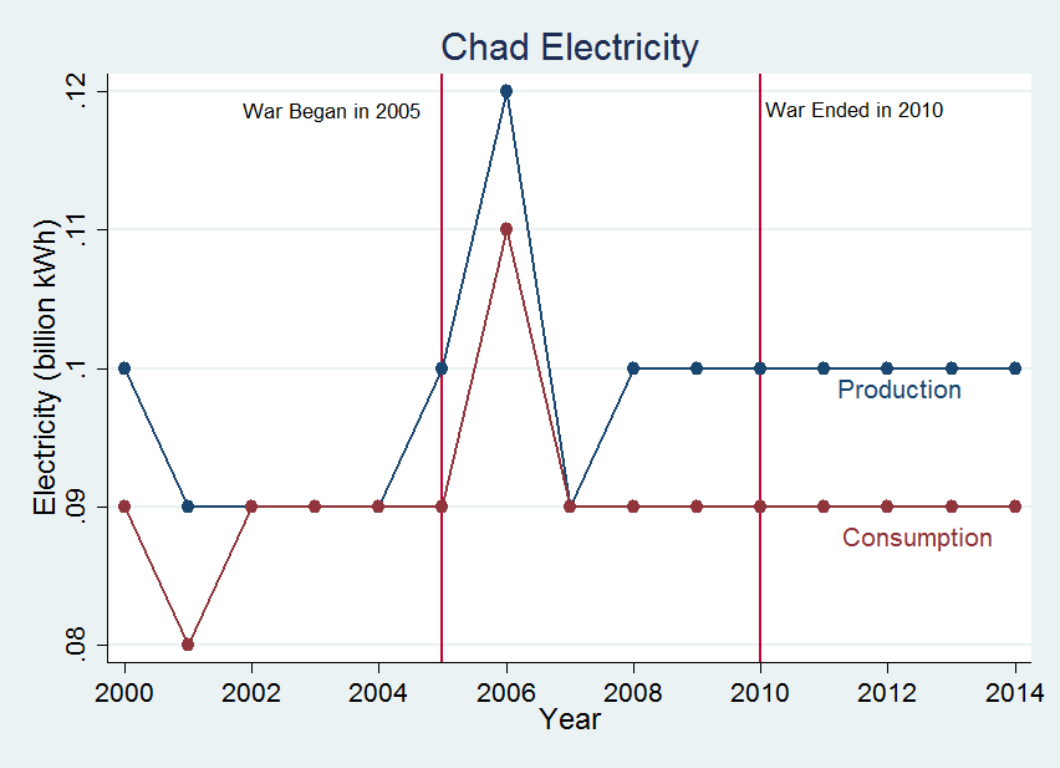
In Figure 2.17, the graph clearly shows an upward trend for Chad GDP growth from 2003 to 2013. The noticeable drop between 2008 and 2009 can be attributed to the violence between Chadian and Sudanese militias' flares in 2008. For Chadian economy, in 2003 Chad became an oil exporter with the opening the pipeline connecting oil fields with Cameroon. In 2006 Chad established the first national oil company (SHT) and expelled US's Chevron and Malaysia's Petronas. Oil trade considerably uplifts Chadian economic growth.

Figure 2.17: Chad GDP from 1990



However, although there has been a terrific economic boost since the oil export in 2003, the electricity production and consumption in Chad has been stagnated. From 2003 to 2013 in Figure 2.18, only 0.1 billion kWh is produced and 0.09 billion kWh is consumed every year, no increase as all across the decade. From this perspective, it is no surprising that the Chad region looks pretty dark in the night light picture.

Figure 2.18: Chad Electricity Production and Consumption from 2000

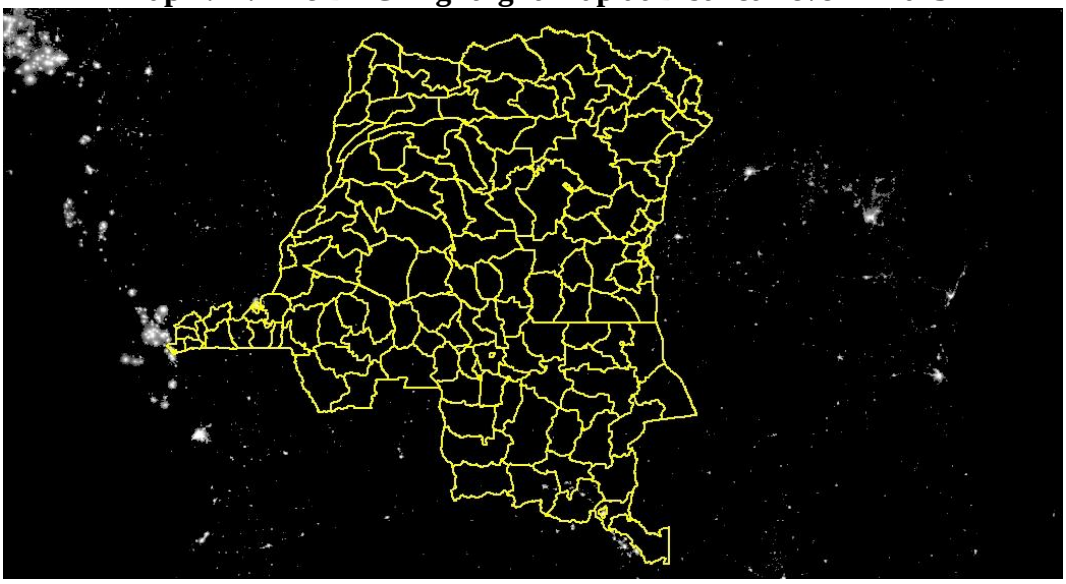


2.6.7 The DRC Conflicts (1996-Present)

Conflict Background

First Congo War commenced in 1996 and finished in 1997. Only one year after, Second Congo War started, nine African countries and twenty armed groups participated in this so-called “African World War”. All sides were accused of using the cover of the war to loot the country's rich economic wealth. In 2001 President Laurent Kabila was assassinated by his body guard, his son Joseph Kabila succeeded the president position.

Map 2.14: The DRC Nightlight Map at District Level in 2013



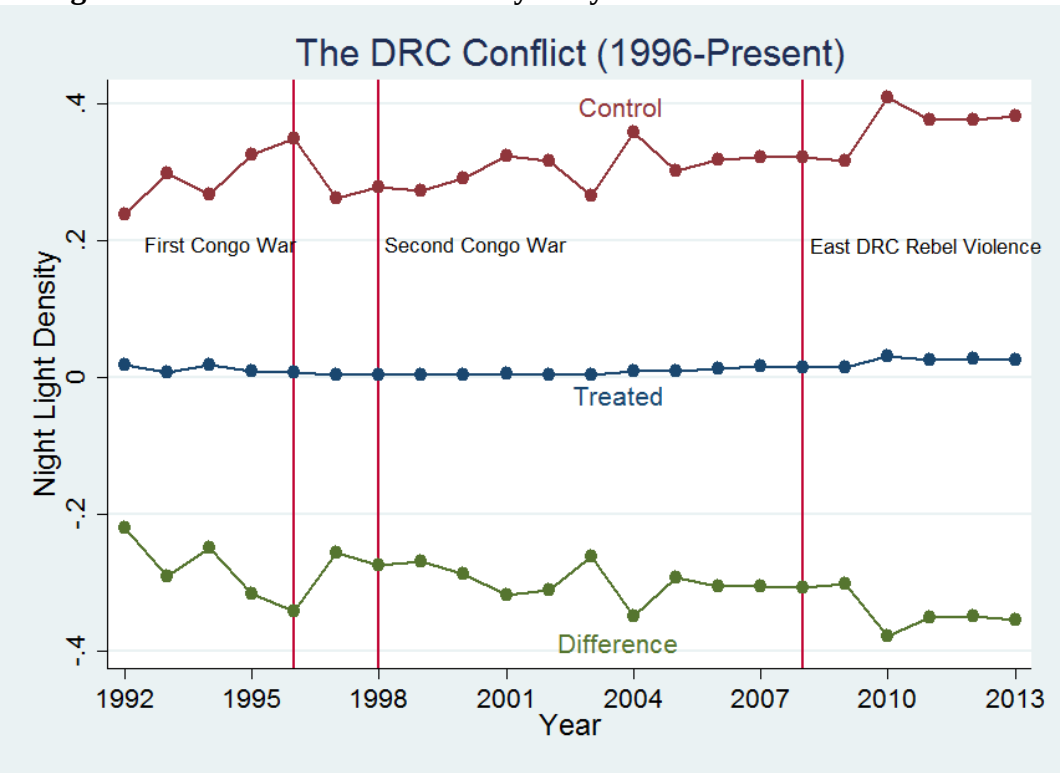
In 2003, Joseph Kabila called for multilateral peace talks to cease the war, Second Congo War officially declared over. But later in 2008, the East DRC rebel violence reignited the country’s conflict. This paper treats both First and Second Congo Wars as the treated periods, actually the rebel group still conducted rampant military activities in the east of the Country. So although the Congo War was officially declared ended in 2003, I cannot conclude that the country has been in peace since then, especially the conflict event and fatality data actually indicate an upward trend of the conflict. Therefore the coefficients before 1996 are regarded

as the before conflict effects, all the coefficients after 2006 are considered as the war onset effects.

Identification and Trend Analysis

In Figure 2.19, the treated regions are mostly dark, because the conflicts concentrate on the east three provinces of the country. The control regions, like capital Kinshasa and other urban regions have provided electricity for their residents and but the absolute value is trivial. With the beginning of the Congo War, however, the difference between conflict regions and peace regions is not evident. The initial low electricity supply implies an insufficient economic endowment in the conflict regions, which limited the night light growth.

Figure 2.19: The DRC Trend Analysis by Control and Treated Districts



Result Interpretation

Both columns in Table 2.7 indicate a negative estimation in 2002 and 2003, the last two years of the Second Congo War. In addition to these two years, neither of the columns reveals any robust estimation for the conflict effects. This presents that the impact of two Congo Wars was largely temporary and the nightlight growth bounced back swiftly. As we have discussed in the previous section, the low electricity development may have constrained the identification strategy. In addition, the DRC has been one of the least developed countries; the conflict impact had been reduced as the original output level was sufficiently low.

Map 2.15: The DRC Conflict Classification at District Level

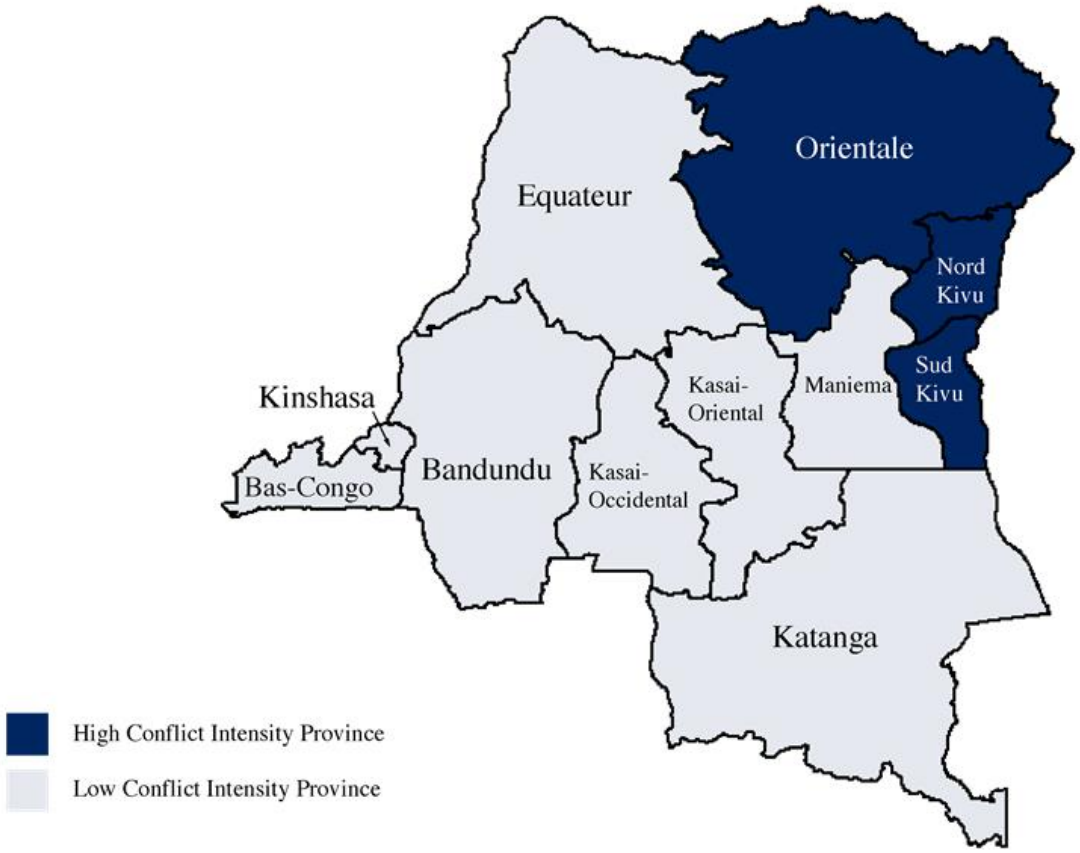


Table 2.7: Congo Wars Impact on Economic Growth

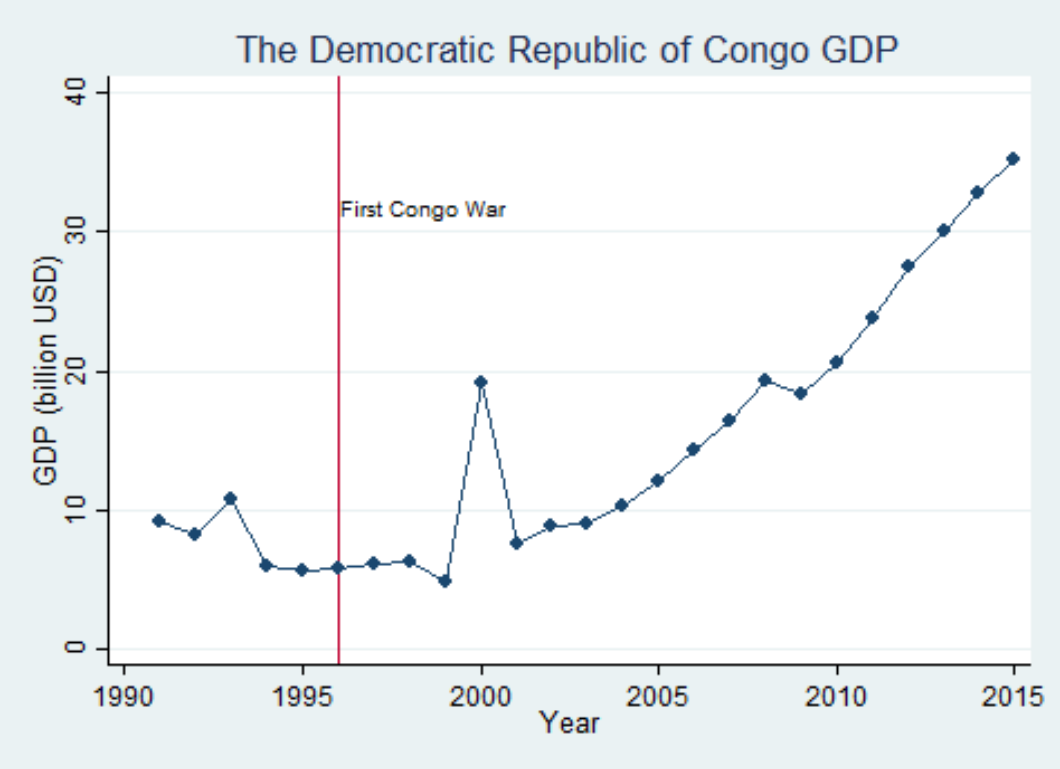
VARIABLES	(1) Night-Light Growth	(2) Night-Light/Area Growth
Conflict×1993	-0.0933	-0.137
	(0.444)	(0.339)
	[0.5105]	[0.3844]
	{0.11447}	{0.13321}
Conflict×1994	0.100	0.132
	(0.479)	(0.428)
	[0.4945]	[0.4444]
	{-0.07733}	{-0.05527}
Conflict×1995	-0.0765	-0.0529
	(0.555)	(0.759)
	[0.5986]	[0.7868]
	{-0.88761}	{-0.04863}
Conflict×1996	-0.152	-0.191
	(0.188)	(0.165)
	[0.2102]	[0.1632]
	{0.27430}	{0.35090}
Conflict×1997	-0.165	-0.193
	(0.141)	(0.149)
	[0.1451]	[0.1502]
	{0.09705}	{0.09139}
Conflict×1998	-0.166	-0.203
	(0.149)	(0.140)
	[0.1451]	[0.1461]
	{0.10579}	{0.10225}
Conflict×1999	-0.183	-0.231
	(0.123)	(0.110)
	[0.1051]	[0.1101]
	{0.09069}	{0.08797}
Conflict×2000	-0.198*	-0.238*
	(0.0852)	(0.0829)
	[0.0611]	[0.0701]
	{0.12479}	{0.12249}
Conflict×2001	-0.132	-0.122
	(0.264)	(0.443)
	[0.3113]	[0.4464]
	{0.31558}	{-0.28475}
Conflict×2002	-0.247*	-0.296*
	(0.0621)	(0.0668)
	[0.0511]	[0.0521]
	{0.24948}	{0.24298}
Conflict×2003	-0.234**	-0.281**
	(0.0489)	(0.0443)
	[0.0230]	[0.0220]
	{0.09914}	{0.07571}
Conflict×2004	-0.178	-0.218
	(0.212)	(0.199)
	[0.2002]	[0.2102]
	{-0.20277}	{-0.18392}

Conflict×2005	-0.178	-0.221
	(0.159)	(0.135)
	[0.1742]	[0.1461]
	{2.37084}	{4.80078}
Conflict×2006	-0.112	-0.150
	(0.432)	(0.365)
	[0.4815]	[0.3884]
	{-0.08749}	{-0.08669}
Conflict×2007	-0.0802	-0.103
	(0.549)	(0.504)
	[0.5876]	[0.5235]
	{-0.03977}	{-0.03725}
Conflict×2008	-0.174	-0.204
	(0.219)	(0.210)
	[0.2132]	[0.2482]
	{-0.11077}	{-0.09455}
Conflict×2009	-0.131	-0.157
	(0.353)	(0.338)
	[0.3884]	[0.3413]
	{-0.07536}	{-0.06752}
Conflict×2010	-0.0372	-0.0336
	(0.812)	(0.851)
	[0.8318]	[0.8609]
	{-0.00618}	{-0.00401}
Conflict×2011	-0.0325	-0.0345
	(0.815)	(0.832)
	[0.8038]	[0.8418]
	{-0.00720}	{-0.00529}
Conflict×2012	-0.0338	-0.0449
	(0.820)	(0.792)
	[0.8298]	[0.7868]
	{-0.00664}	{-0.00636}
Conflict×2013	-0.0338	-0.0449
	(0.820)	(0.792)
	[0.8178]	[0.7938]
	{-0.00664}	{-0.00636}
Constant	-3.996***	-3.774***
	(0)	(0)
Observations	3,300	3,300
R-squared	0.164	0.130
Number of Districts	150	150
District FE	YES	YES
Year FE	YES	YES

Note:
Standard errors are clustered at district level (150 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets, I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces, I report the delta value of the Emily Oster test (Oster 2014).

The GDP graph in Figure 2.20 captures two Congo Wars effects on the DRC economy. The output declined from 1994 to 1999, which were affected by the First Congo War with a high likelihood. Despite there is an unusual spike in 2000, the country moves to a steady growth path from 2011. Although the conflict continued for decades, country obtained revenue from mining sector, especially coltan, cobalt, copper and diamond. However, the upward trend cannot hide the fact that GDP per capita in DRC nearly touched the lowest point in the world.

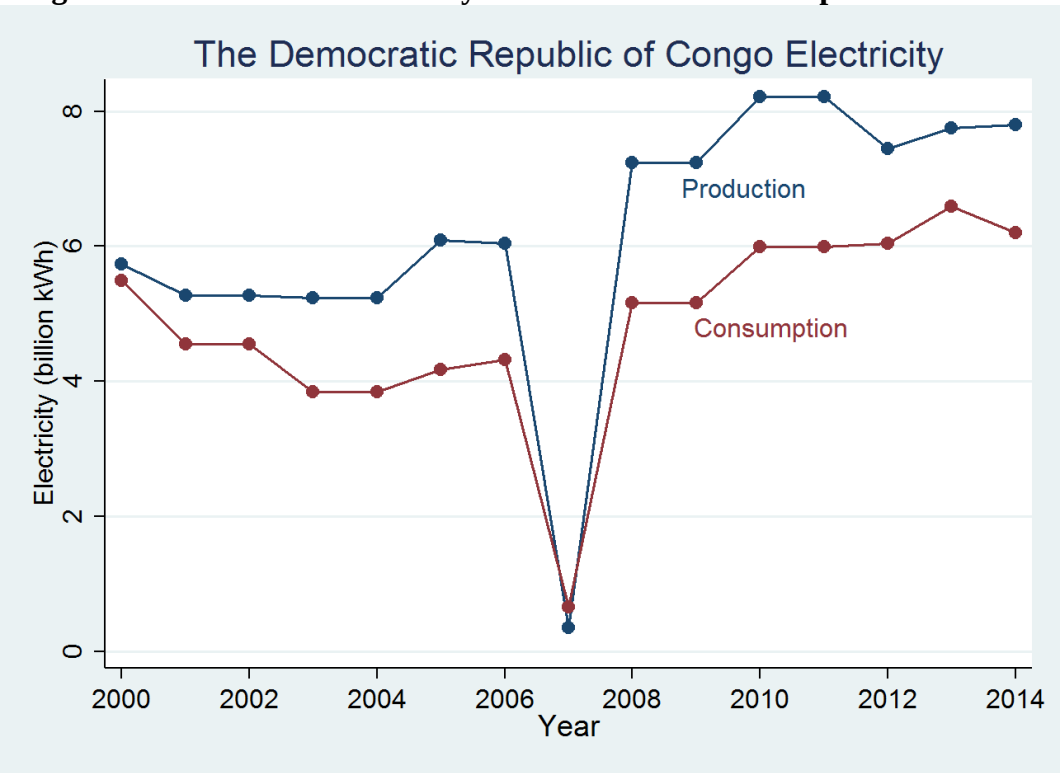
Figure 2.20: The DRC GDP from 1990



Meanwhile in 2005, 90 per cent national income was derived from mineral sector. Another point is that the DRC has been one of the lowest-ranked countries in terms of the Corruption Perception Index. The severe political corruption and mismanagement has cost tremendous fortunate and development opportunity in particular the country is endowed with numerous natural resources. A potential mining industry could have promoted the country's economic development. On the other hand, the persistent conflict in the east of the country also jeopardised the opportunities to make the most of the mineral resources. However, after the

Second Congo War in 2003, there is a clear upward trend for economic development. I expect a strong recovery from the ceasefire.

Figure 2.21: The DRC Electricity Production and Consumption from 2000



In Figure 2.21, the DRC electricity supply is underdevelopment; only 6% of the household have access to electricity in 2007. Therefore, the majority of the country in the night light Map 2.14 are in the darkness, only a few of places show lights at night. Electricity production and consumption graphs do not reveal any improvement potential; there is a drastic tumble in 2007. In addition, for example in 2003, 98.2% of electricity in the DRC was produced by hydroelectric power; in fact, Congo River should have been a natural generator of electricity not only for the DRC but also for the whole Africa. The endless warfare prevents investment to infrastructure. In other words, there is also an implicit conflict effects on economic output.

2.7 Conclusion

This paper applies night light density data to investigate the impacts of conflict on output growth. However, the results are heterogeneous; as a matter of fact, some of the estimations indicate that the wars do not put a significant negative but even positive impact on the economic development based on the variation of the nightlight growth.

The analysis for Afghanistan War identifies that the conflict actually exerted a positive effect on the country's economy as the night light density turns out to be stronger with robust estimation after the war treatment. The reason can be that the war induced more economic activities for the large number of foreign soldiers and civilian personnel. The booming service industry in Afghanistan particularly supported the whole economic situations. This specific case of Afghanistan demonstrates the 'blessing of war'. However, when the foreign army began to exit the country, the economic growth showed a signal of downhill direction. This is not a sustainable development model for the country; the policy-makers should design a long-term blueprint for development after the conflict.

Arabic Spring has dismantled the dictatorship regime in Libya; the subsequent civil war dragged the country into another conflict trap. However, my results do not display statistically significant values; the conflict did not put a severely negative impact on night light density. The reasons are multifaceted. The country has heavily replied on oil production and trade to finance public and private sectors. Therefore, the civil war could not distort the economy as there is hardly any other economic activity or industry development in the country for the crowding out effects. Moreover, the unusually high subsidies on electricity did not decrease the utility's consumptions. This particular policy also interprets why the conflict did not alter the night light density levels.

For country exposing long-term conflict, like Colombia since 1964, apart from the underdevelopment of electricity, the economy has experienced the conflict for so long years that the conflict cannot exert significant marginal impact on the economic growth, especially displacement has taken place and development is almost independent of the conflict.

In the analysis of Chad and the DRC, I do not find significant effects from my estimations. The main reason is that the initial electricity supply or economic endowment is so low that the conflict impact on nightlight variations is marginalised. From the night light map, the vast part of these two countries are dark; the low- or non-electricity condition persists throughout my panels. In addition, economic disadvantages and political distortion can be main factors to decelerate economic development.

Syria War and Iraq War provide examples that war has a harmful effect on economic development for physical capital destroy and large population loss. For Syria War, although I can only investigate the effects until 2013 for the data limit, but three years effects are robust and convincing. For instance, the damage for Aleppo is so devastated that half of the population has been displaced. Since 2001, the treated regions in Iraq have experienced a declining nightlight growth, with an increasing margin. The coalition forces and the subsequent civil conflict significantly deterred the economic growth in Iraq by damaging the infrastructure investment and losing human capital. The Syria and Iraq cases meet the general expectation of a negative correlation between conflict and development.

Empirical analysis with night light methodology gives rise to heterogeneous results. Policy makers should combine the specific economic condition in the country to unlock the economic recoveries.

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B Appendix

Treatment and Control Regions Classifications

Afghanistan

Province	Binary	Casualty Figure
Helmand	1	956
Kandarhar	1	558
Kabul	1	191
Konal	1	177
Paktika	1	146
Wardak	1	130
Zabol	1	124
Ghazni	1	115
Parvan	1	80
Oruzgan	1	69
Lowgar	1	68
Kapisa	1	64
Nangarhar	1	63
Herat	1	54
Farah	1	53
Khost	0	47
Nurestan	0	36
Badghis	0	35
Kondoz	0	33
Paktia	0	30
Laghman	0	26
Balkh	0	23
Baghlan	0	18
Faryah	0	17
Bamyan	0	10
Nimruz	0	6
Jowzjan	0	4
Takhar	0	3
Panjshir	0	2
Ghowz	0	2
Samangan	0	1
Badakhshan	0	0
Sare pol	0	0
Daykundi	0	0

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict Casualty Indicator means the casualty of the International Security Assistance Force from iCasualty. Casualty = the casualty number of coalition army.

Chad

Province	Binary	Conflict Event
Barh El Gazel	0	9
Batha Est	0	2
Batha Oues	0	0
Fitri	0	0
Borkou	1	7
Baguirmi	0	1
Loug Chari	0	1
N'Djamena	0	0
Ennedi Est	0	2
Ennedi Ouest	1	9
Barh Signaka	0	2
Bitkine	0	1
Guéra	0	2
Mangalmé	0	2
Dababa	0	0
Dagana	0	0
Haraze Al Biar	0	3
Kanem	0	0
Nokou	0	3
Mamdi	1	1
Wayi	0	0
Dodjé	0	0
Lac Wey	0	1
Ngourkosso	0	0
Lanya	0	1
Monts de Lam	0	0
Nya Pendé	1	1
Pendé	0	0
Barh Sara	0	4
Mandoul Occidental	0	0
Mandoul Oriental	0	0
Kabbia	0	0
Mayo-Boneye	0	4
Mont Illi	0	0
Lac Léré	0	1
Mayo-Dallah	0	3
Barh Köh	0	2
Grande Sido	0	0
Lac Iro	0	2
Assoungha	1	78
Djourf Al Ahmar	0	26
Ouara	1	34
Aboudeïa	0	1
Barh Azoum	0	9
Haraze Mangueigne	0	4
Djourf Al Ahmar	1	0
Sila	1	66

Béré	0	0
Tandjilé Est	0	0
Tandjilé Ouest	0	0
Tibesti	1	20
N'Djamena	1	87
Biltine	1	19
Dar Tama	1	19
Kobé	1	26

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict event means the number of conflicts event from ACLED. Conflict Event = the number of conflict event

Colombia

Province	Binary	Conflict Event
Amazonas	0	0
Antioquia	1	48
Arauca	1	8
Atlántico	0	1
Bolívar	1	11
Boyacá	0	3
Córdoba	0	3
Caldas	0	4
Caquetá	1	6
Casanare	0	4
Cauca	1	12
Cesar	1	13
Chocó	0	3
Cundinamarca	1	6
Guainía	0	0
Guaviare	0	1
Huila	1	7
La Guajira	0	3
Magdalena	1	6
Meta	1	7
Nariño	0	4
Norte de Santander	1	14
Putumayo	0	4
Quindío	0	0
Risaralda	0	3
San Andrés y Providencia	0	0
Santander	1	19
Sucre	1	5
Tolima	0	7
Valle del Cauca	0	8
Vaupés	0	0
Vichada	0	0

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict event means the number of conflicts event from CERAC. Conflict Event = the number of conflict event/100

The Democratic Republic of the Congo

Province	Binary	Conflict Event
Équateur	0	4
Bandundu	0	0
Bas-Congo	0	1
Kasaï-Occidental	0	0
Kasaï-Oriental	0	2
Katanga	0	8
Kinshasa City	0	4
Kivu	1	49
Orientale	1	24

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict event means the number of conflicts event from ACLED. Conflict Event = Number of conflict event/100

Iraq

Province	Binary	Province	Binary
Abu Ghraib	0	Al Mahawil	0
Al Fallujah	1	Al Misiab	0
Al Haditha	0	Mahmudiya	1
Al Qa'im	0	Adhamiya	1
Anah	0	An Nasiriyah	1
Ar Ramadi	1	Chibayish	0
Ar Rutbah	0	Refai	1
Hit	0	Shatrah	1
Kadhimiya	0	Suq ash Shuyukh	1
Abu al Khasib	0	Amedi	0
Al Faw	0	Dahuk	0
Al Madiana	0	Simele	0
Al Qurnah	0	Zakho	0
Al Zubair	0	Al Khalis	0
Basrah	1	Al Miqdadiyah	0
Shatt Al Arab	0	Ba`qubah	1
Al Khithir	1	Balad Ruz	0
As Salman	0	Khanaqin	0
As Samawah	0	Kifri	0
Rumaitha	1	Ain Al Tamur	0
Ad Diwaniyah	1	Al Jadwal al Gharbi	0
Afak	0	Karbala	0
Al Hamza	1	Al Amarah	0
Shamiya	1	Al Kahla	0
Al Kufa	1	Al Miamona	0
Al Manathera	1	Al Mijar al Kabir	0
Najaf	0	Ali al Gharbi	0
Arbil	0	Qal`at Salih	0
Choman	1	Akre	0

Koisnjaq	0	Al Ba'aj	0
Makhmur	0	Al Hamdaniyah	0
Mergasur	0	Al Shikhan	0
Shaqlawa	0	Hatra	0
Soran	0	Mosul	1
Chamchamal	0	Shekhan	0
Darbandokeh	0	Sinjar	0
Dukan	0	Talafar	0
Halabja	0	Tilkef	0
Kalar	0	Al-Faris	0
Penjwin	0	Al Door	1
Pshdar	0	Al Shirkat	0
Rania	0	Balad	0
Sharbazher	0	Bayji	0
Sulaymaniya	0	Samarra	1
Daquq	0	Tikrit	1
Dibis	0	Touz Hourmato	0
Haweeja	0	Al Hayy	1
Kirkuk	0	Al Kut	0
Al-Mada'in	0	Al Noamania	0
Al Hashimiyah	0	As Suwayrah	1
Al Hillah	1	Badrah	0

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict event means the number of conflicts event from Iraq Body Count. The classification is directly derived from Guerrero Serdan (2009).

Libya

Province	Binary	Conflict Event
Ajdabiya	1	21
Al Butnan	0	7
Al Hizam Al Akhdar	1	155
Al Jabal al Akhdar	0	5
Al Jifarah	0	3
Al Jufrah	0	4
Al Kufrah	0	9
Al Marj	0	1
Al Marqab	1	10
Al Qubbah	0	2
Al Wahah	0	1
An Nuqat al Khams	1	10
Ash Shati'	0	2
Az Zawiyah	1	18
Bani Walid	0	0
Benghazi	0	0
Darnah	1	26
Ghadamis	0	1
Gharyan	1	13
Ghat	0	0

Misratah	1	23
Mizdah	0	2
Murzuq	0	2
Nalut	0	3
Sabha	1	16
Sabratah Surman	0	7
Surt	1	50
Tajura' wa an Nawahi al Arba	1	109
Tarabulus	0	0
Tarhunah-Masallatah	0	4
Wadi Al Hayat	0	5
Yafran-Jadu	0	7

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Conflict event means the number of conflicts event from ACLED. Conflict Event = the number of the conflict event/10

Syria

Province	Binary	Casualty
Al Ḥasakah	0	2
Aleppo	1	31
Ar Raqqah	0	3
As Suwayda'	0	0
Damascus	1	43
Dar`a	1	15
Dayr Az Zawr	1	10
Hamah	1	10
Hims	1	18
Idlib	1	17
Lattakia	0	1
Quneitra	0	1
Rif Dimashq	0	0
Tartus	0	1

Note: Binary Indicator 1 represents treated regions, 0 represents control regions. Casualty means civilian casualty, measured by the real number divided by 1000. The data is acquired from Syrian Martyrs. Casualty = the number of casualty/1000

3. Conflict and Fertility:

A Case Study of the DRC Conflicts

Figo Sze-Yeung Lau

Abstract

This paper employs four nationally representative household surveys to investigate the impact of conflict on fertility in the Democratic Republic of the Congo during two official Congo wars and the subsequent violence between 1996 and 2013. The provincial variation of the conflict intensity across the timeline provides me a quasi-natural experiment to uncover the relationship between war and fertility in the DRC. The results estimated by women between 15 and 49 years old display a lower fertility level during the ceasefire periods. In other words, conflict boosts the fertility level, which can be explained by a risk-insurance effect. However, Oster's Test (2016) detects an omitted variable bias for this result. For younger women samples between 15 and 23 years old, the estimation turns out to be insignificant. Hence, it shows that the conflicts have not had a significant impact on fertility in the DRC. In addition, the paper also studies the conflict impact on fertility preference and maternal care. However, these results do not remain robust. A consistent high fertility rate across the Congolese history is the main reason.

Key words: conflict, Congo Wars, fertility, fertility preference, maternal care, DRC

3.1 Introduction

This paper employs four nationally representative household surveys to investigate the effects of war on fertility in the Democratic Republic of the Congo during two official wars and the subsequent violence between 1996 and 2013. The variation of the conflict intensity across the timeline provides me a quasi-natural experiment to uncover the relationship between war and fertility in the DRC.

This paper contributes to two strands of academic literature. Firstly, the paper investigates the impact of conflict on fertility during ceasefire period after the First and Second Wars and the subsequent East DRC rebel violence period, which has hardly been studied. Four household surveys provide me with four points (2001, 2007, 2010 and 2013) across the DRC conflicts timeline. The long pseudo-panel covers the entire period of the DRC conflicts, enabling me to study the micro individual level impacts of fertility through both short and long-term analysis. Secondly, the analysis also focuses on how conflict affects individual fertility preferences and maternal cares. Understanding the mechanisms through which violent conflict affects fertility is currently a growing area of research.

Empirically, previous studies have attempted to identify the impact of war on fertility; however, the effect of conflict on fertility remains ambiguous. Firstly, a number of studies have exhibited a fertility reduction during the conflict period and a fertility rebound in the post-war period, such as the Eritrea conflict (Blanc 2004), Ethiopia conflict (Lindstrom and Berhanu 1999) and the Angola conflict (Agadjanian and Prata 2002).[21] Secondly, some

[21] Blanc (2004) found this result in Eritrea conflict. He mentions that the delayed age of marriage, with married women being less likely to be living with their husbands in 2002 than in 1995, are the main causes. A similar result is also obtained in Lindstrom and Berhanu (1999); they found a sharp temporary downturn in fertility during the earlier years of military violence and famine in Ethiopia, followed by a fertility rebound. However, in the second decade of the conflict, fertility decreases steadily. They suggested that couples in Ethiopia postponed births to avoid the uncertainty and poverty in the short-term, bearing more risks in the long-tern. Similarly, Agadjanian and Prata (2002) found that women living in violent regions of Angola had lower fertility rates during conflict, followed by a baby boom after the ceasefire.

literature displays a straight reduction in fertility because of conflict, for example following the initial Eritrea conflict (Woldemicael 2008), Post-WWII Russia (Bainerd 2007) and Iraq War (Cetorelli 2014).[22] Thirdly, other studies found a fertility increase following conflicts such as the Afghanistan War (Parlow 2011), and in a global level conflict analysis by Urdal and Che (2013).[23] From Miller et al. (1992) and Arifeen (2008), breastfeeding, the mother's age, prenatal care, delivery assistance, postnatal care, feeding and socioeconomics are the key mechanisms for fertility analysis.[24]

The above papers use a single household survey, which mostly do not cover the entire conflict, or apply the macroeconomic method with cross sectional data. In my paper, four household surveys are used which cover a 13 year's long period conflicts with maternal and household covariates. I take advantage of these factors to assess whether there was a robust fertility variation by conflict treatment.

The results estimated by all of the women samples between 15 and 49 years old display a lower fertility level during the ceasefire periods. In other words, conflict boosts the fertility, which can be explained by a risk-insurance theory. This also lends support to the conclusions of Agadjanian et al. (2002) and Woldemicael (2008). For younger women samples between 15 and 23 years old, the estimation turns out to be insignificant. The while estimation is consistent with the findings of Romaniuk (2011) and recent DRC paper Lindskog (2016).

[22] Woldemicael (2008) analysed the Eritrea conflict and finds a remarkable decline in fertility. He also explained the mechanisms of this: delay of marriage, and cessation of childbearing. Bainerd (2007), who explored Russian birth rates after World War II, draws a similar conclusion. He found that the war caused a decrease in the marriage level among the population, which resulted in lower fertility. Cetorelli (2014) estimated fertility rates based on household data and used these predicted fertility rates to describe a fertility decline during the Iraq War from 2003 to 2011 compared with the period before 2003.

[23] Urdal and Che (2013) compared wars at a global level and use country level data from 1970 to 2005, using battle related deaths to explain the effects of war on fertility. They found that armed conflict might contribute to sustain high fertility levels through increased social insecurity, loss of reproductive health services and lower female education. Parlow (2011) studied the war-related violence between 2007 and 2010 in Afghanistan and found that fertility was higher for households living in provinces affected by high violence even after control migrations and community fixed effects, an insurance effect was present.

[24] Miller et al. (1992) found breastfeeding, mother's age and socioeconomic variables were of the priority for fertility from exploring Bangladesh and the Philippines conflicts. Additionally, Arifeen (2008) also investigated Bangladesh and discovered skilled attendance at delivery, postnatal care for the new-borns, feeding of the young infant and child infections are the key variables.

Older cohort may have already had more children before the Congo War; this omitted variable bias is detected by the Oster's (2016) test. In addition, I also study the conflict impact on fertility preference and maternal cares. However, these results do not remain robust.

The remainder of the article is organised as follows. Section 3.2 introduced theoretical framework. Section 3.3 presents the data and samples. Section 3.4 lays out the empirical strategy and methodology. Section 3.5 describes the results, while Section 3.6 demonstrates the robustness check for the results. Finally, I draw conclusions over the impact of the DRC conflicts on fertility.

3.2 Theoretical Framework

The seminal paper from Becker in 1960 starts the combination between economic theory and fertility choice. Becker considers children as consumption durables and parents obtain utilities from both the quantity and the quality of their children constrained by income, child cost, knowledge, uncertainty, and tastes. It is the trade-off between quantity and quality under budget limit that determines the fertility behaviours in each household (Doepke 2015). Under the context of the conflict, there are multiple theoretical frameworks to predict the impact on fertility.

On one hand, conflict can reduce fertility:

i. A direct military violence can trigger social and economic disruption, displacement, couple separation, shrinking the likelihood for pregnancy and desire for children (Lindstrom and Berhanu, 1999; McGinn, 2000).
ii. The tumbles of family income and family-external support results in delay or avoidance for wartime pregnancy (Eloundou-Enyege et al., 2000). To have high quality children in future, couples may opt to have fewer children during economic hardship by the war (Rutenberg and Diamond, 1993).
iii. Conflicts can damage the health services and the channels for nutritional intakes especially harmful to pregnant women (Palloni et al., 1996). Meanwhile military violence also incurs psychological impairment. Either physical or mental shocks jeopardises the reproductive status during the war period (Chaudhury et al., 2003).

On the other hand, conflict can also boost the fertility:

i. Couples can anticipate children loss by the war attacks. Their desires for replacement increase fertility to response to lower child survival as a risk-insurance strategy (Agadjanian and Prata, 2002; Verwimp and van Bavel, 2005).
ii. Under the condition of household member loss and economic uncertainty, couples may plan to have more children as a potential source of economic support in future (Nugent, 1986), which implies the insurance value of the additional children.
iii. Conflict can reduce the level of education for women. Less educated women inclined to have children earlier (La Mattina, 2017), shooting up the fertility level.

It is indicated that the impact of war on fertility is the combination of different mechanisms conditional on the specific environment. The quantity-quality model lays the foundation for these outcomes. Therefore, the previous empirical studies have displayed diverse outcomes of fertility variations by the impact of conflict.

3.3 Data and Sample Descriptions

To apply micro-study on economics of conflict, I make use of household surveys collected by MICS and DHS, which contain interview questions on woman's fertility and maternal behaviours. Besides, I implement ACLED to identify conflict intensity in different provinces of the DRC.

3.3.1 MICS (2001), DHS (2007), MICS (2010) and DHS (2013)

There are four household surveys in the DRC currently available, which were conducted in 2001, 2007, 2010 and 2013 respectively. Four time points facilitate a dynamic analysis for exploring the effects of war on fertility. The household surveys cover households, women, men and children living in different conditions across the whole country. Not only am I able to interpret the influences of violent environment on fertility, but I can also pick up the variables to investigate maternal support like prenatal care and birth delivery assistance.

Firstly, I describe two household surveys from Multiple Indicator Cluster Surveys (MICS) conducted by COSIT and the Ministry of Health together with UNICEF. MICS has been technically used by Unicef to monitor the situation of children and women in developing countries in order to achieve the child-related global Millennium Development Goals. MICS investigate women between 15-49 years old and children under 5 years old, covering indicators including nutrition, sanitation, education, child health, immunisation, anthropometry and child labouring. Unicef helps developing countries to collect and disseminate the datasets, develop the methodologies and indicators to assess the development in general and the situation of children and women in particular.

The next two household surveys are from Demographic and Health Survey (DHS). DHS has provided over 290 surveys to advance global understanding of health and population in developing countries and to improve health and nutrition programme. The measure of DHS projects is funded by USAID aiming in using policy designing, programme planning and monitoring. Similar to MICS, DHS is also a nationally representative household survey, collecting and disseminating data information on fertility, nutrition, maternal and child health, family planning and illness. There are questionnaires of general household, individual woman, individual man, children, and biomarker. I mainly use the individual woman survey to explore the elements of fertility. The DRC DHS was conducted in two phases: from January to March 2007 in capital Kinshasa and from May to August 2007 in the other provinces. Specifically, 9995 women and 4757 men aged 15 to 59 were interviewed. DHS 2013 took place from November 2013 to February 2014. During this survey, 18827 women aged 15-49 in all selected households and 8656 men aged 15-49 in half of selected households were interviewed.

However, neither MICS nor DHS incorporates displacement information for the household interviewed, which adds confounding factors for my analysis as I cannot identify a woman as a displaced person or an original resident. This can be a potential bias for the result estimation.

3.3.2 ACLED

To measure the level of the military conflict in different province, I use the Armed Conflict Location & Event Dataset (ACLED), which is designed for disaggregated conflict analysis and crisis mapping. ACLED is a publicly accessible data resource from University of Sussex. The dataset records political and civil conflicts from over 50 developing countries and covers all the African countries from January 1997 and the Asian countries from 2010.

All round conflict information is attached in the datasets including the date and location of the conflict, casualty number, event type and the information sources. Specifically, the types of event include battles, civilians killed, protests, change of territories control and fatalities; the latitude and longitude are added for geographic precision. ACLED information come from diverse sources, from official state agency, international media including BBC and CNN, to humanitarian agencies, research publications and the NGOs. The goal of ACLED is to present a numerical and comprehensive assessment of political, military and domestic conflicts in developing states for academic and policy analysis.

For the ACLED DRC datasets, it records specific conflict casualty and events since 1997. These fatalities and event information grant me a research opportunity to differentiate the provinces of the DRC by the level of conflict intensity.

3.3.3 Preliminary Observation

Table 3.1 lists fertility and control variables in this paper. Throughout the four household surveys, averagely women aged between 15 and 49 give three births. Turning to woman's individual characteristics, the mean age is around 28 years old. Around 40 per cent of them live in urban areas. From MICS 2001 to DHS 2013, the proportion of women who never received education has been decreasing from 26.26 percent to 17.83 percent, which implies the younger generation has a higher opportunity to go to school, especially for receiving secondary school education.

In terms of household characteristics, it is displayed an upward trend for the share of the female household head; particularly in 2013, almost a quarter of the household are led by female member. Next, I describe the wealth distribution in each survey. MICS 2001 makes up the greatest proportion of the richest family, over 25 per cent; however, DHS 2013 is consisting of less than 20 per cent. The bottom of the table describes the observation size.

Table 3.1: Woman and Household Characteristics

VARIABLES	MICS 2001	DHS 2007	MICS 2010	DHS 2013
Fertility:				
Total Birth	3.172	2.956	3.163	3.148
	(3.188)	(2.941)	(3.058)	(2.939)
Individual Characteristics:				
Women Age	28.16	28.19	28.22	28.30
	(9.504)	(9.383)	(9.392)	(9.408)
Residence Type: Urban	0.393	0.479	0.439	0.363
	(0.488)	(0.500)	(0.496)	(0.481)
Woman Education (%):				
No Education	26.26	21.08	19.51	17.83
Primary School	39.58	37.80	37.10	38.88
Secondary School	33.05	38.20	43.38	40.31
Non-Standard Curriculum	1.06	2.91	0.02	2.98
Unknown	0.06			
Household Characteristics:				
HH Head Gender: Female	0.144	0.212	0.176	0.236
	(0.351)	(0.408)	(0.381)	(0.424)
Household Wealth Index (%):				
Poorest	18.42	19.03	16.71	23.19
Poorer	17.63	17.64	16.62	19.87
Middle	17.74	18.38	18.65	19.41
Richer	19.25	20.17	22.09	18.01
Richest	25.96	24.78	25.93	19.53
Number of Observations	12,409	9,995	12,853	18,827

3.4 Identification Strategy

3.4.1 Conflict Background

First Congo War commenced in 1996 and finished in 1997. Only one year after, Second Congo War started, nine African countries and twenty armed groups participated in this so-called “African World War”. All sides were accused of using the cover of the war to loot the country's rich economic wealth. In 2001 President Laurent Kabila was assassinated by his bodyguard, his son Joseph Kabila succeeded the president position. In 2003, Joseph Kabila called for multilateral peace talks and the Second Congo War officially declared ended. However, the conflicts have been still ongoing in the DRC, especially in the eastern regions. Two rebel groups, the FDLR (the Democratic Forces for the Liberation of Rwanda) and M23 (the Congolese Revolutionary Army) appeared respectively; they acted as a proxy war between Rwanda and the Kinshasa government. From 2008 to 2013, M23 still conducted military violence in the east DRC. It has been widely reported that mass rapes, killings and other atrocities committed by rebels and government troops continued. In this way, this paper treats the First and Second Congo Wars (1996-2003) and the subsequent East DRC rebel violence (2008-2013) as war treated period, the ceasefire period (2003-2008) as control period.

3.4.2 Conflict Identification

Therefore, the identification is based on the assumptions that the conflicts across the country had exerted an econometrically exogenous effect on household fertility behaviours. Based on the brief history above, I emphasize the following points to support the assumption validities.

Rwanda Genocide in 1994

In 1994, within three months between 500,000 and 1 million of the Tutsi minority and moderate Hutu were killed by a Hutu-Dominated regime in Rwanda. Later in 1994 when Tutsi rebels regained the power, the failed Hutu militias and over 1 million Hutu refugees fled into Zaire.

Although factors like public resentment against the corrupted and mismanaged regime had already been prevalent in Zaire at that moment, this external event triggered the collapse of the Zaire Mobutu regime and the subsequent First Congo War.

Rwanda and Uganda Invasion – The First Congo War

In 1996, Rwanda and Uganda attacked Zaire to oust dictator Mobutu. They installed Laurent Kabila as the new president and hoped to gain political and economic interest from his regime. The roles of Rwanda and Uganda were external factors but crucial to the conflict outcome.

Kabila Dispatched the Rwanda and Uganda Troops – The Second Congo War

The Congolese people experienced around one-year ceasefire from 1997 to 1998; probably they expected no more war in the country. However, Laurent Kabila did not provide specific benefits to Rwanda and Uganda and ordered to return their countries. The alliances broke up, in 1998, the Congolese rebel forces backed by Rwanda and Uganda attempted Kabila's forces and conquered the east. Ultimately, nine countries and twenty-five armed groups participated in the war, the Second Congo War. Rwanda and Uganda did not expect that Kabila would break the alliances; the Second Congo War was not necessarily anticipated.

Sudden Peace Deal – The Assassination of Laurent Kabila

The war had not ceased until Laurent Kabila was shot dead by one of his bodyguards. Later his son Joseph took the power and committee Rwanda to withdraw the army. In 2002,

Rwanda, Uganda and the DRC signed a peace deal. He formed a transitional government in June 2003. So the peace process was not expected ceased in such a process. Household obtained a non-violent environment.

The All-Round Conflict

The conflicts in the DRC swept the treated regions indiscriminately. Especially because of the ethnic hatred or severe militia's violent exchanges, even schools and hospitals were not avoided or could not be avoided. IDMC Global Report states that returned children cannot find schools and hospitals were also destroyed in Kivu region.

Hence, I regard the DRC conflict has an exogenous impact on fertility conditions.

3.4.3 Conflict Level Classification

There are eleven provinces in the Democratic Republic of Congo (1997-2014)[25]. In order to label a child or a woman born in province with different level of conflict treatment, at first I need to categories the DRC's provinces by the number of conflict event against civilians.

There are different types of conflict based on the military target. ACLED groups the military actions like a battle between government and non-government actor, headquarter or base established, non-violent transfer of territory, riots or protests, strategic development, and violence against civilians.

[25] Note: in 2015 the DRC are reclassified into 25 provinces. In this paper, I use the previous administrative classification standard.

Table 3.2: The Number of Violent Conflicts against Civilians

Province	MICS 2001 1997-2001	DHS 2007 2002-2007	MICS 2010 2005-2010	DHS 2013 2008-2013
Orientale	58	90	461	780
Nord-Kivu	44	146	245	669
Sud-Kivu	63	155	154	343
Katanga	37	37	29	172
Equateur	10	4	14	47
Kinshasa	19	8	10	43
Maniema	6	11	9	35
Kasai-Oriental	12	10	7	25
Kasai-Occidental	4	1	4	17
Bandundu	2	6	4	11
Bas-Congo	6	1	4	7

To be consistent with year of the four household surveys, I count the number of conflict events against civilians during five years before the four household surveys by ACLED[26], counting from the oldest children in the group in each province. Table 3.2 describes the number of violence against civilian increases greatly across the four household survey years; but most of the events locate in the east part of the country. I use the number to indicate the conflict treatment effect for any child based on the province of residence from each household survey.

3.4.4 Econometric Framework

To implement a precise estimation of the conflict effect on fertility and child mortality, I need to observe a woman exposed by the conflict meanwhile I need to observe the same woman who did not experience the war during the same period. However, this is not feasible in reality. Furthermore, the four household surveys do not trace the same households as they

[26] For the whole picture, the ACLED provides the conflict information for the DRC since 1997. The Second Congo War commenced in 1998. Please refer to Paper 1.

interviewed previously to record the household conditions, women fertility and maternal conditions across the timeline.

Four household surveys are from MICS and DHS, which address on four different points across the conflict time line. Based on the conflict fatality figures in different provinces in the Armed Conflict Location and Event Dataset (ACLED), I can categorise the DRC provinces by their conflict events against civilians. The woman interview date and the place of residence specify the level of conflict exposed to the war. Putting the information together, I can constitute a pseudo-panel to compare the fertility conditions in provinces influenced by different intensity of the conflict.

Based on the geographical and temporal difference, I apply the difference-in-differences strategy with categorical treatment effects and multiple periods to explain the conflict impacts on fertility; in addition, I use the number of conflict events against civilians to classify the conflict treatment to each individual woman in each province of the DRC.

The four household surveys constitute a pseudo-panel including data for the periods 2001, 2007, 2010 and 2013.

$$Fertility_{ijt} = \alpha_t + \delta_j + \sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j + \boldsymbol{X_i'}\gamma \cdot + \varepsilon_{ijt}$$

Where $Fertility_{ijt}$ is the number of children for woman *i* in province *j* at woman age *t*. The α_t represents woman age fixed effects, the δ_j denotes a set of the DRC province fixed effects. $\boldsymbol{X_i}$ is a vector of woman individual and household covariates and ε_{ijt} is an idiosyncratic term. d_τ is an indicator variable, showing whether the region is treated by the conflict at household survey year τ. The treatment variable is V_j, which corresponds to the number of conflict events against civilians in province *j* during household survey τ. The coefficient of interest is

$\{\beta_\tau\}$, τ stands for the year (2001, 2007, 2010, and 2013) of the four household surveys. $\sum_{\tau \in 01,07,10,13} \beta_\tau \times d_\tau \times V_j$ indicates a separate interaction for each household year in the total τ.

The previous section has argued the econometric exogeneity of the DRC wars on household behaviours. The MICS 2001 cohorts are supposed to be the most severely affected as the cohort experienced both First and Second Congo Wars. Therefore, I expected the coefficients of interest on DHS 2007 and MICS 2010 should be significant as these cohorts live in relatively peaceful periods, and be ambiguous for DHS 2013 as this cohort was exposed to the reignited conflict since 2008.

For fertility preference and maternal care investigations, I use a categorical treatment effect in a two period model. Therefore, the econometric framework is updated as follows:

$$Y_{ijt} = \alpha_t + \delta_j + \beta_1 \cdot (Conflict\ Level \times Post)_{jt} + X_i\gamma + \varepsilon_{ijt}$$

Where Y_{ijt} is the variables of interest.

All standard errors are robust, clustered at the province level to capture potential serial correction in the residual error term. For the fewer cluster number (11 provinces), I further report score wild cluster bootstrap p-values (Kline et al. 2012) generated using *boottest* command in Stata 14 (Roodman et al. 2016) like my first chapter in this thesis.

3.5 Result Interpretation

3.5.1 Fertility

The first three columns in Table 3.3 cover the women aged from 15 to 49 years old in the DRC; I use the number of total births per woman to measure fertility. The pseudo-panel omit the MICS 2001 cohort because these women were exposed to both First and Second Congo Wars. Column (2) adds woman individual controls and column (3) adds both individual and household controls. The theoretical framework provides uncertain predictions contingent on the environment. The DRC has been experiencing continuous conflict since 1996. The only period with relative peace was only a few of years after signing the peace deal in 2003. Therefore, I expect the cohort from DHS 2007 survey should show a significant outcome.

Coefficients of interest from all three columns for the DHS 2007 cohort are significant with negative values, which indicate the DHS 2007 women cohort tended to have fewer children than the MICS 2001 women cohort. However, the estimations for MICS 2010 and DHS 2013 cohorts have no statistical robustness, which indicate the fertility level for the cohorts after the ceasefire has a similar scale to that during the First and Second Congo War era.

These results are meaningful, which imply that the fertility during war periods actually increased compared to fertility during the ceasefire period. Risk-insurance effect should take place. In this case, quantity trades off quality because the low nutritional supply, poor medical service and insecure environment. The parents would make more children in replacement of the lost ones.

However, from column (1) to column (3), I use the woman aged 15 to 49 years old from the four household surveys. It is conceivable that the women may have children older than five years old or probably a senior adult.

Table 3.3: Conflict Impact on Fertility

VARIABLES	(1) All Samples	(2) All Samples	(3) All Samples	(4) Weighted	(5) Weighted	(6) Weighted
Year2007×Conflict Level	-0.00234**	-0.00188**	-0.00163*	-0.000165	0.000140	0.000125
	(0.0222)	(0.0271)	(0.0514)	(0.493)	(0.594)	(0.636)
	[0.0420]	[0.0611]	[0.0651]	[0.4945]	[0.7678]	[0.8549]
	{-3.49108}	{-5.29510}	{-8.27079}	{-0.10886}	{0.18969}	{0.16502}
Year2010×Conflict Level	-0.000340	-1.91e-05	5.61e-06	-4.78e-06	0.000272*	0.000286*
	(0.106)	(0.908)	(0.972)	(0.957)	(0.0769)	(0.0627)
	[0.3353]	[0.9109]	[0.9520]	[0.9096]	[0.0881]	[0.1502]
	{-3.80223}	{0.16794}	{-0.04411}	{-0.00401}	{0.51691}	{0.57793}
Year2013×Conflict Level	-0.000309**	-0.000157	-7.53e-05	4.68e-05	0.000210***	0.000214***
	(0.0400)	(0.183)	(0.524)	(0.381)	(0.000601)	(0.000235)
	[0.3003]	[0.2362]	[0.2793]	[0.4805]	[0.1161]	[0.1161]
	{-2.38586}	{-5.33871}	{3.57688}	{0.06113}	{0.57194}	{0.60232}
Constant	-0.939***	-0.457**	-0.248	-0.329***	0.0421	0.182**
	(6.40e-05)	(0.0379)	(0.290)	(9.04e-05)	(0.497)	(0.0332)
Observations	54,084	54,084	54,084	20,773	20,773	20,773
R-squared	0.608	0.618	0.622	0.318	0.353	0.357
Province FE	YES	YES	YES	YES	YES	YES
Woman Age FE	YES	YES	YES	YES	YES	YES
Individual Characteristics		YES	YES		YES	YES
Household Characteristics			YES			YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
In braces I report the delta value of the Emily Oster test (Oster 2014).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

To exclude the older child selection bias, I take advantage of the MICS 2001 and MICS 2010 individual child dataset to calculate woman's average age when having a first child during the past five years. As a result, the average in MICS 2001 is 22.6745 and in MICS 2010 is 23.2123. Hence, I choose the age of 23 as a cut-off point to maximise the likelihood that the child cohort I am going to investigate is less than 5 years old. In other words, if a woman has a birth history and she is under 23 years old during the household survey, her children are under 5 years old with high likelihood. Therefore, the women targeted in the last three columns of Table 3.3 are aged from 15 to 23 years old.

The robustness is displayed in the DHS 2013 cohort; however, when using the bootstrapping clustering methods, the statistical power vanishes. In column (6) adding all of the individual and household covariates, no estimation is significant in this way. Therefore, for young women below 23 years old, across the DRC conflict periods since 1996, there is no statistically different across the four cohorts. A fact stands out that the DRC fertility rate has been one of the highest in the world, persistent across the DRC history (Romaniuk, 2001). Even a low economic condition has already motived the women to have more children. According to MICS and DHS report, fertility levels are 6.3 in 2007 and 2010, 6.6 in 2013. However, the teenage fertility is high as well, 24 percent in 2007, 28 percent in 2010 and 27 percent in 2013 teenagers (15-19 years old) have begun childbearing.

Conflict should have enhanced this level, however, almost seven children per woman, the fertility in the DRC has been so high that the war treatment has been marginalised.

3.5.2 Fertility Preferences and Age at the First Marriage

Firstly, I take advantages of DHS 2007 and DHS 2013 these two surveys to explore the war impacts on woman fertility preferences. (MICS 2001 and MICS 2010 do not provide this information.)

I cover the timeline between 2007 and 2013, representing the east DRC rebel violence period since 2008. Briefly, the household survey asks the women about their fertility preference like whether they would like to have more babies in the coming future, if not how long you would wait for giving the births, and their ideal number of children, on both boys and girls.

However, the coefficient of the interaction term is still insignificant. The conflict in the east DRC since 2008 does not change how long the woman would wait for another birth from 2007 to 2013, which partially interpret the conflict did not have an effect on fertility and child mortality.

In Table 3.4, column (3) to column (5) exhibits the war impact on the ideal number of births of every woman, the variables for future expectations. The numerical number stands for how many children the woman would like to have throughout life. By bootstrapping clustering estimation, the insignificance of column (3) show the east DRC rebel conflict did not change the expectation of women to have more or less children. However, the last two columns indicate that women in the DHS 2013 cohort intend to have fewer boys and fewer girls than in the DHS 2007 cohort. In sum, the conflict effects on fertility preference are not significant. This result is consistent with the fertility and child mortality analysis in the previous section. The reason would be that the people have adapted to the living in a violent

Table 3.4: Conflict Impact on Fertility Preferences by DHS 2007 and DHS 2013

VARIABLES	(1) Fertility Preference	(2) Wait Time	(3) Ideal Number of Either Sex	(4) Ideal Number of Boys	(5) Ideal Number of Girls
Conflict×Year 2013	-1.47e-05	0.000761***	0.00142***	-0.00228***	-0.00162***
	(0.745)	(8.57e-06)	(0.00274)	(0.000382)	(0.000310)
Constant	0.884***	4.118***	3.820***	7.766***	7.788***
	(6.36e-10)	(7.25e-11)	(9.12e-08)	(3.86e-10)	(2.75e-10)
Observations	27,107	14,838	26,829	26,829	26,829
R-squared	0.249	0.177	0.014	0.038	0.033
Province FE	YES	YES	YES	YES	YES
Woman Age FE	YES	YES	YES	YES	YES
HH Characteristics	YES	YES	YES	YES	YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

environment since the First Congo War in 1996. Another conflict starting from 2008 in east Congo could not stir tremendous shocks on household behaviours or family planning.

Table 3.5: Conflict Impact on Age at First Marriage

VARIABLES	(1) Age at First Marriage	(2) Age at First Marriage	(3) Age at First Marriage
Year2007×Conflict Level	-0.00447	-0.00489	-0.00496
	(0.220)	(0.191)	(0.189)
	[0.2633]	[0.2122]	[0.1952]
	{-0.59653}	{-0.27754}	{-0.25781}
Year2010×Conflict Level	0.00736	0.00743	0.00742
	(0.145)	(0.151)	(0.154)
	[0.1361]	[0.1782]	[0.1582]
	{0.09182}	{0.11955}	{0.11949}
Year2013×Conflict Level	-0.00105*	-0.00113*	-0.00115*
	(0.0847)	(0.0532)	(0.0529)
	[0.2673]	[0.2503]	[0.2242]
	{0.03608}	{0.05126}	{0.05328}
Constant	16.83***	16.45***	16.38***
	(5.45e-09)	(1.02e-08)	(1.96e-08)
Observations	31,970	31,970	31,970
R-squared	0.027	0.033	0.034
Province FE	YES	YES	YES
Woman Age FE	YES	YES	YES
Individual Characteristics		YES	YES
Household Characteristics			YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
^significant at 10%, ^^significant at 5%, and ^^^significant at 1%.
In braces I report the delta value of the Emily Oster test (Oster 2014).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

To investigate the reasons behind the fertility, I take advantage of the variable of the age at first marriage for each woman to gauge any marriage preference change in the DRC. Blanc (2004), Lindstrom and Berhanu (1999) and Woldemicael (2008) all proposed that delay of marriage is the major factor to effect fertility result with conflict exposure. Four household

surveys all include the information about the age of the women getting first married, with the identical specification the variable of interest is marriage age.

Consistent to the results of fertility, the results in Table 3.5 do not indicate the conflict has a significant impact on the age at first marriage. Based on the DHS report, the Congolese women get married at the age of 18.6 in 2007, and I calculate other household surveys, women averagely married around 18 years old. This low age of marriage already touches the threshold in the marriage market, consistent to fertility outcomes.

3.5.3 Maternal Cares

The seminal paper from Trivers-Williard 1973 suggests that prenatal shocks may increase fetal loss and reduce the number of boys relative to girls at birth and Valente (2015) verified this hypothesis. Based on these theories, I attempt to explore the variations of prenatal care and birth delivery to interpret the fertility results by in the DRC.

However, MICS and DHS household surveys have two similar but different interview questionnaires for prenatal care and birth delivery. To minimise measurement errors and remain consistent gauge standard, I use MICS and DHS household surveys separately. The first regression is between MICS 2001 and MICS 2010, representing the impacts during the ceasefire periods after the First and the Second Congo War; the second regression is between DHS 2007 and DHS 2013, representing the impact of the subsequent East DRC rebel conflicts from peace to conflict environment. Under this circumstance, the interaction term is the product between the number of conflict event against civilians and an indicator variable for the subsequent year.

MICS household survey asks women which specific pattern of prenatal care they have received, options including doctor, nurse, mid-wife, traditional birth attendant or other person

providing prenatal care for the woman. In Table 3.5.3.1, the first column asks a general question about whether the woman received the pregnancy care before giving births. However, the interaction term is not robust. Column (2) to column (6) further asks the different categories of the prenatal care. However, the only significant variable is in the last column, fewer women in the MICS 2010 chose alternative prenatal care compared to the MICS 2001 cohort.

In Table 3.6 and 3.7, DHS 2007 and DHS 2013 represent the impact on prenatal care from ceasefire period in the East DRC rebel conflict since 2008. DHS also includes a variety of questions for prenatal care category as shown from column (1) to column (7), however, these estimations are not significant as well. The last column asks the DRC women whether nobody took care during the prenatal period. Therefore, a robust and negative value indicates that more women in fact received prenatal care during the DHS 2013 period that the DHS 2007 period by the conflict treatment. Based on the DHS 2007 and DHS 2013 report, 85 percent women have benefited from antenatal care by trained professionals in 2007; the number in 2013 is 88 percent, which interpret our robust estimation.

Delivery assistance is another key variable for fertility success. Like the analysis for prenatal care, I use MICS and DHS household surveys separately. However, both Table 3.8 and 3.9 do not present any significant estimation; DRC conflicts did not change the delivery assistance across the timeline. Actually, majority of the pregnant women in the DRC gave birth in health facility, based on the MICS and DHS report, 74 percent in 2007, 75 percent in 2010, and 80 percent in 2013. Although my regressions do no show a robust estimation in single delivery assistance, the whole level of the DRC maternal care has been improving in health facility and trained health professionals.

Table 3.6: Conflict Impact on Prenatal Care by MICS 2001 and MICS 2010

VARIABLES	(1) Prenatal Care	(2) Doctor	(3) Nurse	(4) Matron	(5) Traditional	(6) Other
Conflict Level×Year2010	0.000104	0.000210	0.000493	-0.000370	-1.59e-05	-0.000167**
	(0.175)	(0.374)	(0.106)	(0.189)	(0.873)	(0.0211)
	[0.3544]	[0.6056]	[0.6517]	[0.5626]	[0.8999]	[0.0080][
Constant	0.713***	0.231***	0.378***	0.373***	0.108	-0.0214
	(5.74e-07)	(0.000391)	(0.00568)	(0.000885)	(0.280)	(0.387)
Observations	7,423	2,527	5,000	3,754	1,970	1,955
R-squared	0.104	0.676	0.379	0.464	0.304	0.312
Province FE	YES	YES	YES	YES	YES	YES
Woman Age FE	YES	YES	YES	YES	YES	YES
Household Characteristics	YES	YES	YES	YES	YES	YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

Table 3.7: Conflict Impact on Prenatal Care by DHS 2007 and DHS 2013

VARIABLES	(1) Doctor	(2) Midwife	(1) Auxiliary Midwife	(3) Birth Attendant	(4) Maman du Quartier	(5) Traditional Healers	(6) Others	(7) No one
Conflict×Year2013	5.50e-06	-0.000186	-6.07e-06	0.000148	-2.15e-05	-1.26e-06	-6.98e-06***	-6.98e-06***
	(0.630)	(0.501)	(0.893)	(0.379)	(0.126)	(0.444)	(0.00387)	(0.00371)
	[0.6246]	[0.7037]	[0.9289]	[0.5876]	[0.4545]	[0.4545]	[0.1041]	[0.0761]
Constant	0.176***	0.220***	0.0587***	-0.0815*	0.0102***	0.00306	0.00249	0.00326
	(7.03e-05)	(0.000449)	(0.00309)	(0.0877)	(0.00397)	(0.347)	(0.223)	(0.118)
Observations	16,752	16,752	16,752	16,752	16,752	16,752	16,752	16,752
R-squared	0.226	0.086	0.037	0.221	0.008	0.002	0.004	0.003
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Household Characteristics	YES	YES	YES	YES	YES	YES	YES	YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

Table 3.8: Conflict Impact on Birth Delivery Assistance by MICS 2001 and MICS 2010

VARIABLES	(1) Doctor	(2) Nursem	(3) Matrone	(4) Childbirth Trauma Care	(5) Parent Childbirth Assistance	(6) Other
Conflict Level×Year 2010	0.000178	0.000155	-2.77e-05	0.000344**	-4.98e-05	-6.89e-05**
	(0.238)	(0.326)	(0.858)	(0.0308)	(0.666)	(0.0385)
	[0.4505]	[0.3614]	[0.8669]	[0.2332]	[0.7868]	[0.1702]
Constant	0.0976***	0.260**	0.488***	-0.0410	0.0836	0.0138
	(0.00363)	(0.0127)	(0.000164)	(0.726)	(0.287)	(0.550)
Observations	3,020	4,677	4,989	3,191	2,868	2,763
R-squared	0.772	0.627	0.437	0.507	0.448	0.660
Province FE	YES	YES	YES	YES	YES	YES
Woman Age FE	YES	YES	YES	YES	YES	YES
Household Characteristics	YES	YES	YES	YES	YES	YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

Table 3.9: Conflict Impact on Birth Delivery Assistance by DHS 2007 and DHS 2013

VARIABLES	(1) Doctor	(2) Midwife	(3) Auxiliary Midwife	(4) Birth Attend	(5) Maman du Quartier	(6) Traditional Healer	(7) Others	(8) No One
Conflict Level×Year2013	2.56e-05	-2.89e-05	4.96e-06	0.000254	-8.55e-05	6.31e-07	-1.40e-05	1.06e-05
	(0.450)	(0.906)	(0.938)	(0.110)	(0.228)	(0.735)	(0.155)	(0.425)
	[0.5716]	[0.9009]	[0.9670]	[0.2192]	[0.4725]	[0.7888]	[0.2272]	[0.5896]
Constant	0.110***	0.332***	0.0785***	-0.00240	0.167***	0.00622*	0.0152***	0.0351***
	(4.06e-05)	(7.41e-05)	(0.00257)	(0.959)	(0.000890)	(0.0557)	(0.000267)	(3.71e-05)
Observations	27,617	27,617	27,617	27,617	27,617	27,617	27,617	27,617
R-squared	0.091	0.076	0.036	0.189	0.068	0.004	0.010	0.013
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Household Characteristics	YES	YES	YES	YES	YES	YES	YES	YES

Note:
Standard errors are clustered at *Province* level (11 clusters). Robust p-value in parentheses, *** p<0.01, ** p<0.05, * p<0, *significant at 10%, **significant at 5%, and ***significant at 1%.
In square brackets I report score wild cluster bootstrap p-values (Kline et al. 2012) generated using boottest command in Stata 14 (Roodman et al. 2016).
Woman individual controls include woman education and woman residence type; household controls include gender of household head and household wealth.

Prenatal care and delivery assistance are not significantly jeopardised by the DRC conflict. In fact, the DRC antennal level service has been increasingly provided, especially for education women, 99% of them received antenatal care from a trained professional based on DHS and MICS report. This fact also helps to interpret the high fertility level during the high conflict period; antenatal care promotes fertility and maternal health.

3.6 Robustness Check

3.6.1 Unobserved Endogenous Household Characteristics

Omitted variable bias has been a common concern to almost all of the quasi-natural experimental estimations in economics. For instance, the conflict literature shows that conflict may target wealthy household in particular (Serneels and Verpoorten 2015). Econometricians attempted to rule out this problem by including observed controls. However, in many studies, observed controls are not a complete proxy for the entire real omitted variable. Especially for child health condition, socioeconomic status plays a major role as well. To explore this validity of the real omitted factors, I specifically use Emily Oster's (2016) test to assess the endogenous nature of conflict.

To explore the sensitivity of treatment effects to the inclusion of observed controls, Oster (2016) concludes that if a coefficient is stable after inclusion of the observed controls, this is regarded as a sign that omitted variable bias is limited. For all the essential estimations in this paper, I have applied Oster test on the variables of interest, the results are displayed in braces under the coefficient of interest.

Based on the Oster (2016), I calculate the value of delta for which the true effect equals zero, given an assumption on R squared max. In other words,

Delta=1 means controls and omitted variables are equally important determinates.

Delta<1 means controls are more important.

Delta>1 means omitted variables are more important.

The issues occur from the first three columns in Table 3.3, the delta values of Oster test for DHS 2007 cohort and DHS 2013 cohorts are all larger than one, which implied the estimations are highly sensitive to the omitted variables. I suggest that the senior generation had given births before the First Congo War commenced; the conflict treatment did not affect these cohorts.

On the other hand, as can be seen from estimating weighted woman sample between 15 and 23 years, there is no any value larger than 1. I specifically compare the variations of the test values after adding household covariates, however, the values in braces do not change significantly and still less than 1. Younger generation lived throughout the DRC conflict era; therefore, confounding factors were limited. The results of interest do not suffer from the omitted variable impact by weighed sample.

Hence, based on the Oster test, the conflict impact on fertility is not robust. It could be a mixed outcome by a variety of factors according to our theoretical framework. In addition, the DRC fertility rate has been one of the highest in the world before the DRC wars; probably this is another reason that the conflict cannot boost the value furthermore.

3.6.2 Aggregation at Provincial Level

Provinces in the DRC are large. For example, the size of Orientale is more than 500,000 square kilometre; Katanga is approaching to 500,000 square kilometre; Equateur is larger than 400,000 square kilometre. These sizes are equivalent to major European countries like Germany (357,386), the UK (242,495) and Spain (505,990). In terms of econometric specifications, if large geographical entities were distinguished by affected and non-affected within a particular cohort, this would contribute to measurement error and attenuation bias, as well as risking that confounding factors cannot be isolated.

For this issue, I tried to classify the DRC into district level or even into household level to avoid the attenuation bias. However, MICS household survey does not have a uniform classification standard like DHS household surveys and did not provide the information or document for this classification. I cannot constitute a consistent data samples across the four household surveys. However, I use the number of conflict against civilians of each province in each household survey to have a more accurate war treatment measurement on each child to minimise the error effect.

Moreover, only eleven provinces (1996-2015) in the DRC results in the problem of few clusters in the estimation, which leads to 'overfitting' in the OLS regression. Downward biased clustering-robust variance matric estimate and over-rejection (too narrow confidence interval) emerge (Cameron and Miller, 2014). To correct this issue, I use wild cluster bootstrap method to correct the standard errors, which are all stated in the squared brackets in the tables.

3.6.3 Displacement and Refugees

The disadvantage of the MICS and DHS household survey is lack of information about the displacement of each household. The DHS Survey asked the household how many years they lived in the region, but did not ask their previous location. Therefore, I cannot identify the households as original residents or displaced migrants. Because of the war, it is highly likely that people were displaced from their initial settlement.

The First and Second Congo Wars have triggered tremendous internal and external displacement across the DRC; numerous documents have raised the disastrous issues of humilities because of the movement (Kandala et al. 2014). Based on the Global IDP (Internal

Displaced Persons) Report[27] from Norwegian Refugee Council, there are 2,045,000 IDPs in Sep 2001, 1,075,297 in Feb 2007, 1,706,591 in Nov 2010 and 2,963,700 May 2014, the corresponding years of our four household surveys taken. (Data sources are from UN OCHA). Meanwhile most of the displacement occurred in the East part of the country, and over half of them concentrated in the provinces of Nord and Sud Kivu. The figures clearly describe the dynamics between the conflict level and the displacement,

The first factor affecting my result is the placement of the refugees. In fact, most of the DRC refugees did not live in the UN camps in the conflict regions. According to IDMC Global Overview 2014, in December 2013, 2 per cent of IDPs were living with host families and 28 per cent in informal sites and camps. IDPs may only be displaced for a few days or weeks at a time, but others have been living in protracted displacements for years. Nord Kivu IDPs have generally been displaced longer, but Sud Kivu IDPs much shorter (IDMC, 2015). The host families would accept the refugees as being considered as cheap labour supply. Therefore, the conflict impacts on household living condition are from other dimensions.

Secondly, the destinations of the IDPs are crucial for my identification. By IDMC 2015, Displacement mapping displays that IDPs often choose their place of refuge based on family links and ethnic ties to their host community. This fact reflect the tribal nature of the conflict, people went to another villages nearby to avoid the militias conflict and tried to return when the conflict was ceased. For instance, in Masisi and Uvira, 60 per cent said that 'about half' or 'more than half' of the people from their home villages fled to the same location. Even in macro context, the DRC displacement peaked in 2003 (3.4 million) but returns outnumbered new displacements in the east in 2007, when the peace deal signed. These results also implied

[27] IDMC is a global monitor and analyst for internal displacement worldwide. IDMC is part of the Norwegian Refugee Council (NRC) and has been endorsed by United Nations General Assembly resolutions. The internal displacement is separated as the conflict-induced and the natural disaster-induced. To the date of this paper, the datasets for the DRC displacement are still not available after request. However, IDMC generates an Internal Displacement Profile (IDP) for the DRC based on IDP database. The IDP provides figures and tables containing the displacement number at the province level from February 2000 to December.

that the majority of the East DRC displacement would be within the province although the cross-province and international displacement has been remaining high.

However, IDMC has not uploaded a detailed dataset for the DRC internal displacement to the date I write this paper. To address this significant mechanism, including the displacement variable into the identification strategy will be the principal element to identify the issues for future research.

3.7 Conclusion

This paper takes four nationally representative household surveys to study the impact of war on fertility by exploring the temporal and spatial variations of the DRC conflict.

Firstly, by using all of the samples, I find that during the ceasefire period after the First and Second Congo Wars, fertility level in fact was reduced in comparison with the conflict periods. Oster test suggests that this estimation suffers omitted variable bias. Next, I specifically choose women aged between 15 and 23; however, the DRC conflict did not put a significant impact on fertility, consistent with the findings of Lindskog (2016) and Romaniuk (2011). Secondly, I tried to evaluate the conflict impact on fertility preference and maternal care. However, the estimations are also insignificant; no single variable can be principal mechanism to explain the results.

DRC has the persistence of high fertility rate since 1950s (Romaniuk, 2011), socioeconomic factors and cultural behaviours tend towards a bigger family. Even during the most violent period, there is no signal about a decreased fertility trend, which implied DRC couple did not postpone their fertility plans. Probably the high conflict may trigger the preference towards risk-insurance effects; however, the DRC fertility has been considerably high, the effect cannot break the threshold level to be statistically significant. Agricultural sector dominates the DRC economic development; households intend to demand more family members for higher economic interest in future.

On the other hand, the results show prenatal care and delivery assistance were not dramatically jeopardized, which helped to sustain the survival rate for the new-borns. Besides, international communities have assisted the DRC. In 2011, the DRC was classified as a fragile country. In this way, international community has provided substantial financial

investment and humanitarian assistance for Congolese people. Based on the Global Humanitarian Assistance report in 2010, the DRC has received 4 billion dollar (equal to its 17 per cent gross national income) assistance from the developed world; furthermore, since 2000 the donation to the DRC has been increasingly growing every year. This could help to explain the high fertility level by nutrition and medical care.

However, the estimation may suffer the endogenous factor of displacement, as there is no data resource to incorporate into the whole estimation. Understanding the conflict effects on fertility and child mortality is critical for meeting MDG targets. For future study, including cultural, environmental and socioeconomic variables into the investigation will provide a better understanding of the mechanisms behind impact of war on fertility and child mortality.

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4. Summary

The first and the third chapters jointly take the Great Congo Wars as a quasi-natural experiment to explore the temporal and geographic variations in child health and fertility, respectively. Four household surveys established four points in the conflict timeline enable me to exhibit the dynamics between the conflicts and the variables of interest. The second chapter takes advantage of the nightlight density data to study the typical relationship between war and development. Heterogeneous results indicate there is no certain causality from the impact of conflict on economic growth.

Results from the first chapter meet the general expectation that war can put negative impact on child nutritional intakes. There is an evident health improvement during the ceasefire period in my estimation. The First and Second Congo Wars and the subsequent conflicts among militias all deteriorated children's nutritional conditions. In particular, I can identify that children who were aged less than three years old were more vulnerable than the older cohort, which is consistent to other economic and medical studies. However, no gender differences were obtained in the long run analysis. In short-term estimation, the results are still robust within a five years panel analysis.

The first five years of human life is crucial to construct the subsequent life abilities. At the household level, children under five years of age are supposed to acquire sufficient nutritional intakes for subsequent life development, in particular for the first three years of life, the most sensitive and vulnerable period for human growth. At the national level, on other hand, a lower HAZ score in the DRC implies both physical and cognitive loss in future. In fact, the DRC began to experience conflict turbulence when Zaire was collapsed but until now the conflict is still on going. The estimation indicates a peaceful environment significantly

supports child health condition and potentially leads to a higher living standard for their future. The DRC authority should attempt to negotiate with different groups of interest to avoid further conflict; a peaceful environment is the foundation for the country's future.

The third chapter applies the same identification strategy to look into the conflict impact on fertility. However, the estimations do not display any significant results on fertility, fertility preferences or maternal behaviours. The classic quantity-quality trade-off theory cannot be identified. The reason is the persistent high fertility rate in history of the Congolese community such as having a big family is a virtue for Congolese culture. The marginal effect of the conflict is limited; averagely each Congolese woman gives seven births in life even during both war and peace era.

In connection with the first chapter, such a high fertility level in the DRC requires a child-growing environment with peace. Women, especially during pregnancy, are in great need of sufficient nutrition from the utero stage and psychological stability. During the conflict period, assistance from international communities shielded the health of children and women.

For both chapters, there are potential biases for the results as well as potential opportunities for future studies. The first one is lack of displacement data to trace the residence of the household. Although the documents imply displacement should not threaten the explanatory power of the results, obtaining household surveys in alliance with displacement and refugee information is crucial for future studies. The second one is that MICS and DHS household surveys contain inconsistencies at district level or even lower classification, if the estimation could be equipped with household level fixed effects, some confounding factors would be efficiently eliminated. The MICS6 and DHS 2017-18 are under process, I expect the new household surveys will contain broader variables to enable researchers to control the necessary covariates.

The second chapter focuses on the classic relationship between war and economic development. The previous studies have been constrained by the lack of sub-national data; nightlight density data, however, enables me to identify the conflict impact at any geographic level. Specifically, nightlight growth has been proved as a proxy for income growth. With the benefit of the data access from 1992 to 2013, I evaluate seven major conflicts in the post-world war period. With year and region fixed effect estimation, I acquire a variety of results. Syria War and Iraq War, the main conflict events in recent years, exhibit a reduced nightlight growth, corresponding to a damaged physical capital and human capital as well as the population loss due to displacement. Afghanistan War, on the contrary, displays an enhanced nightlight growth during the war. Millions of coalition forces boosted the Afghan service industry, in other words, Afghanistan is a war economy. When the troop withdrew from the country in 2012, the national GDP figure turned downward. Besides, no robust estimation is obtained in Libya, Colombia, Chad and the DRC. Again, the interpretations are heterogeneous, conditional on the country-specific factors.

Nightlight data is so easy to access that a large number of literature will apply this methodology to identify economic activities. In this thesis, I have applied seven countries to generalise the causality between war and development. In fact, it is feasible to apply nightlight data into all of the conflict events in modern history, either in a short-term conflict or in a long-term conflict, to generate a large-N panel data. Alternatively, researchers can investigate a specific country with insightful interpretation between conflict and output growth. Combining both case studies and large-N panel data results, future studies can filter the most significant variables to support a country to boost output growth especially in the post-war era.

The heterogeneity of the estimation implies there would be no single equilibrium from the impact of war on economy; multiple equilibria would be the result. After WWII, Japan and

Germany displayed extraordinary development paths; however, these routes did not apply on the case studies in this chapter. Local policy designers should reply on the specific economic conditions and country characteristics to trigger further development. There is no an ultimate solution to promote a country's development with certain success and prosperity. At least, Japan and Germany proved peace and social stability in domestic economy and neighbouring economies was one of the significant variables to recover from the war wounds.

Therefore, either to improve child and woman health condition resulting from wars or to stimulate economic growth after the war, peace is the conclusion and solution from this thesis.