THREE ESSAYS ON CIVIL CONFLICT

A Dissertation

by

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ABSTRACT

This dissertation consists of three essays investigating the determinants of civil conflict from the aspects of history, geography, and external assistance, respectively. Each of the essays uses empirical economic techniques to analyze how these factors affect the spatial and temporal distributions of modern conflict events.

I explore the long-run effects of slave trade on conflict in Africa. By using a geo-coded disaggregated dataset in sub-Saharan Africa and exploiting variation of slave trade intensity within countries, I find a robust positive relationship between slave exports from a region and current conflict prevalence. Evidence from an instrumental variable approach suggests that the relationship is causal. I then discuss the potential causal channels underlying the relationship, suggesting that slave trade is correlated with mistrust, local institution deterioration, and a weaker sense of national identity.

I then examine how slave trade in history affects the relationship between weather shock and civil conflict. Exploiting weather variation during the growing season of the locally dominant crop, I find that adverse weather shock significantly increases the likelihood of conflict incidence, onset, and intensity. Furthermore, the effect of weather shock on the risk of civil conflict is substantially amplified by the exposure to slave trade.

I also study the dynamic interdependences among foreign aid, development, and conflict. Although foreign aid is sensitively responsive to the conflict or development shock, its effects on reducing conflict and improving development are largely dependent on the wealth level and conflict proneness of the recipient country. I find that foreign aid only mitigates conflict in middle income developing countries, but can enhance the development of the poor and conflict-prone countries.

DEDICATION

This research is dedicated to my parents, Ping Zhang and Qinghua Zhao.

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Contributors

Part 1, faculty committee recognition

This work was supervised by a dissertation committee consisting of Professor Edwin Price [advisor], David Bessler [co-advisor], Marco Palma and Reid Stevens of the Department of Agricultural Economics.

Part 2, student/collaborator contributions

All work for the dissertation was completed independently by the student, under the advisement of Dr. Price and Dr. Bessler of the Department of Agricultural Economic.

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NOMENCLATURE

DAG	Directed Acyclic Graph
PVAR	Panel Vector Autoregression
SPEI	Standardized Precipitation Evapotranspiration Index
SSA	Sub-Saharan Africa

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CHAPTER I

INTRODUCTION

There has been a steady rise in the number of civil conflicts since the end of World War II. In any year over the last decade, 25-30 countries had an internal armed conflict. I also find a great coincidence that almost 80% of conflict-affected nations are the poorest countries. Since civil conflict is documented to be negatively related with economic development, it is portrayed as “development in reverse” (Collier, 2004), which described civil conflict and development as two sides of the same coin.

What are the rooted causes of civil conflicts? Answers to this critical question have evolved over time.

Since late 1990s, a group of researchers at the World Bank's “Economics of Civil War, Crime, and Violence" project, led by Paul Collier, have introduced econometrics models into the field of conflicts and development (Collier and Hoeffler; 1998, 2004). Together with a few other economists (for example, Fearon and Laitin, 2003), they have made great contributions towards finding the correlates of civil conflict. It is now well known that the occurrence of civil conflict is robustly linked to the economic conditions (income per capita, for example), ethnic fragmentation and polarization, population, natural resources, political institution, trade, as well as rough terrain. However, as Blattman and Miguel (2010) argued: “In many cases it is still not clear which of the above correlates actually cause war and which are merely symptoms of deeper problems.”

Later, the focus switched to the identification strategies based on exogenous variation in the economic conditions, in order to convincingly avoid endogeneity problem and identify causal relationships. Miguel *et al*. (2004) made the first attempt to use rainfall growth as an instrument to show the causal effect of economic shocks on civil conflict in sub-Saharan Africa (SSA). After their influential work, many subsequent conflict-related empirical studies began to explore the relationship between climate variability and conflict, finding the significant impact of weather on conflict in Africa, India, and China from past till now (Burke et al., 2009; Bai and Kung, 2011; Bohlken and Sergenti, 2010; Couttenier and Soubeyran, 2014).

More recently, the attention has moved to the subnational- or disaggregated-level analysis since the country-level studies have inherent limitations. In national-level analysis, it is hard to precisely estimate the individual- and group-level conflict determinants, such as ethnic characteristics and regional resource endowments. In practice, the country-level framework is either split by administrative regions (Hodler and Raschky, 2014) or grid cells of 1 degree of latitude by 1 degree of longitude (Harari and La Ferrara, 2014). Furthermore, a burgeoning literature seeks to discover ever deeper causes of civil conflict rooted in history. Besley and Reynal-Querol (2014) shown that the modern era violence is correlated with the historical conflict in Africa in the precolonial period between 1400 and 1700. Their research shed light on the importance of long-term effects that historic events can have on civil conflict.

In Chapter II, we investigate the long-term effects of slave trade on civil conflict in Africa in the present days. By using a geo-coded disaggregated dataset in sub-

Saharan Africa and exploiting variation of slave trade intensity within countries, we find a robust positive relationship between slave exports from a region and current conflict prevalence. Evidence from an instrumental variable approach suggests that the relationship is causal. We then discuss the potential causal channels underlying the relationship, suggesting that slave trade is correlated with mistrust, local institution deterioration, and a weaker sense of national identity.

There are other possible "rooted causes" for civil conflict. For example, proponents of the geography view argue that weather variations may affect the likelihood of violence persistently and globally. Chapter III examines the climate-war hypothesis and discusses the interaction between weather shock and exposure to the slave trade on civil conflict. Exploiting weather variation during the growing season of the locally dominant crop, we find that (i) adverse weather shock significantly increase the likelihood of conflict incidence, onset, and intensity; (ii) this effect of weather shock on the risk of civil conflict is substantially amplified by the exposure to slave trade. The interactive effect of weather shock and slave trade remain robust to the use of instrumental variable approach and extensive robustness checks. This chapter relates to the debates between the “geography matters” and the “history matters” views (Nunn, 2009). Our interaction analysis suggests that both geographic and historic characteristics (in our study, weather shock and slave trade) can jointly affect the contemporaneous conflict.

Given the historic and geographic conflict determinants mentioned above, it seems that the likelihoods of conflict events are largely a consequence of a country’s own endowments. Collier uses the term “conflict trap” to describe a set of countries that are conflict prone. The importance of conflict trap is that conflict degrades the structural factors, such as infrastructure, commerce, education, and governance, which tends to facilitate future conflict. Chapter IV examines whether foreign assistance could help the recipient countries emerge from conflict trap and poverty. We find that foreign aid is sensitively responsive to the conflict or development shock. Furthermore, the effects of foreign aid on reducing conflict and improving development are largely dependent on the wealth level and conflict proneness of the recipient country: foreign aid only mitigates conflict in middle income developing countries, but can enhance the development of the poor and conflict-prone countries.

CHAPTER II

THE LONG-RUN EFFECTS OF SLAVE TRADE ON CIVIL CONFLICT IN SUB-SAHARAN AFRICA

2.1 Introduction

Civil conflict is widely studied in the realm of African economic development because conflict prevalence is strikingly high in Africa. According to the Armed Conflict Database (ACD), an African country is 1.7 times more likely to have at least 1,000 battle-related deaths per year than countries in the rest of the world over the last 60 years. Within this continent that has fallen into the "conflict trap", most of the conflict events have broken out in sub-Saharan Africa (SSA). For instance, 198 of 199 African civil wars[1] that were recorded in the Armed Conflict Location and Event Data Project (ACLED) since 1997 occurred in SSA. These statistics illustrate the importance of understanding the causes of civil conflict in SSA.

There is a large body of research in economics on the determinants of conflict. As shown by Collier and Hoeffler (1998, 2004) and Fearon and Laitin (2003) among many others, income level, institution, and natural endowments are robustly related with the likelihood of civil conflict. By utilizing Murdock's (1959, 1967) pre-colonial African ethnicity map and ethnicity level slave data from Nunn and Wantchekon (2011), we advance this literature by focusing on the following research question: Why do some

[1] A civil war is conventionally defined as a civil conflict that causes more than 1,000 battle deaths.

ethnic homelands in SSA experience civil conflict (more frequently) while others do not? This chapter attempts to answer this question by studying the link between slave trade and contemporary civil conflict.

A key concern in this paper is why slave trade that took place centuries ago would matter for present violence. On a broader scale, Nunn (2009) argues that past events can have long-run impacts by altering deep determinants of contemporary economic and political outcomes. As one of the most significant events in Africa's history, slave trade can drastically affect some deep-rooted determinants, including domestic institutions and cultural norms of behavior. One of the most remarkable features of Africa's slave trade is that slaves were commonly captured through wars, raids, and kidnappings. Historical accounts show that ethnicities raided other ethnicities, and villages raided other villages, no matter how close they had been; individuals were enslaved by acquaintances, friends, or even relatives and family members (Inikori, 2000; Nunn, 2008; Nunn and Wantchekon, 2011). The resultant uncertainty and insecurity within and across communities created an atmosphere of hostility and mistrust among individuals, villages, and ethnicities, which in turn have had a bearing on the spatial distribution of civil conflict in SSA. Besides conflict, a growing set of literature (Acemoglou et al. 2005; Nuun, 2008; Nunn and Wantchekon, 2011; Dalton and Leung, 2014) shows that slave trade could influence several other contemporary socio-economic outcomes. Details will be given in the following parts.

We conduct empirical analysis at the ethnic level instead of country level for several reasons. First, country-level studies have inherent limitations, since the within-country heterogeneity may bias the estimates. Given that the range of civil conflict is usually less than one-quarter of a country's territory (Raleigh and Hegre, 2009), there might exist a possible mismatch between conflict and its driving factors in different regions within the same country. Second, the African countries acceded to independence only since 1956. Thus, the history of SSA countries as sovereign nations is comparatively short (at most 60 years). Moreover, even the contemporary African political boundaries were artificially drawn by European powers during the "Scramble for Africa" at the end of the 19th century, when in fact 843 ethnic groups had occupied the African continent for hundreds of years (Murdock, 1967). Michalopoulos and Papaioannou (2013) provide ample evidence that ethnic-specific traits have long-lasting effects on today's local societies in Africa, although national borders have partitioned many ethnic groups. In other words, the chronicles of contemporary African nations are too short to cover the historical legacies of the tribal era, implying that disaggregating data at the ethnicity level makes sense when we study conflict in SSA. Third, we display the spatial discrepancy of civil conflict in SSA in either a present administrative map (left panel) or a historical ethnicity map (right panel) in figure 2.1. We use darker colors to indicate more conflict fatalities between 1997 and 2014. The ethnicity map appears to be better at capturing the spatial heterogeneity of civil conflict. It shows that some ethnic groups within a modern country are more prone to conflict than others. The graphical evidence that SSA civil conflict may be ethnically distributed again supports our argument: subnational study of Africa should be implemented at the ethnic level.

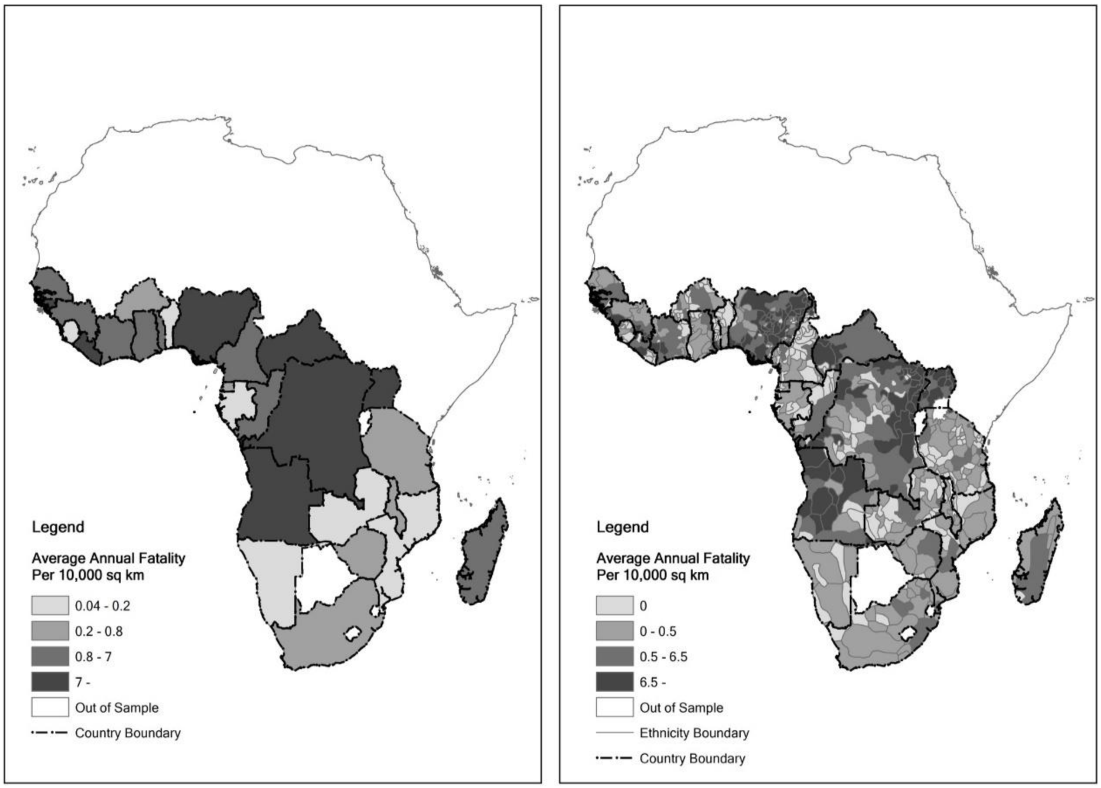

Figure 2.1 Civil Conflict Intensity in SSA by Country Borders and Ethnic Borders

Our empirical investigation exploits cross-sectional variation from the numbers of slaves exported from SSA ethnic homelands during 1400-1900, and it uncovers a positive relationship between slave trade and modern conflict prevalence. The SSA ethnic homelands that are more prone to conflict today are those from which more slaves were exported through transatlantic and Indian Ocean trade routes. This relationship is robust to a battery of subnational controls ranging from geographic and location characteristics to historical ethnic-level factors.

We further pursue the instrumental variable (IV) approach to examine whether this relationship is causal. As mentioned above, the procurement of slaves mainly occurred through internal warfare, raids, and kidnapping, which could be viewed as types of historical civil conflict in Africa. Thus, it might be possible that ethnic homelands experience more conflict events today because those ethnic groups were initially susceptible to conflict. Motivated by Nunn's (2008) study, we use the distances from each ethnic group to the locations where slaves were demanded as the instrumental variables for slave exports in order to address potential endogeneity. Unlike Nunn's instruments, which are sailing distances at the country level, we constructed our own instruments at the ethnic level and include both overland distances and sailing distances. In addition, we only need two instruments for trans-Atlantic slave trade and Indian Ocean slave trade instead of all 4 slave trade routes, since our sample was little involved in the other two routes (the Red Sea and Saharan slave trades). Trade distances are plausible instruments for slave exports, since the location of slave demand is determined by exogenous natural endowments for producing particular commodities such as sugar and tobacco and, thus, not influenced by the location of slave supply. As such, this paper also relates to the empirical approaches recently taken by Becker and Woessmann (2009) and Rubin (2014), who also employ distance indicators as IVs to investigate the effects of a historic event. The IV approach makes it credible to assert that the correlation between slave trade and contemporary conflict is a causal relationship. The IV coefficients are positive and approximately 9 times greater than the OLS coefficients, suggesting that the OLS method tends to bias the effects of slave trade toward zero.

We then perform several robustness checks regarding the IV regressions. First, we replace the outcome variable of conflict prevalence by a number of alternative measures from different data sources. The result shows that the effects of slave trade hold regardless of how conflict prevalence is coded. Second, to mitigate concerns related to the exclusion restriction, we examine the reduced-form relationship between trade distances and conflict prevalence inside and outside of our SSA sample. Within our sample, the reduced-form relationship implies that ethnic homelands that are farther away from the location of slave demand are less prone to conflict. This is what we expect, since our SSA sample covers all areas that were largely involved in the trans-Atlantic slave trade and Indian Ocean slave trade. If the exclusion restriction is satisfied, then the reduced-form relationship should be insignificant outside of our SSA sample. Otherwise, it suggests that the distance instruments do not affect conflict prevalence only through slave trade. We examine the areas within SSA but not in our sample, as well as all the rest of African areas outside of our sample, finding that the reduced-form relationships are indeed statistically insignificant outside of our sample. Third, we further relax the perfect exclusion restriction assumption and allow the instruments to have direct effects on the outcome variable in the second stage of IV regression. Using a Bayesian method introduced by Conley, Hansen, and Rossi (2012), we find that the direct effects of the instruments on conflict should be approximately two-thirds of the overall effects (direct effects and indirect effects of instruments) to render our IV results insignificant, which is very unlikely.

Although the major contribution of this chapter is to empirically identify the causal relationship between slave trade and contemporary conflict, we also discuss the underlying mechanisms. We find that slave trade acts on conflict via both the wealth level and cultural and institutional factors. These results provide evidence that the procurement and export of slaves give rise to mistrust among individuals, diminishing local governance and the formation of stronger ethnic identity rather than national identity, which in turn increases the likelihood of civil conflict incidence.

The next section reviews the literature on the historic determinants of civil war and the role of slave trade on contemporary economic outcomes. We describe our data in section 2.3. In section 2.4, we document the correlation between slave trade and conflict and further discuss the causality issue in section 2.5. In section 2.6, we then turn to the discussion of potential channels of causality, with an emphasis on non-economic factors. Section 2.7 concludes.

2.2 Existing Literature

Blattman and Miguel (2010) have already provided a comprehensive review of the theoretical and empirical studies on civil conflict and summarized the oft-cited correlates of conflict. Thus, we do not attempt to go through these details but instead concentrate on the recent research about the deep-rooted determinants of conflict.

Besley and Reynal-Querol (2014) show that the violence of the modern era is correlated with historical conflict in Africa in the precolonial period between 1400 and 1700. Arbatli *et al*. (2015) demonstrate that the degree of genetic diversity, determined during the prehistoric "out of Africa" migration, has significantly contributed to the distribution of civil conflict nowadays. Depetris-Chauvin (2015) finds that long historical exposure to statehood leads to less contemporary conflict through people's attitudes toward national identity. Their research sheds light on the importance of historic events that can impact civil conflict. This paper adds to this literature by examining the effect of slave trade on the likelihood of present civil conflict in SSA. On a broader scale, our work relates to a strand of literature that documents how the deep-rooted factors in Africa still play an important role in shaping modern African development. Michalopoulos and Papaioannou (2012, 2013) note that the historical legacies, such as the "scramble for Africa" and pre-colonial political institution, are related to contemporary regional economic development. Others investigate the impacts on institution and culture, including Gennaioli and Rainer (2007), who find that African countries with more-centralized precolonial political institutions also sustain higher levels of government quality, and the recent study by Gershman (2016), which shows the effects of traditional witchcraft beliefs on trust and other measures of social capital.

Moreover, this paper complements the burgeoning body of work on the long-run effects of slave trade. Acemoglu *et al*. (2005) argue that the rise of Western Europe after 1500 is largely due to access to Atlantic trade, which of course consists of slave trade with Africa. Nunn (2008) provides an empirical analysis of the negative relationship between the scale of slave trade and contemporary economic development in African countries. Nunn and Wantchekon (2010) then find that people's trust levels within Africa can be explained by slave trade. The long-term effects of slave trade on Africa's social structure are studied as well. Dalton and Leung (2014) document that males were disproportionately enslaved, which has led to prolonged abnormal sex ratios and high polygyny rates.

Finally, our IV approach enables us to overcome the endogeneity problem, adding to a large body of research that examines the underlying causes of civil conflict. There have been ample studies on the causes of temporal distribution of conflict events, beginning with Miguel et al. (2004), that use rainfall growth as an instrument to show the causal effect of economic shocks on civil conflict in SSA (*e.g.*, Burke *et al*., 2009; Bai and Kung, 2011; Couttenier and Soubeyran, 2014). The core research question that these studies pursue is why conflict events wax and wane over time in the same ethnicity-country region. Unlike research in the temporal dimension, the endeavor of this paper is to explore the causality in the cross-sectional dimension, searching for the deeper time-invariant causes that make some ethnic homelands experience civil conflict more frequently while holding all else constant.

2.3 Data

Based on Murdock's (1959) ethnolinguistic map, the starting step of constructing our dataset is to divide the SSA continent into irregular polygons that are shaped by both modern country and historic ethnicity borders, as shown in the right panel of figure 2.1. Researchers studying the link between weather shocks and conflict often disaggregate data into smaller pixels. We do not follow this approach, because the slave exports data are measured at the ethnic level. Furthermore, pixels that overlap more than one ethnicity may result in biased estimates. Our sample consists of 813 regions covering 601 ethnic homelands and 28 SSA countries. We focus on the impacts of slave trade only through the transatlantic and Indian Ocean trade routes due to data limits.

Consequently, a few SSA countries are not included in the sample because they are significantly affected by slave trade through trans-Saharan and Red Sea trade routes.

The main outcome variable is collected from the ACLED dataset (Raleigh et al., 2010), which has been widely used in recent disaggregated conflict research (for example, Michalopoulos and Papaioannou, 2011; Harari and Ferrara, 2013; Besley and Reynal-Querol 2014). ACLED records a range of civil conflict events in African states, including battles, violence against civilians, remote violence, rioting and protesting against a government, and non-violent conflict within the context of war. We use several outcome measures. In the baseline econometric model, the conflict intensity of an ethnicity-country region is coded as the log transformed fraction of years with at least one type of conflict event during 1997-2014. With respect to the sensitivity analysis, we also employ alternative measures of conflict prevalence from ACLED and another conflict data source, the Uppsala Conflict Data Program Georeferenced Events Dataset (UCDP GED) developed by Croicu *et al*. (2012).

The measure of slave exports is taken from Nunn and Wantchekon (2011), who compile ethnic-level slave exports data for the transatlantic and Indian Ocean trade routes during 1400-1900. The transatlantic slave trade route was the largest trade route of all and it affected almost all countries in our sample. According to Manning's (1990) estimates, approximately 12 million slaves entered the transatlantic route, accounting for two-thirds of total slaves shipped from Africa. Compared to the transatlantic slave trade, the range of Indian Ocean trade is smaller and confined primarily to the eastern coast of Africa. As expected, many countries in our sample, for instance, Madagascar, Malawi, Mozambique, Uganda, Zambia, and Zimbabwe, are largely affected by both the transatlantic and Indian Ocean trade. Thus, we use the measure of the total number of slaves taken through the two trade routes in the empirical analysis.

A merit of our study is that we capture the regional geography and location factors. Control variables reflecting natural resources (precious metals, industrial metals, and diamonds) are drawn from the Mineral Resource Data System (U.S. Geological Survey, 1996) by the United States Geological Survey (USGS) and the PRIO Diamond Resources dataset (Gilmore, 2005). The land endowment data, including land area, average elevation, and terrain ruggedness, is collected from the GTOPO30 global digital elevation model (U.S. Geological Survey, 1996). Besley and Reynal-Querol (2014) recommend the inclusion of historical conflict between 1400 and 1700, because they find that civil wars in the past have a bearing on contemporary conflict in the same region. We use their data and add a binary indicator for the historical conflict to our regression specifications. To account for other potential historical confounding factors, we also include the pre-colonial characteristics of ethnicities and European contact in the colonial period in some specifications. The importance and sources of these variables will be discussed when they are introduced.

Table 2.1 reports descriptive statistics for the variables of interest at the country-ethnic homeland level. Panel A gives summary statistics for the full sample. Panel B displays summary statistics for observations of the sample that suffered from slave trade, while Panel C describes the rest of the sample that was not affected by the trade. At first glance, it appears that the prevalence and intensity of civil conflict in the homelands that experienced slave trade are significantly higher. Table 2.1 shows that the mean difference in years of conflict events is around 1 year, and the difference is significant at the 99% confidence level. As regards the measure for conflict intensity, the average number of conflict fatalities in Panel B is 2.4 times more than the respective number in Panel C. We also find cross-sectional differences in mean nightlight density in 1996, which is employed to proxy for initial regional economic development. The mean difference in nightlight density is 0.17. The descriptive statistics reveal that contemporary conflict seems more likely to occur in areas that were engaged in slave trade between 1400 and 1900.

Table 2.1 Summary Statistics

	Obs.	Mean	St.Dev.	min	max
Panel A: Full sample					
Conflict prevalence (years)	813	4.81	5.28	0	18
Average number of yearly conflict fatalities	813	19.96	247.68	0	6852.66
Slave exports	813	256.47	2034.94	0	38389.53
Normalized slave trade (ln(exports/area))	813	0.66	1.26	0	6.02
Log of nightlight density in 1996	813	-0.89	2.72	-6.83	6.07
Panel B: Observations with slave trade					
Conflict prevalence (years)	382	5.32	5.43	0	18
Average number of yearly conflict fatalities	382	28.76	352.29	0	6852.66
Slave exports	382	545.85	2943.97	0.09	38389.53
Normalized slave trade (ln(exports/area))	382	1.40	1.53	0	6.02
Log of nightlight density in 1996	382	-0.80	2.63	-6.83	6.07
Panel C: Observations without slave trade					
Conflict prevalence (years)	431	4.36	5.11	0	18
Average number of yearly conflict fatalities	431	12.16	75.78	0	1421.28
Slave exports	431	0	0	0	0
Normalized slave trade (ln(exports/area))	431	0	0	0	0
Log of nightlight density in 1996	431	-0.97	2.80	-6.46	5.28

2.4 Estimating Equations and Empirical Results

We estimate the relationship between past slave exports and the contemporary prevalence of civil conflict across country-ethnic regions. For ethnic groups that are divided by national borders, we assign each partition to the corresponding country as a separate observation. The estimating equation is:

$$\boldsymbol{y_{i,c} = \alpha_c + \beta * slave\ trade_i + X'_{i,c}\Omega + Z'_i\Gamma + \varepsilon_{i,c}} \qquad (\mathbf{2.1})$$

where $y_{i,c}$ is the outcome measure of civil conflict in the homeland of ethnic group *i* in country c. α_c is a country fixed effect to exploit within-country variation. $slave\ trade_i$ denotes the degree of slave trade that ethnic group *i* experienced between 1400 and 1900. Taking into account the differences in the size of ethnic groups, we normalize the total slave exports from the transatlantic and Indian Ocean trade routes by tribal land area.

Given the extensive literature on the correlates of conflict (e.g., Fearon and Laitin, 2003; Nunn and Puga, 2012; Buhaug and Lujala, 2005), the vector $X_{i,c}$ consists of a rich set of country-ethnic level covariates that capture the regional geography and location characteristics. The geographic controls include land area, three dummy variables for natural resource (precious metals, industrial metals, and diamonds) endowment, average elevation, terrain ruggedness, temporal variability in temperature in 1995-2014, and an indicator for access to rivers.[2] The location controls include absolute

2 We do not include the factor for trade convenience in our baseline model because the relationship between trade and civil conflict is ambiguous and mixed (Blattman and Miguel, 2010). However, augmenting the specification with the log of coastline divided by land area, ln(coastline/area) will not change our conclusions. These results are available upon request to the author.

latitude, the distance from an ethnicity-country region to the corresponding capital city, and an indicator for historical conflict between 1400 and 1700. Considering that slave trade may affect contemporary conflict through its impacts on economic development, we log nightlight density in 1996 in several specifications. The inclusion of initial economic development level allows us to explore the direct effects of slave trade on conflict risk while controlling for its indirect effects through wealth level.

Table 2.2 reports OLS estimates of interest when the aforementioned controls are included. The dependent variable is measured as the log fraction of years with at least one civil conflict event. Column (1) shows the results of regressing current conflict prevalence on slave exports with country fixed effects only. Column (2) includes the geographic controls, and column (3) further includes the location controls. The relationship between slave trade and civil conflict is positive and statistically significant across all three specifications. The estimated coefficient of slave exports is as economically meaningful as that of temporal variability in temperature. In terms of standardized beta coefficients of column (3), a one standard deviation increase in slave exports leads to a 0.14 standard deviation increase in predicted prevalence of conflict, while a one standard deviation increase in temperature variability is associated with a 0.17 standard deviation increase in conflict.

Table 2.2 OLS Estimates - Relationship between Slave Exports and Civil Conflict

	Log fraction of years with at least one civil conflict event			
	(1)	(2)	(3)	(4)
Slave exports	0.032***	0.027***	0.023***	0.019**
	(0.008)	(0.007)	(0.007)	(0.007)
	[0.009]	[0.008]	[0.008]	[0.008]
	{0.007}	{0.007}	{0.007}	{0.007}
Land area		0.072***	0.073***	0.069***
		(0.009)	(0.009)	(0.010)
Precious metal		0.117**	0.109**	0.093**
		(0.046)	(0.049)	(0.044)
Industrial metal		0.059***	0.055**	0.037**
		(0.018)	(0.020)	(0.017)
Diamond		0.035	0.035	0.033
		(0.034)	(0.032)	(0.030)
Mean elevation		-0.001	-0.009	-0.005
		(0.040)	(0.035)	(0.029)
Ruggedness		0.026	0.036*	0.036*
		(0.019)	(0.019)	(0.019)
Climate variability		0.258	0.372***	0.361***
		(0.152)	(0.099)	(0.089)
Access to river		-0.002	0.004	-0.001
		(0.014)	(0.015)	(0.012)
Absolute latitude			-0.011**	-0.012**
			(0.004)	(0.005)
Distance to Capital city			-0.010	-0.003
			(0.061)	(0.054)
Historical conflict in 1400-1700			0.073**	0.046
			(0.034)	(0.033)
Initial light density				0.02***
				(0.003)
Country fixed effects	Yes	Yes	Yes	Yes
Number obs.	813	813	813	813
Adj. R-squared	0.21	0.46	0.47	0.51

Notes: The unit of observation is ethnicity-country region. The dependent variable is the log transformed fraction of years with at least one conflict incidence during the period 1997-2014. The slave exports variable is the log transformed number of slaves exported through the transatlantic and Indian Ocean routes between 1400 and 1900 normalized by land area.

Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses. The alternative standard errors are also reported below the slave exports variable: standard errors adjusted for two-way clustering within countries and ethnolinguistic families are reported in square brackets, and Conley (1999) standard errors adjusted for two-dimensional spatial correlation are reported in curly brackets. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

One natural concern with the estimates in the first three columns in Table 2.2 is that slave trade correlates with conflict mainly through its effects on current economic performance (Nunn, 2008). To look at this, we include initial nightlight density to account for regional differences in income level. As shown in column (4), although the magnitude of the estimated coefficient of slave exports is decreased by 17%, the coefficient remains positive and significant. The estimates are quantitatively meaningful, suggesting that wealth condition may not be the only major mediator between slave trade and conflict.

Three types of standard errors are reported in Table 2.2. Firstly, we cluster standard errors at the country level. Given that the 813 ethnic groups are classified into 84 ethnolinguistic families (Murdock, 1967) and share similar ethnic characteristics within an ethnolinguistic family, we also employ the multi-way clustering approach (Cameron *et al*., 2012) and cluster standard errors at the country level and at the ethnolinguistic-family level. When analyzing geo-referenced data with potential spatial interdependence, it is appropriate to use Conley's (1999) method, which is robust to spatial interdependence of unknown form in the error term. To save space, we only present the three sets of standard errors below the estimates of slave exports. It turns out that these approaches yield essentially identical standard errors.

Another concern is that the correlation is confounded by omitting historical ethnic-level characteristics. As we mentioned, Africa had been made up of a number of ethnicities for a long time. It is highly possible that an ethnicity has its unique traditional features that are correlated with the proneness to slave trade and contemporary conflict.

As documented in Nunn and Wantchekon (2011), Michalopoulos and Papaioannou (2011), and Acemoglu *et al*. (2001), the potential confounders include pre-colonial institution, colonial rule, initial levels of prosperity, and European explorer contact. The vector Z_i in equation (1) denotes the ethnic-level variables that are meant to account for such factors. We employ the number of jurisdictional hierarchies beyond the local community to account for pre-colonial ethnicities' political institutions, and we use categorical measures of settlement patterns to proxy for pre-colonial economic development. Both variables are collected from the Ethnographic Atlas (Murdock, 1967). With respect to colonial rule, the historical disease conditions, especially the prevalence of malaria, plays an important role in determining the impacts of colonial rule in Africa. The malaria index is derived from the Malaria Stability Index developed by Kiszewski *et al*. (2004). It is also necessary to distinguish the effects of slave trade and non-slave trade European contact on African conflict. We use data on European explorer travel records from The Century Atlas (1911), which stretches back to 1768, as an indicator for non-slave trade European influence on modern conflict.

Table 2.3 shows the estimation results when additional ethnic-level controls are added in the analysis. We report standard errors adjusted for clustering within countries in parentheses, and standard errors adjusted for multi-way clustering within countries and ethnolinguistic families in square brackets. Due to data availability, the sample size is reduced to 456 when we control for settlement pattern in column (1) or jurisdictional hierarchy in column (2). All historical controls except for European explorer contact have a bearing on contemporary conflict. Column (5) of Table 2.3 gives the most comprehensive specification. Here, we find that the slave exports variable remains positive and statistically significant at the 1% level. Comparing column (5) of Table 2.3 with column (4) of Table 2.2, we find that the magnitude of the coefficient estimate of slave exports even increases after conditioning on ethnic-level controls.

Table 2.3 OLS Estimates - Relationship between Slave Exports and Civil Conflict, with Additional Ethnic-Level Controls

	Log fraction of years with at least one civil conflict event				
	(1)	(2)	(3)	(4)	(5)
Slave exports	0.024***	0.024***	0.024***	0.021***	0.024***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
	[0.009]	[0.008]	[0.008]	[0.008]	[0.009]
Jurisdictional hierarchy		0.020*			0.026**
		(0.012)			(0.011)
European explorer contact			-0.018		-0.023
			(0.016)		(0.023)
Malaria index				-0.005*	-0.004
				(0.002)	(0.003)
Settlement pattern	Yes	No	No	No	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Number obs.	456	456	813	813	456
Adj. R-squared	0.47	0.47	0.47	0.48	0.49

Notes: The unit of observation is ethnicity-country region. The dependent variable is the log transformed fraction of years with at least one conflict incidence during the period 1997-2014. The slave exports variable is the log transformed number of slaves exported through the transatlantic and Indian Ocean routes between 1400 and 1900 normalized by land area. Settlement pattern includes eight dummies indicating eight levels of sophistication of precolonial settlement of ethnic groups. Geographic controls at the ethnicity-country level include the natural log of land area, three measures of natural resource (precious metals, industrial metals, and diamonds) endowment, average elevation, terrain ruggedness, temporal variability in temperature in 1995-2014, and an indicator for access to rivers. Location controls at ethnicity-country level include absolute latitude, the distance from an ethnicity-country region to the capital city, and an indicator for historical conflict between 1400 and 1700.
Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses. The standard errors adjusted for two-way clustering within countries and ethnolinguistic families are also reported below the slave exports in square brackets. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

2.5 Identifying Causal Relationships

In the previous section, the OLS estimates demonstrated the positive correlation between slave trade and contemporary conflict risk. Nonetheless, such correlation cannot pin down the causal effects of slave trade on proneness to conflict. Indeed, slave exports were unlikely to be randomly distributed across ethnic homelands in our sample. On the one hand, there may be unobserved factors that are correlated with slave exports and conflict and would bias the estimates of interest. For example, one might argue that regions that had been inherently more conflict-inclined before 1400 were more likely to be affected during slave trade, and these areas continue to be conflict-prone today. On the other hand, if the explanatory variable, slave exports in history, is mismeasured, the resulting attenuation bias would shrink the coefficient estimates toward zero. To assess whether the uncovered relationship is causal, we pursue an IV approach by employing the distances from the centroid of each ethnicity to the locations where slaves were demanded.

The instruments consist of two parts: overland distance and sailing distance. For the trans-Atlantic slave trade, we calculate the overland distance from the centroid of each ethnic group to the closest point along the seacoast and the sailing distance from the African coast to the closest major market in America. According to Nunn (2008), nine major markets are selected while constructing the sailing distance: Havana, Cuba; Haiti; Kingston, Jamaica; Dominica; Martinique; Guyana; Virginia, USA; Salvador, Brazil; and Rio de Janeiro, Brazil. For the Indian Ocean slave trade, the overland distance is calculated in the same way, and the sailing distance measures the closest distance from the coast to the most important destinations in the Middle East: Mauritius and Muscat, Oman. The distance instruments capture an ethnicity's exposure to the trans-Atlantic and Indian Ocean slave trades. The longer the trade distances were, the less likely it was that the locals were enslaved. Thus, the instruments are correlated with slave exports. The slave trade distances are intuitively plausible to satisfy the exclusion restriction, since the destinations of slave exports were chosen largely due to the suitable exogenous climate conditions for plantation economy.

We report IV estimates in Table 2.4. The first column reports estimates controlling for the country fixed effects, the second column adds geographic controls, the third column further includes the location controls, and the fourth column controls for our baseline set of control variables, including the ethnic-level controls and control variables in column (3). In column (5), we include initial nightlight density to account for regional economic development. The first-stage estimates are reported in the bottom panel of Table 2.4. The relationship between the instruments and slave exports are strongly negative: The Transatlantic and Indian Ocean slave trade distances are both significantly related to slave exports at over 95% confidence (column 4). A shorter trade distance is typically associated with a greater number of slaves shipped, since the transportation cost is lower. The F-statistic is 9.24 in column 4, implying that the instruments are not weak.

Table 2.4 IV Estimates on the Effect of Slave Exports on Civil Conflict

	(1)	(2)	(3)	(4)	(5)
Second stage: Dependent variable is fraction of years with at least one civil conflict event					
Slave exports	0.118**	0.216***	0.220***	0.190***	0.176***
	(0.051)	(0.076)	(0.067)	(0.047)	(0.045)
	[0.054]	[0.087]	[0.076]	[0.046]	[0.046]
Initial light density	No	No	No	No	Yes
Ethnicity-level controls	No	No	No	Yes	Yes
Location controls	No	No	Yes	Yes	Yes
Geographic controls	No	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	No
Hausman test (*p*-value)	0.07	0.00	0.00	0.00	0.00
Overidentification test (*p*-value)	0.24	0.34	0.14	0.63	0.58
Number obs.	813	813	813	456	456
First Stage: Dependent variable is slave exports					
Transatlantic distance	-0.217***	-0.101*	-0.123**	-0.153**	-0.146*
	(0.054)	(0.050)	(0.054)	(0.074)	(0.077)
Indian Ocean distance	-0.241***	-0.202***	-0.194***	-0.264***	-0.257***
	(0.075)	(0.052)	(0.054)	(0.065)	(0.073)
F-stat of excl. Instrument	8.28	9.20	6.69	9.24	6.91
Adj. R^2	0.21	0.24	0.28	0.30	0.30

Notes: The unit of observation is ethnicity-country region. The dependent variable is the log transformed fraction of years with at least one conflict event during the period 1997-2014. The slave exports variable is the log transformed number of slaves traded through the transatlantic and Indian Ocean routes between 1400 and 1900 normalized by land area. Geographic controls at the ethnicity-country level include the natural log of land area, three measures of natural resource (precious metals, industrial metals, and diamonds) endowment, average elevation, terrain ruggedness, temporal variability in temperature in 1995-2014, and an indicator for access to rivers. Location controls at the ethnicity-country level include absolute latitude, the distance from an ethnicity-country region to the capital city, and an indicator for historical conflict between 1400 and 1700. Ethnicity-level controls include eight fixed effects for the sophistication of precolonial settlement, the number of precolonial jurisdictional political hierarchies beyond the local community, ranging from 1 to 4, an indicator for contact with precolonial European explorers, and a malaria prevalence index.

Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses. For the slave exports variable, standard errors adjusted for two-way clustering within countries and ethnolinguistic families are also reported in square brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The second-stage estimates are reported in the top panel. The coefficients for slave exports are generally positive, suggesting that the more slaves it exported, the more likely a region is prone to civil conflict in the contemporary era. Furthermore, the magnitudes of the IV estimates are approximately 9 times higher than those of the analogous OLS estimates, which is probably because selection into the slave trade and measurement error largely bias the OLS estimates downward. As evidence, the Hausman test in all specifications rejects the null hypothesis that slave exports can be treated as exogenous. The effects of slave trade on conflict remain significantly positive when controlling for the initial light density in column (5).

To further explore the sensitivity of our findings, we replace the outcome variable by alternative measures of civil conflict prevalence. As described in the previous section, the main outcome measure of ACLED civil conflict events comprises both battles and non-violent incidents, such as the establishment of rebel bases and political protests. Therefore, it is possible that slave trade affects the prevalence of conflict by merely acting on the non-fatal and non-violent events. In Table 2.5, we conduct the IV estimation using alternative conflict measures that focus on fatal and/or violent events. In columns (1)-(2), we apply the subjective 10-deaths threshold to measure conflict events. Note that in the country-level analysis, the standard threshold to identity civil conflict is 25-deaths. Such conventional threshold does not exist for subnational analysis; nonetheless, there are reasons to believe that a 10-deaths threshold can screen out non-fatal conflict events at the subnational level. In columns (3)-(4), the dependent variable only use battles to account for violent conflict events. In columns

(5)-(6), we restrict its domain to battles that result in at least 10 deaths. In odd-numbered columns, we control for location and geography. In even-numbered columns, we augment the specification with ethnicity-level historic controls. The results show that there is a significantly higher prevalence of fatal violence when a region has more slave exports. We also provide results by using the UCDP GED dataset in columns (7)-(10). Unlike ACLED, the UCDP GED dataset is less inclusive, tracing conflict incidents that result in at least one direct death. On the other hand, the UCDP GED dataset has events starting from 1989. These features of UCDP GED allow us to check the effects of slave trade on the risk of fatal conflict over a longer period (1989-2014). Not surprisingly, the results using UCDP GED data paint a consistent picture.

Table 2.5 Sensitivity Checks for IV Estimates, with Different Measures of Civil Conflict Prevalence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Second-stage Dependent variable	Log fraction of years with at least one civil conflict event									
	Any event 10 deaths		Any battle		Any battle 10 deaths		Any UCDP event		Any UCDP event 10 deaths	
Slave exports	0.203***	0.170***	0.137***	0.096***	0.037***	0.021*	0.101***	0.082***	0.052***	0.040***
	(0.060)	(0.038)	(0.037)	(0.030)	(0.009)	(0.014)	(0.029)	(0.021)	(0.014)	(0.009)
	[0.067]	[0.037]	[0.039]	[0.029]	[0.007]	[0.011]	[0.033]	[0.021]	[0.017]	[0.009]
Ethnicity-level controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Location controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test (*p*-value)	0.00	0.00	0.00	0.03	0.00	0.34	0.00	0.00	0.00	0.00
Overidentification test (*p*-value)	0.13	0.54	0.29	0.73	0.21	0.41	0.15	0.28	0.14	0.16
Number obs.	813	456	813	456	813	456	813	456	813	456
	First Stage: Dependent variable is slave exports									
Transatlantic distance	-0.123**	-0.153**	-0.123**	-0.153**	-0.123**	-0.153**	-0.123**	-0.153**	-0.123**	-0.153**
	(0.054)	(0.074)	(0.054)	(0.074)	(0.054)	(0.074)	(0.054)	(0.074)	(0.054)	(0.074)
Indian Ocean distance	-0.194***	-0.264***	-0.194***	-0.264***	-0.194***	-0.264***	-0.194***	-0.264***	-0.194***	-0.264***
	(0.054)	(0.065)	(0.054)	(0.065)	(0.054)	(0.065)	(0.054)	(0.065)	(0.054)	(0.065)
F-stat of excl. instrument	6.69	9.24	6.69	9.24	6.69	9.24	6.69	9.24	6.69	9.24

Notes: The unit of observation is ethnicity-country region. In columns (1)-(2), the dependent variable is the log fraction of years with at least one conflict event that results in 10 or more deaths. In columns (3)-(4), the dependent variable is the log fraction of years with at least one battle event. In columns (5)-(6), the dependent variable is the log fraction of years with at least one battle event that resulted in 10 or more deaths. In columns (7)-(8), the dependent variable is the log fraction of years with at least one UCDP conflict event. In columns (9)-(10), the dependent variable is the log fraction of years with at least one UCDP conflict event that resulted in 10 or more deaths. Geographic controls, Location controls, and Ethnicity-level controls are the same as we mentioned in Table 2.4.

Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses. For the slave exports variable, standard errors adjusted for two-way clustering within countries and ethnicities are also reported in square brackets. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

One thing to note is that the test statistics for the test of overidentifying restrictions in Tables 2.4 and 2.5 are not significant across all specifications, which gives us the confidence that our instrument set is appropriate. We also undertake several tests to ensure the validity of the instruments.

A potential concern with the exclusion restriction condition is that the overland distance of slave trade, which is part of the total trade distance, may be correlated with the accessibility of the country to other kinds of sea-based trade. To alleviate this concern, we estimate the reduced-from relationship between the prevalence of conflict and sailing distance instruments, that is, total slave trade distance minus the overland distance. In columns (1) and (3) of Table 2.6, we look first at the relationship between total slave trade distances and contemporary conflict. Column (3) includes the ethnicity-level historic controls at the price of a smaller sample. The results in both columns resonate with previous findings reported in Table 2.4: ethnic homelands that were closer to the slave trade markets are more likely to have conflict today. Columns (2) and (4) of Table 2.6 explore whether sailing distance is still negatively correlated with the likelihood of civil conflict. The coefficients are the same in significance and even larger when we only use the sailing distances as instruments. This provides strong evidence that the relationship between slave trade and conflict does not pick up the effect of other kinds of international trade by mere coincidence.

Table 2.6 Reduced Form Relationship between Slave Trade Distance and Civil Conflict, with or without the Overland Distance Part

	Log fraction of years with at least one civil conflict event			
	(1)	(2)	(3)	(4)
Transatlantic distance	-0.012*		-0.023**	
	(0.007)		(0.010)	
	[0.007]		[0.11]	
Indian Ocean distance	-0.043***		-0.050***	
	(0.007)		(0.011)	
	[0.008]		[0.12]	
Transatlantic sailing distance		-0.015*		-0.034**
		(0.009)		(0.017)
		[0.009]		[0.017]
Indian Ocean sailing distance		-0.049***		-0.063***
		(0.010)		(0.019)
		[0.011]		[0.021]
Ethnicity-level controls	No	No	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Number obs.	813	813	456	456
Adj. R-squared	0.49	0.48	0.50	0.49

Notes: The unit of observation is ethnicity-country region. The dependent variable is the log transformed fraction of years with at least one conflict event during the period 1997-2014. Transatlantic distance and Indian Ocean distance measure the distance from the centroid of the ethnic group to the closest major market of either the Atlantic or Indian Ocean slave trades, including both sailing distance and the distance from the centroid of the ethnic group to the African seacoast. Transatlantic sailing distance and Indian Ocean sailing distance only measure the distance from the African seacoast to the closest major market of slave trade, excluding the overland distance from the centroid of the ethnic group to the African seacoast. Geographic controls, Location controls, and Ethnicity-level controls are the same as we mentioned in Table 2.4. Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses, and standard errors adjusted for two-way clustering within countries and ethnicities are reported in square brackets. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels according to the standard errors in parentheses.

We also perform a second falsification test motivated by Nunn (2008) to examine the reduced-form relationship between total slave trade distance and conflict outside of our sample. The idea is that if the distance instruments affect contemporary conflict only through the Transatlantic and Indian Ocean slave trade, then there should be no significant correlation between distance instruments and conflict outside of our sample. Otherwise, it could be the case that the distances to the slave markets are correlated with distances to other locations that have a bearing on current conflict events. The first two columns of Table 2.7 report the reduced-form relationship outside the sample but within the African continent. With or without the ethnic-level historic controls, we do not find a significant relationship between slave trade distance and prevalence of contemporary conflict. Given that regions within sub-Saharan Africa (SSA) are more similar in terms of economic and social structures than those in Northern Africa, we undertake the same reduced-form estimates for regions that are in SSA and hardly affected by the Transatlantic and Indian Ocean slave trade. As shown in columns (3) and (4), this insignificant relationship is robust to focusing only on SSA counterparts.

Taking a step back, how robust are our IV estimates if we relax the perfect exogeneity assumption? In this way, we allow the instruments to be only "plausibly exogenous" (Conley, Hansen and Rossi, 2012). Since our analysis includes two instruments, we use principal components analysis to combine our instruments into one variable. We then let the instrument have a potential direct effect on current conflict in the second-stage regression with a coefficient γ.

Table 2.7 Out-of-sample Reduced Form Relationship between Slave Trade Distance and Civil Conflict

	Log fraction of years with at least one civil conflict event			
	(1)	(2)	(3)	(4)
Transatlantic distance	-0.011	-0.020	-0.011	-0.027
	(0.011)	(0.025)	(0.010)	(0.033)
	[0.011]	[0.026]	[0.010]	[0.042]
Indian Ocean distance	-0.008	-0.007	-0.012	-0.010
	(0.006)	(0.009)	(0.006)	(0.010)
	[0.006]	[0.009]	[0.007]	[0.013]
Ethnicity-level controls	No	Yes	No	Yes
Geographic controls	Yes	Yes	Yes	Yes
Location controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
SSA only	No	No	Yes	Yes
Number obs.	342	104	246	65
Adj. R-squared	.49	.46	.59	.54

Notes: The unit of observation is ethnicity-country region. The dependent variable is the log transformed fraction of years with at least one conflict event during the period 1997-2014. Transatlantic distance and Indian Ocean distance measure the distance from the centroid of the ethnic group to the closest major market of either the Atlantic or Indian Ocean slave trades, including both sailing distance and the distance from the centroid of the ethnic group to the African seacoast. Geographic controls, Location controls, and Ethnicity-level controls are the same as we mentioned in Table 2.4. Below all estimates, standard errors adjusted for clustering within countries are reported in parentheses, and standard errors adjusted for two-way clustering within countries and ethnicities are reported in square brackets. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

Following Conley *et al*. (2012), we use the union of confidence interval approach to estimate the 90% confidence interval of the main effect. Figure 2.2 presents the results. The Y-Axis shows the coefficient of slave exports in the second-stage regression. It shows that the lower bound intercepts with the zero-line at γ =0.085. That is, as long as the direct effect of the instrument on current conflict is smaller than 0.085, our second-stage coefficient on slave exports is still significant at the 10% level. Note that the overall reduced-form effect of the principal component instrument on conflict is 0.148. Therefore, the direct effect of the slave trade distance on prevalence of conflict would have to be approximately two-thirds of the overall reduced-form effect to render our IV results insignificant. In other words, slave exports only account for one-third of the impacts of the distances to the slave markets on conflict, which seems unlikely. Thus, our IV estimates are robust even allowing for possible deviations from perfect exogeneity.

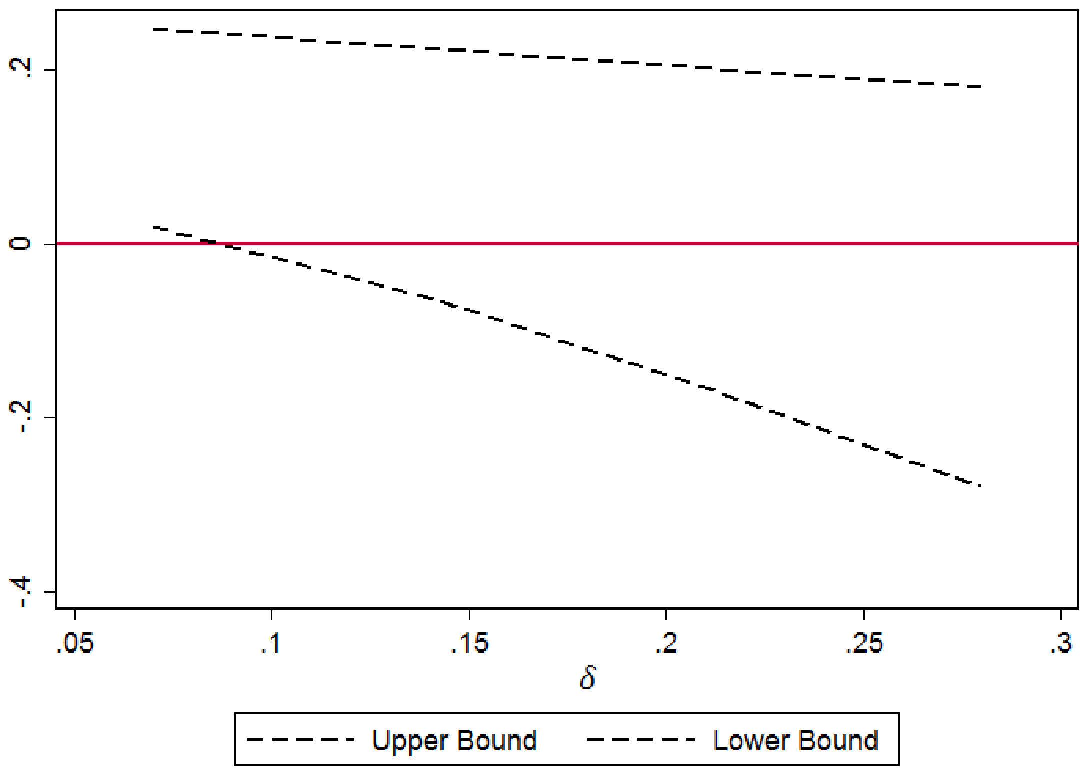

Figure 2.2 90% Confidence Interval of the IV Effect on Contemporary Conflict

2.6 Discussing the Possible Channels of Causality

Slave trades may affect the modern distribution of civil conflict through two major channels: economic development and non-economic factors, such as ethnic identities, cultural norms of behavior, and local institutions. In both OLS and IV estimations, we examine how the inclusion of a proxy for initial economic development affects the estimated impact of slave trade. After over-controlling for nightlight density, slave exports continue to have a significant and sizable impact, suggesting that the non-income channels play an important role in explaining the mechanisms.

We look first at the causal relationship between slave trade and the key institutional and cultural variables—ethnic identity, trust, and local governance. The 2005 Afrobarometer surveys collect individual-level attitudinal data on self-ascribed identity, trust, and local government performance. Its surveyed area covers nearly 20% of our sample, that is, 161 country-ethnicity regions in 13 countries of SSA. In the Afrobarometer surveys, the respondents self-report their identity attitudes: ethnic identity only, ethnic identity more than national identity, national and ethnic identities equally, national identity more than ethnic identity, and national identity only. To construct a measure for ethnic identity, we create a dummy variable equal to 1 if an individual feel attached to ethnicity only or more ethnic identity than national identity. The generalized trust question asks respondents whether most people can be trusted. The respondents answer either 0 ("You must be very careful in dealing with people") or 1 ("Most people can be trusted"). For local government performance, the respondents are asked to provide scores on a four-point scale, where 1 is "Strongly Disapprove", 2 is "Disapprove", 3 is "Approve", and 4 is "Strongly Approve".

The IV estimates for all respondents are reported in Panel A of Table 2.8. The specification used in Table 2.8 controls for several individual and regional characteristics, which are listed in the notes to the table. Columns (1)-(3) examine individual response towards ethnic identity, generalized trust, and local governance, respectively. The results lend credence to the view that slave trade may lead to mistrust and weak local governance. These results resonate with previous findings by Nunn and Wantchekon (2011) on the origins of mistrust in Africa. However, the coefficient for ethnic identity is positive but insignificant, probably because some respondents are immigrants, so their ancestors did not belong to the historic ethnicity in the surveyed area. We then concentrate on the non-mover respondents only (i.e., the individuals' current location is the same as their ancestors'). The results are reported in Panel B of Table 2.8. As we would expect, more slave exports yield a stronger sense of ethnic identity. Since ethnic identity and national identity are two sides of the same coin, slave trade also weakens the sense of national identity. Given that the non-mover group accounts for approximately 53% of all respondents, the channel through non-movers' ethnic identity seems fairly important. Columns (2) and (3) of Panel B report the estimates on trust and local governance using the non-mover respondents only: the coefficients remain negative and significant, with size of the effects being even larger.

Table 2.8 IV Estimates on the Effect of Slave Trade on Identity, Trust, and Local Governance

	(1)	(2)	(3)
Dependent Variable:	Ethnic Identity	Trust	Local Governance
	Panel A: All respondents		
Slave exports	0.022	-0.029*	-0.168***
	(0.020)	(0.017)	(0.043)
Individual controls	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Ethnic-country level controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Number obs.	10,295	10,295	9,561
	Panel B: Non-mover respondents only		
Slave exports	0.064**	-0.070**	-0.251***
	(0.028)	(0.002)	(0.077)
Individual controls	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Ethnic-country level controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Number obs.	5,583	5,583	5,195

Notes: The table reports the second-stage results of the IV estimation. The dependent variables are individual responses to ethnic trust, trust, and local governance from the Afrobarometer survey. All regressions include individual's age, age squared, gender, education, occupation, religion, living condition, and district's ethnic structure. We also include all ethnic-country level controls and country fixed effects used in Table 2.4.

We then turn to a qualitative analysis of the relationship between the non-economic factors and the prevalence of contemporary civil conflict. Due to the limited coverage of Afrobarometer, our sample size would be drastically decreased if we match it with the measures for trust, local institution, and ethnic identity.[3] With less than 14% of the overall sample observations, it is difficult to identify the quantitative relationships

[3] Within the 813 observations in the original sample size, only 58 have measures for non-mover ethnic identity at the ethnicity-country level, while 113 observations have measures for local governance and trust at the ethnicity-country level.

with precision. However, there are some notable findings we can reference from previous studies. First, Rohner, Thoenig, and Zilibotti (2013) document the negative correlation of civil war with a lagged measure of trust. Their measure of trust comes from the 2011 World Values Survey, which asks respondents the same question as Afrobarometer does. Second, the role of ethnic identity on triggering conflict is well studied (see, for example, Akerlof and Kranton, 2000; Esteban and Ray, 2008, 2011; Mitra and Ray, 2014) by both theoretical and empirical works. Third, previous studies demonstrate that institutional quality is essential for economic growth (Acemoglu, Johnson, and Robinson, 2001; Michalopoulos and Papaioannou, 2014) and conflict mitigation (Depetris-Chauvin, 2015).

2.7 Conclusions

This paper adds to a growing body of literature on the deep-rooted determinants of civil conflict. In particular, we address the issue of regional disparities of civil conflict likelihood in SSA. Using data for a sample of 813 subnational regions in SSA, this paper investigates the relationship between slave trade and the prevalence of civil conflict incidence. We find that the long-term effects of slave trade on modern risk of conflict are statistically significant and economically meaningful. This relationship is robust to potentially confounding characteristics at the ethnic level. It holds even if we narrow the outcome measures down to fatal and violent incidence.

To determine whether this relationship is causal, we pursue an IV estimation that uses the distances from each ethnicity to the slaves' demand locations as instruments for slave exports. The magnitudes of the IV estimates are approximately 9 times higher than those of the analogous OLS estimates. We also perform a number of checks concerning issues related to the exclusion restriction condition. These checks assess the validity of the instruments and the tolerable bounds to possible deviations from the perfect exogeneity assumption.

We then elucidate the mechanisms underlying the uncovered relationship. By employing the nightlight data, we show that economic development may not be the only major channel. According to our estimates, most impacts of slave trade can be explained by the non-economic factors. Using the Afrobarometer individual-level survey data, we emphasize the channels through cultural and institutional factors: the large-scale slave procurement gave rise to mistrust and a stronger sense of ethnic identity, and it weakened local governance, all of which increase the likelihood of civil conflict today.

Overall, our findings highlight the importance of slave trade, as an historic event, in shaping contemporary political development. In terms of policy implications, there is no need to feel despair for the regions that have been heavily affected by slave trade. Instead, it is better to understand the role of slave trade or other historic events and call for tailored conflict mitigation policies.

CHAPTER III

WEATHER SHOCK, SLAVE TRADE, AND CONFLICT: EVIDENCE FROM SUB-SAHARAN AFRICA

3.1 Introduction

Civil conflict has been widespread and become one of the major obstacles for development, particularly in the sub-Saharan African countries in their post-independence period. Not surprisingly, understanding the causes of conflict has gained increasing attention from academics (Blattman and Miguel, 2010).

One of the core research questions in this strand of literature is that: Why civil conflict events wax and wane over time in the same country or subnational region? Proponents of the geography view argue that weather variations may affect the likelihood of violence persistently and globally. For instance, Iyigun et al. (2017) shows that declining temperature is associated with higher frequency of conflict during 1400-1900 in Europe, North Africa, and the Near East; further, Hsiang et al. (2013) cover time periods from 10,000 BCE to the present and all major world regions, finding that rainfall or temperature anomalies have substantial influence on conflict. However, the climate-war relationship in Africa has been seriously challenged recently. On one hand, the primary determinants of civil conflict may be political instead of environmental conditions (Buhaug, 2010; Theisen et al., 2011); on the other hand, it is possible that the association between weather variables and conflict is in fact largely driven by the coincident movements of the global time series (Couttenier and Soubeyran, 2014).

Is the geography (climate-war) hypothesis true for the African countries? If it is true, what is the underlying channel? If weather is not the (only) main determinant of civil conflict in Africa, then which other factors can explain the prevalence of conflict? The goal of this study is to empirically address the above questions. We first construct a geo-coded disaggregated dataset in sub-Saharan Africa (SSA) over 1997–2014. It does so by dividing the SSA continent into cells of 0.5 degree of latitude × 0.5 degree of longitude, approximately 50 × 50 KM near the equator. We then calculate the within-year growing season weather shock for each cell by combining the monthly remote sensing-based meteorological index of drought, high-resolution land use information, and monthly global cropping calendar. The empirical investigation, conducted at the cell-year level, establishes that weather shock occurred during the growing season are strongly associated with the risk of conflict, no matter what kind of conflict measure it is. In contrast, the relationship between the whole year weather shock and conflict is rather weak. These results suggest that weather anomalies affect the likelihood of conflict mainly through agricultural production shock. Regarding the last question, we propose a hypothesis that the historical legacy, such as slave trade, within the African context also matters in affecting conflict. To check it, we exploit both weather shock as well as its interaction with variation in the exposure to the slave trade during 1400-1900. It shows that the effect of adverse weather shock is amplified in areas heavily exposed to the slave trade. Since slave trade is one of the most influential events in Africa's history, the significant interactive effect between weather variation and slave trade implies that geography and history work simultaneously in determining the likelihood of conflict.

Our empirical strategy contributes to the existing literature in four ways. First, the cell-year panel dataset allows us to explore the relationship between weather variation and conflict at the disaggregated level. Previous country-level debates on the role of weather conditions have inherent limitations, since the within-country heterogeneity may bias the estimates. Given that the range of civil conflict is usually less than one-quarter of a country's territory (Raleigh and Hegre, 2009), there might exist a possible mismatch between conflict and its driving factors in different regions within the same country.

Second, motivated by Harari and La Ferrara (2015) and von Uexkull et al. (2016), we develop a more efficient measure for weather shock. Our raw climate index is drawn from the Standardized Precipitation-Evapotranspiration Index (SPEI) (Beguería et al., 2014). Weather condition is a nonlinear function of rainfall, temperature, and evaporation. Therefore, simply using rainfall and/or temperature cannot fully account for the impact of climate. As a recently-developed drought index, SPEI is based on the monthly climatic water balance as a whole. In other words, the SPEI's main advantage lies in its ability to capture the joint effects of precipitation and evaporation (e.g., temperature and wind speed). Furthermore, considering that most African countries are agrarian societies, conflict sensitivity to weather shock may be largely due to their impact on agricultural production. Monthly SPEI data allows us to examine these potential channels. If weather variation in the crop growing season is more relevant to the risk of conflict and carries more weight than that in the non-growing season, we may claim that agricultural income shock might be the main pathway underlying the climate-war relationship.

A third contribution of our paper is the econometric specification. The usual specification in the literature (Burke et al., 2015) controls for country fixed effects and generic/country-specific time trends. Couttenier and Soubeyran (2014) recommend including the country and year fixed effects. A noteworthy feature of the differences-in-differences specification is that it captures the aggregate time shocks, such as global warming, geopolitical transitions, and prices movements of the primary commodities. In other words, the omission of year fixed effects might lead to spurious relationship between weather shock and conflict. We employ the standard differences-in-differences specification as the benchmark model and control for the country-specific trends in some specifications. We demonstrate that the association between weather shock and civil conflict is robust to the inclusion of year fixed effects and country-specific trends.

A forth contribution is that we look at the interaction between weather shock and exposure to the slave trade. The findings show that the more slaves it exported, the more sensitive a cell is to weather variation in terms of risk of conflict. These results are robust when controlling for the interaction between weather shock and a battery of other possible confounding variables. Furthermore, we pursue the instrumental variable (IV) approach to overcome the potential endogeneity of slave trade on civil conflict. Motivated by the study of Nunn and Wantchekon (2011), we use the interaction between distance from the seacoast and weather shock as the instrumental variables for the interaction between slave exports and weather shock. Unlike Nunn and Wantchekon's instrument, which are seacoast distance at the ethnic level, we calculate our distance variable at the cell level and multiply it with weather shock. As such, this paper also relates to the empirical approaches recently taken by Becker and Woessmann (2009) and Rubin (2014), who also employ distance indicators as IVs to investigate the effects of a historic event. The IV approach makes it credible to assert that the historical legacy of slave trade exacerbates the impact of weather shock on contemporaneous conflict risk.

This chapter is related to a large and growing body of literature on climate and violence. The cornerstone research by Miguel, Satyanath, and Sergenti (2004) firstly use year-to-year rainfall variation to instrument economic shocks, and document the strong causal effect of adverse income shocks on civil conflict in sub-Saharan Africa (SSA) before 2000. Many subsequent empirical studies also support the relationship between weather variability and conflict, e.g. in SSA (Burke, Miguel, Satyanath, Dykema, & Lobell, 2009; Couttenier & Soubeyran, 2014), Somalia (Maystadt, Ecker, & Mabiso, 2013), Kenya (Adano, Dietz, Witsenburg, & Zaal, 2012), India (Bohlken & Sergenti, 2010), and historical China (Bai & Kung, 2011; Jia, 2014). Nevertheless, this strand of research is recently challenged from two directions. First, the ethno-political conditions for African countries are more relevant than weather variables in explaining the occurrence of violent conflict (Buhaug, 2010; Theisen et al., 2011). Second, the relationship between weather shock and conflict seems not robust across different econometric specifications and measures of weather variable (Couttenier and Soubeyran, 2014). We advance this literature by introducing a more prominent weather measure and examining the link between the two at disaggregated levels. Our results resonate with most previous studies that acknowledge the relationship between weather shock and conflict. In addition, our findings suggest that agricultural production shocks may be the major pathway through which weather variation affects the likelihood of conflict.

This chapter also speaks to the literature on the role of slave trade for conflict and development. Acemoglu et al. (2005) argue that the rise of Western Europe after 1500 is largely due to access to Atlantic trade, which of course consists of slave trade with Africa. Nunn (2008) provides an empirical analysis of the negative relationship between the scale of slave trade and contemporary economic development in African countries. Nunn and Wantchekon (2011) then find that people’s trust levels within Africa can be explained by slave trade. The long-term effects of slave trade on Africa's social structure are studied as well. Dalton and Leung (2014) document that males were disproportionately enslaved, which has led to prolonged abnormal sex ratios and high polygyny rates. Our paper adds to the existing literature by documenting the interactive effect between slave trade and weather shock.

On a broader scale, this work relates to the debates between the “geography matters” and the “history matters” views (Nunn, 2009). Proponents of the geography view stress the importance of geographic factors, such as climate, natural resources, and the disease environment in determining the current development and conflict. To some extent, the climate-war relationship can be classified as a strand of the “geography matters” view. On the other hand, proponents of the “history matters” view argue that despite the direct effect of geography on contemporaneous development, geographic characteristics also have an indirect effect through their influence on historical events.

For example, Nunn and Puga (2007) explore the two channels for geographic characteristic, terrain ruggedness. On one hand, terrain ruggedness has a direct negative effect on current economic development. On the other hand, ruggedness in Africa increased the costs of slave procurement since people could hide themselves in caves and mountains to escape from the slave raiders. So, terrain ruggedness also has an indirect positive effect on long-run development through history. In the case of terrain ruggedness, the positive effect of geography through history is economically more meaningful than its negative direct effect. In addition to Nunn and Puga's explanation, our interaction analysis provides another point of view: both geographic and historic characteristics (in our paper, weather shock and slave trade) can jointly affect the contemporaneous conflict.

The remainder of this chapter is organized as follows. Section 3.2 discusses data and measurement. The effect of weather shock on civil conflict is presented in Section 3.3. The interaction results are reported in Section 3.4. Section 3.5 concludes.

3.2 Data and Measurement

We disaggregate our sample into 0.5×0.5 decimal degrees' grid cells, which consists of 62,460 cell-year observations from 27 SSA countries over 1997-2014. The sample size is limited due to the subnational level data availability of slave exports. Details will be given when the source of slave exports is introduced in the following parts. The panel structure of the data allows us to study how weather shock affects the occurrence and intensity of conflict within countries, while controlling for the cell level heterogeneity.

Data on civil conflict, our outcome variable, is collected from the ACLED (Armed Conflict Location and Event Data) (Raleigh et al., 2010). Regarded as the most comprehensive dataset, ACLED records a range of civil conflicts in African states, including battles, violence against civilians, remote violence, rioting and protesting against a government, and non-violent conflict within the context of the war. The measure of conflict used in the baseline model is conflict incidence, which equals one if at least one conflict event happened in the given cell-year, otherwise zero. In some scenarios, we are also interested in the effect of weather shock on the outbreak and intensity of conflict. For instance, as a persistent variable, the likelihood of conflict incidence in the current year might be largely influenced by lagged conflict events. Hence, we construct conflict onset as an alternative measure of dependent variable, which equals to 1 if $Conflict\ incidence_t = 1 | Conflict\ incidence_{t-1} = 0$ for a given cell. The conflict intensity measure takes into account the total number of conflict events occurred in the cell-year. Figure 3.1 maps the incidence of conflict in the sample. It shows that Uganda, Rwanda, Zimbabwe, as well as the Western African countries were more likely being under fire in the past two decades.

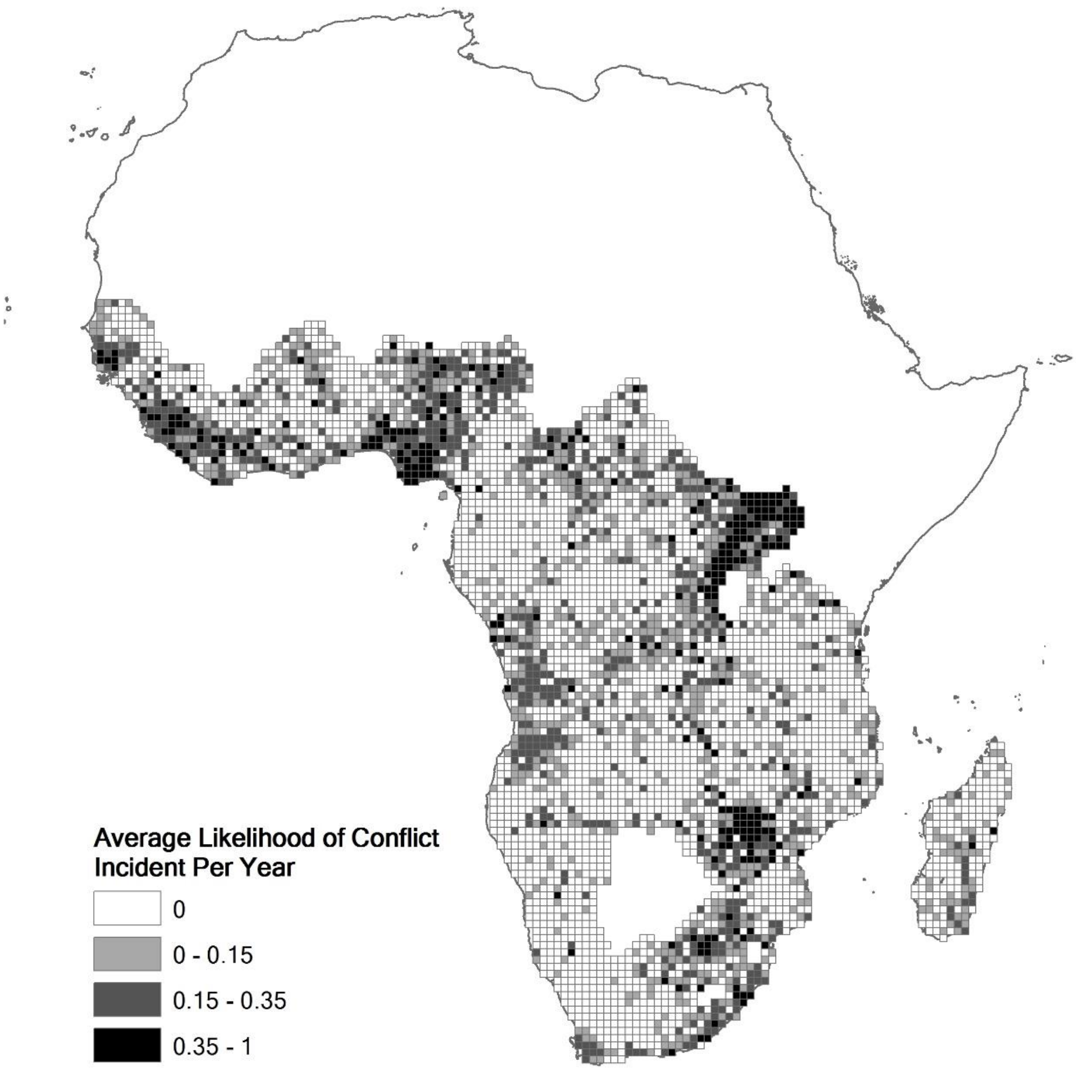

Figure 3.1 Average Likelihood of Civil Conflict Incidence per Year at the Cell Level

We calculate weather shock based on the SPEI drought index (Vicente-Serrano *et al*., 2010; Beguería *et al*., 2014). The gridded SPEI dataset is available at spatial resolution of 0.5 × 0.5-decimal degrees and provides monthly climate indicators from 1901 to 2014. The average value of SPEI is 0, and the standard deviation is 1. The standardization of SPEI allows us to compare SPEI values over time and space. We firstly construct the within-year weather variation, SPEI shock, by measuring fraction of 12 months in which SPEI value was below its mean by at least one standard deviation.

We also consider the possibility that weather shock in certain months carries more weight than those in the rest of the year. If agricultural production is the major channel through which climate influences conflict, then it makes more sense to focus on the effect of weather shock during the crop growing season. Thus, we rely on the 2005 Spatial Production Allocation Model (You et al., 2014) to identify the main crop for each cell by harvest area, and then retrieve the growing-season months for these main crops by overlaying the SAGE Crop Calendar Dataset (Sacks et al., 2010). The top seven main crops planted in Africa is displayed in Figure 3.2. The growing season SPEI shock is measured as a share of growing season months with SPEI ≤ -1. Figure 3.3 portrays the distribution of average growing season SPEI shock per year.

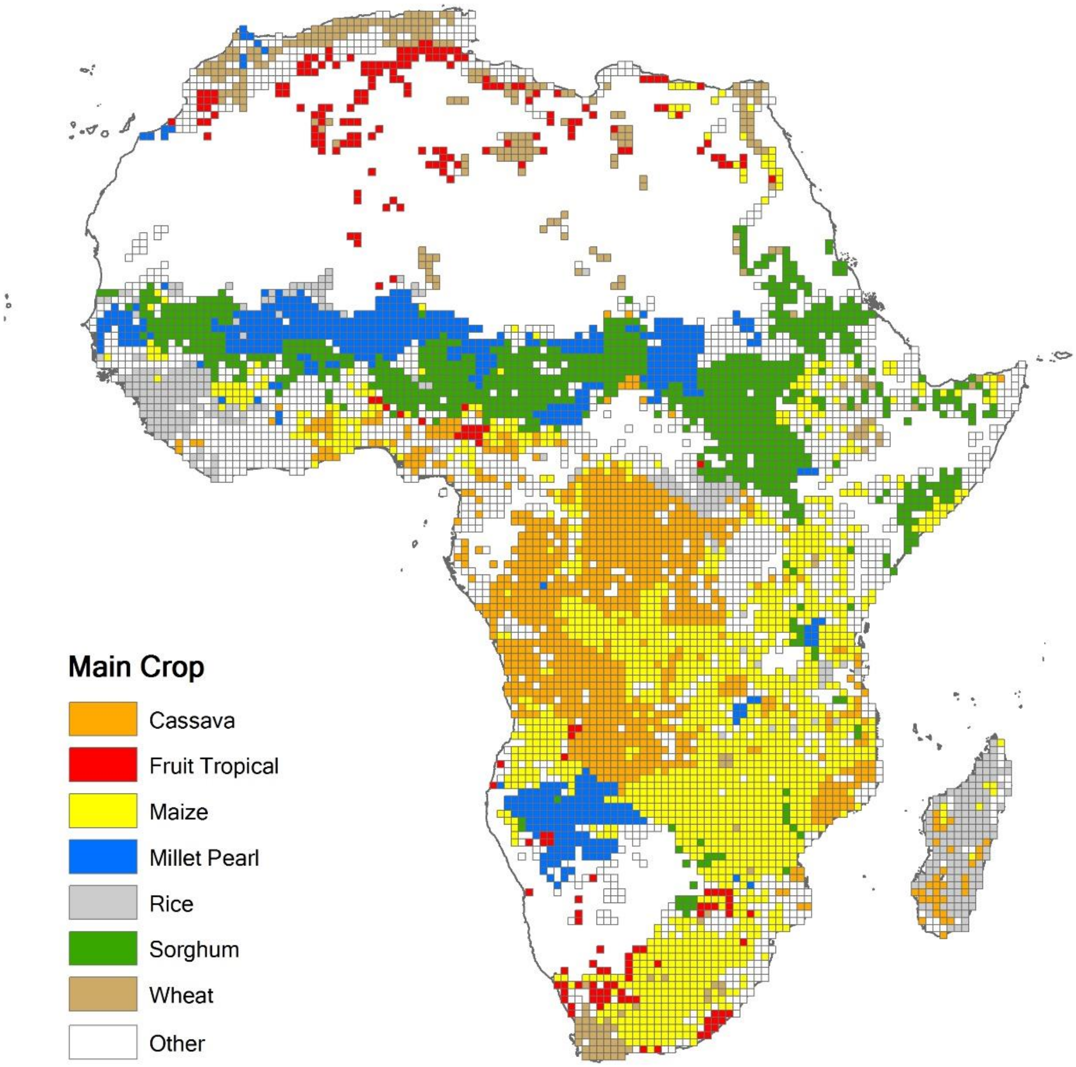

Figure 3.2 The Spatial Distribution of Popular Main Crops in Africa at the Cell Level

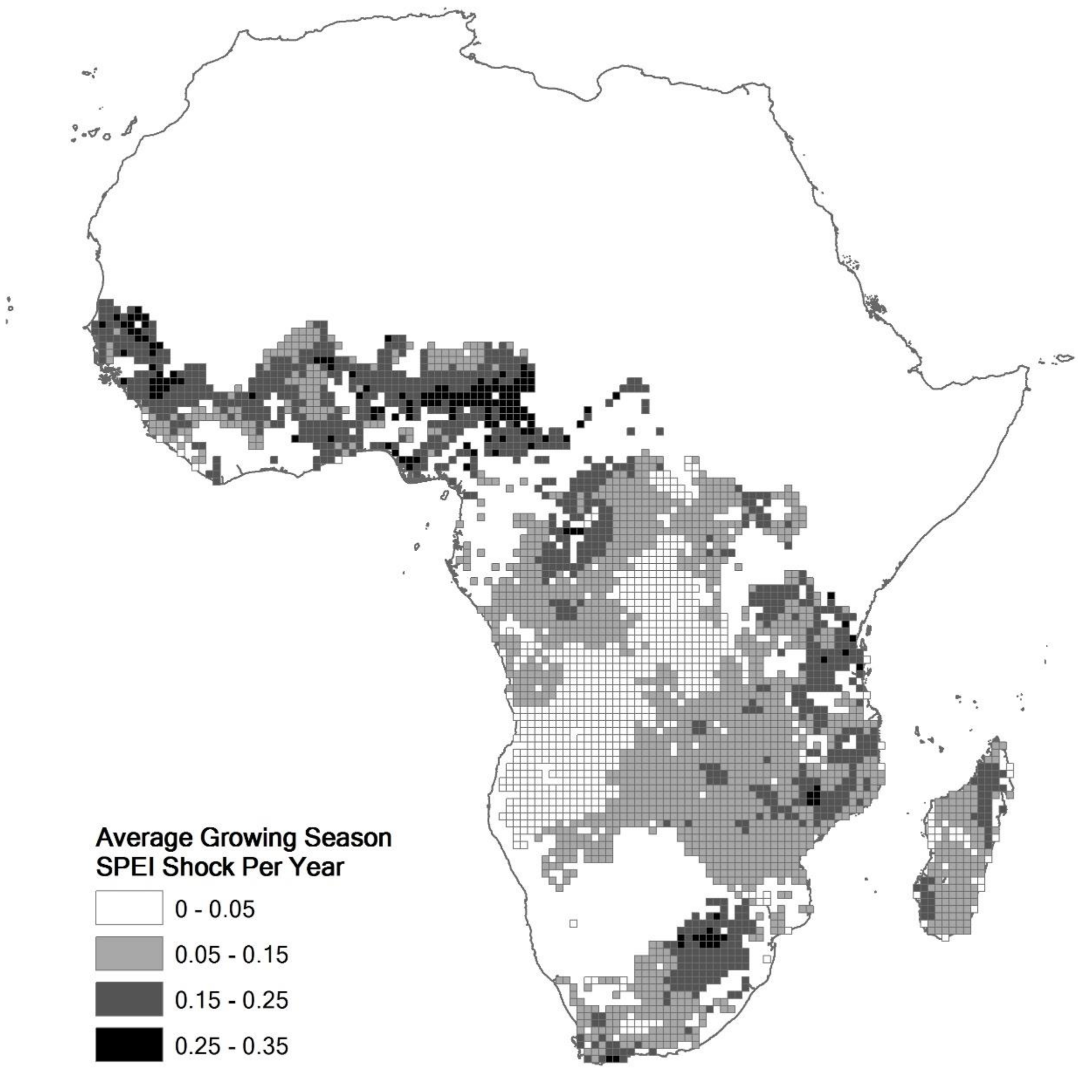

Figure 3.3 The Average Growing Season SPEI Shock per Year at the Cell Level

Another independent variable of interest is the severity of slave trade. Nunn and Wantchekon (2011) trace slave exports through the transatlantic and Indian Ocean trade routes during 1400-1900 at the ethnic level. We further disaggregate Nunn and Wantchekon's data into the cell level by combining information on the distribution of ethnic groups from Murdock's (1959) ethnolinguistic map. Besides the transatlantic and Indian Ocean trade routes, there existed two other slave trade routes, namely the Red Sea and trans-Saharan routes. However, the subnational slave exports data is not available yet for the latter two routes. Thus, we have to drop off the countries that were mainly affected by the Red Sea and trans-Saharan slave trade routes. Figure 3.4 maps the distribution of slave exports in our sample. As shown in Figure 3.4, slave trade through the transatlantic and Indian Ocean routes has a bearing on most of the SSA areas. Taking into account the differences in the size of cells across different latitudes, we normalize the slave exports by surface land area.

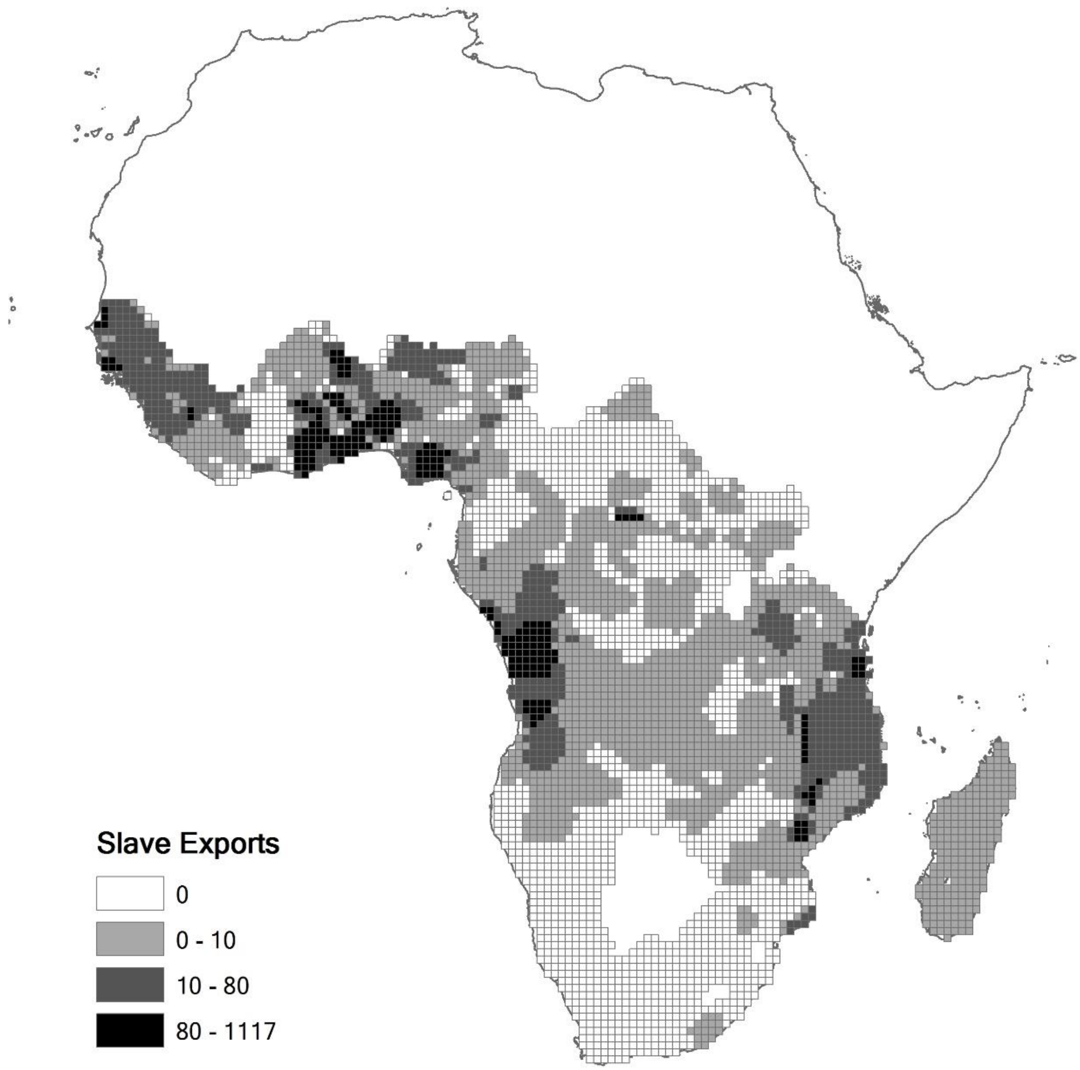

Figure 3.4 The Number of Slave Exports at the Cell Level

Table 3.1 presents the summary description of our panel sample. First, the average likelihood of conflict incidence is almost 10% per year, while the likelihood of new conflict outbreak is approximately 5%. Second, the mean probabilities of SPEI shock and growing season SPEI shock are very similar (12%), implying that a great number of cells suffer weather shock in the months outside the growing season. Third, on average there are about 24 slaves taken for each cell. In addition, we also include a set of time varying control variables, such as the index for democracy and rule of law, the log of population and GP per capita. The country-level characteristics on population and income level are often cited in the literature of conflict (Blattman and Miguel, 2010). Buhaug (2010) recommends the inclusion of political conditions because they find that African civil wars can be explained by political variables instead of climate variation. To account for the political institutions, we also include the country-level Polity IV indicator as a proxy for democracy, as well as assessment score for rule-of-law from the World Bank's Worldwide Governance Indicators (Kaufman et al., 2011).

Table 3.1 Descriptive Statistics of Panel Sample

	Observations	Mean	S.D.	min	Max
	Panel A Conflict				
Conflict incidence	62,460	0.091	0.288	0	1
Number of conflict events	62,460	0.159	0.608	0	8
Conflict onset	58,990	0.048	0.213	0	1
	Panel B Weather shock				
SPEI shock	61,848	0.121	0.158	0	1
Growing season SPEI shock	62,460	0.120	0.184	0	1
Growing season consecutive SPEI shock	62,460	0.108	0.168	0	1
	Panel C Slave exports				
Total slave exports 1400-1900	62,460	24.044	109.845	0	1117
Normalized slave exports	62,460	0.774	1.220	0	5.979
	Panel D Other time variant variables				
Polity IV index for democracy	59,352	2.198	4.213	-7	9
Rule and Law index	52,050	-0.946	0.637	-2.205	0.366
Log (population)	62,460	3.120	0.916	-0.227	5.179
Log (GDP per capita)	62,460	7.637	0.861	5.976	10.59

3.3 The Effect of Weather shock on Conflict

We first investigate the effect of weather shock on the likelihood of civil conflict within countries. Let us denote by *i* a gridded cell, *c* a country and *t* a year. In general, the empirical specification takes the following form:

$$y_{i,c,t} = \alpha_{i,c} + \beta Shock_{i,c,t} + X'_{c,t}\Omega + Z'_{i,c,t}\Gamma + \eta_t + \varepsilon_{i,c,t} \qquad (3.1)$$

where $y_{i,c,t}$ denotes the outcome variables of incidence, onset, or intensity of a conflict in a given cell of a country, during a given year. $Shock_{i,c,t}$ represents the cell-year SPEI weather variation: alternatively (i) the *SPEI* shock that aggregates the weather variation over the whole year; (ii) the *growing season SPEI shock*; (iii) the lagged weather shock is included in some specifications, in case weather anomalies might induce conflict events to be displaced in time. In all estimations, we control for location fixed effects $\alpha_{i,c}$ and year fixed effects η_t. The former captures the unobserved time-invariant cell-specific characteristics. The latter accounts for the effect of yearly worldwide changes. In some specifications, we also include country-specific time trends, as they are often used in the literature. The vector $X_{i,c}$ consists of a set of country level covariates that capture the time varying characteristics, such as indicators for democracy, rule-of-law, GDP per capita, and populations. $\mathrm{Z}_{i,c,t}$ is a cell-level dummy variable indicating whether a location *i* was involved in civil conflict during the previous year.

When the dependent variables are binary (incidence and onset of conflict), the two-level mixed effects logit estimator is our preferred estimator. The mixed logit model extends the standard conditional logit model by allowing for random effects for many levels of nested clusters. In our study, a two-level mixed effects logistic regression can specify random intercepts to take into account the dependence between observations within countries and cells over time (Gelman and Hill, 2006). When the dependent variable is the number of conflict events, we employ the fixed-effects linear model. Across all specifications, the robust standard errors are clustered at the cell level.

We first consider the whole year weather shock. As mentioned earlier, the whole year SPEI shock is measured as a ratio of the number of months within a year with SPEI ≤ -1 over 12. Table 3.2 reports the relationship between the whole year weather shock and the likelihood of conflict incidence. The first three columns estimate the contemporaneous effect of SPEI shock, while the last three columns estimate both contemporaneous and lagged effects of SPEI shocks. Column (1) and (4) show the simplest differences-in-differences specification, including only the location fixed effects and year fixed effects. In Column (2) and (5), we add several time varying covariates, such as indicators for democracy and rule-of-law, log population, log GDP per capita, and incidence of past conflict incidence (lagged by one 4-year period). Column (3) and (6) includes additional country-specific time trends. The results show that the link between whole year weather shock and conflict is generally positive but weak, with most of the coefficients of interest across all specifications are insignificant. Our cell-year analysis echoes the previous findings by Buhaug (2010) and Couttenier and Soubeyran (2014) at the country level and Theisen *et al*. (2011) at the subnational level that the relationship between whole year weather anomalies and conflict is not robust.

Table 3.2 Whole Year Weather shock and Conflict

	Dependent Var.: Conflict Incidence					
	(1)	(2)	(3)	(4)	(5)	(6)
Whole year SPEI shock	-0.039	0.178	0.136	-0.030	0.223*	0.159
	(0.113)	(0.119)	(0.127)	(0.110)	(0.129)	(0.137)
Whole year SPEI shock, t-1				-0.050	0.016	-0.156
				(0.103)	(0.120)	(0.130)
Time varying controls	No	Yes	Yes	No	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	No	Yes	No	No	Yes
Observations	82,512	65,313	65,313	82,512	60,950	60,950

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

We then consider conflict sensitivity to the growing season weather shock, which is measured as a share of main crop growing season months with SPEI ≤ -1. Table 3.3 provides our results. The model specifications used in Table 3.3 are the same in Table 3.2. Columns (1)-(3) explore whether conflict incidence is correlated with contemporaneous growing season drought. In all three columns, there is a positive and significant correlation between growing season SPEI shock and the risk of conflict incidence. The effect is also quantitatively meaningful: the odds ratio of experiencing at least one conflict event will be increased by a range between 20%-31% if a given cell suffers weather shock during the entire growing season. In columns (4)-(6) we look to see whether the lagged growing season SPEI shock is also correlated with the prevalence of conflict, conditioning on current shock. The results show that the magnitude and significance of the impact of current growing season weather shock remains similar to the ones in columns (1)-(3) of Table 3.3. The occurrence of conflict appears to be hardly affected by the lagged growing season SPEI shock. This is not surprising as SPEI is a cumulative meteorological measure that combines climate conditions for a range of accumulation periods.

Table 3.3 Growing Season Weather shock and Conflict

	Dependent Var.: Conflict Incidence					
	(1)	(2)	(3)	(4)	(5)	(6)
Growing season SPEI shock	0.175*	0.278**	0.215*	0.169*	0.260**	0.240*
	(0.105)	(0.114)	(0.119)	(0.106)	(0.125)	(0.130)
Growing season SPEI shock, t-1				0.047	0.083	-0.132
				(0.100)	(0.114)	(0.124)
Time varying controls	No	Yes	Yes	No	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	No	Yes	No	No	Yes
Observations	62,442	49,436	49,436	62,442	46,130	46,130

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In Table 3.4 we replicate the analysis using two different measures of conflict: conflict onset and intensity. We focus on the contemporaneous growing season SPEI shock since the lagged shock does not substantially affect the prevalence of conflict. We find that an increase in the duration of drought during the growing season significantly increases the probability of conflict onset (columns (1)-(3)) and intensity (columns (4)-(6)). It is worth noting that conflict intensity is a count variable that gives the number of conflict events. Hence, we employ a linear probability model when dealing with conflict intensity. The quantitative interpretation of our results on conflict intensity is straightforward: in terms of standardized beta coefficient of column (6), a one standard deviation increase in growing season SPEI shock leads to a 0.16 standard deviation increase in predicted number of conflict events.

Table 3.4 Growing Season Weather shock and Conflict, with Different Measures of Conflict

Dependent Var.	Conflict Onset			# Conflict Events		
	(1)	(2)	(3)	(4)	(5)	(6)
Growing season SPEI shock	0.203*	0.296**	0.306**	0.025*	0.037**	0.048***
	(0.111)	(0.119)	(0.123)	(0.015)	(0.156)	(0.014)
Time varying controls	No	Yes	Yes	No	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	No	Yes	No	No	Yes
Observations	58,973	49,436	49,436	62,460	49,450	49,450

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Comparing the impacts of whole year and growing season SPEI shocks, the results from Table 3.2 to 3.4 suggest that weather shock during main crop growing season carries more weight than that in the rest of the year. Since the growing season SPEI value is essentially an agriculture-relevant drought indicator, our primary independent variable proxies a sudden fall in agricultural yields induced by drought. The loss in main crop harvest may result in a severe income shock in agrarian economies in Sub-Saharan Africa. This clearly implies that climatic extremes affect civil conflict through agricultural incomes. In the next section, we also look to see whether contextual history enlarges the effect of weather-induced crop failure.

3.4 Interactions Between Weather Shock and Slave Trade

As we mention above, slave trade has a long-run effect on the current economic and political outcomes. Chapter II particularly demonstrates a robust relationship between intensity of the slave trade and prevalence of civil conflict in contemporaneous Africa. They argue that slave trade persistently affects the distribution of conflict through two equally important channels: economic development and non-economic factors, such as ethnic identities, local institution, and the level of trust. It is reasonable to assume that these altered cultural and institutional factors may interact with short term weather shock in triggering conflict. An underlying implication of this hypothesis is that conflict sensitivity to weather shock varies across places due to the exposure to the remarkable past event that took place hundreds of years ago.

To investigate this issue, we exploit the interaction of agricultural-relevant weather shock with intensity of the slave exports to estimate the following equation:

$$y_{i,c,t} = \alpha_{i,c} + \gamma Shock_{i,c,t} + \lambda Shock_{i,c,t} * Slave_{i,c} + X'_{c,t}\Omega + \mathrm{Z}'_{i,c,t}\Gamma + \eta_t + \varepsilon_{i,c,t} \qquad (3.2)$$

where $Slave_{i,c}$ denotes the number of slaves traded through the transatlantic and Indian Ocean routes between 1400 and 1900 normalized by land area at the cell level. $Shock_{i,c,t}$ denotes the growing season SPEI shock in a given location, during a given year. The whole year SPEI shock is not used since we do not find it is significantly correlated with the prevalence of conflict. Similar with equation (3.1), the specification includes cell and year fixed effects, as well as a set of time-varying controls. Note that, the inclusion of cell fixed effects allows us to account for the main effects of any time-invariant location-specific characteristics, including the slave trade. The standard errors are clustered at the cell level. The main coefficient of interest in this section is λ. Under the null hypothesis $\lambda=0$, the effect of growing season weather shock on conflict is isolated and irrespective of exposure to the slave trade. We expect the sign of λ to be positive: the locations from which more slaves were shipped are less developed in terms of wealth level and institutions, and should be more relatively affected by weather-induced agricultural income shocks.

Table 3.5 delivers the baseline results of equation (3.2). In odd-numbered columns, we take the standard differences-in-differences specification. In even-numbered columns, we augment the specification with country-specific time trends. Once we condition on the interactive effect between slave trade and weather shock, the main effects of growing season weather shock remain positive in all specifications except for column (6), although it is only statistically significant in column (3). In columns (1)-(2) and (5)-(6), we find the coefficients on our interaction term are all positive and statistically significant, that is, areas heavily exposed to the slave trade are more sensitive to the effect of growing season weather shock on the probability of conflict incidence or conflict intensity. Nevertheless, the coefficients on the interaction term are positive and insignificant in columns (3)-(4), indicating that the effects of weather shock on conflict onset are not heterogeneous across the intensities of slave trade.

Table 3.5 Growing Season Weather shock, Slave Trade, and Conflict

Dependent Var.	Conflict Incidence		Conflict Onset		# Conflict Events	
	(1)	(2)	(3)	(4)	(5)	(6)
Growing season SPEI shock	0.169	0.043	0.251*	0.227	0.017	-0.017
	(0.135)	(0.141)	(0.140)	(0.146)	(0.021)	(0.019)
Growing season SPEI shock×Slave	0.133*	0.219**	0.051	0.096	0.023*	0.026**
	(0.080)	(0.089)	(0.089)	(0.092)	(0.012)	(0.011)
Time varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	Yes	No	Yes	No	Yes
Observations	49,436	49,436	49,436	49,436	49,450	49,450

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

The results in the previous section suggest that places that have longer extreme weather conditions in the growing season more prone to conflict. Furthermore, the effect is amplified if the places severely suffered from slave trade. However, one might argue that the consecutive weather anomalies during the growing season are more relevant to agricultural production than the separate extreme weather events. Following Harari and La Ferrara (2015), we also measure weather shock by using the fraction of consecutive growing season months in which SPEI ≤ -1. Table 3.6 contains the results for this alternative weather shock variable. The odd-numbered columns repeat the estimation for the main effects of weather shock on the incidence, onset, and intensity of conflict; while the even-numbered columns re-examine the intensifying effect of slave trade on weather shock. The results are very similar: first, consecutive weather shock is positively correlated with the conflict outcome variables, although the effect is not statistically significant for the intensity of conflict; second, regions that have fewer slaves exported seem relatively resilient to weather shock. Consistently with the results shown in Table 3.5, the coefficients of the interaction term are significant for the incidence and intensity of conflict at the 95% confidence level and not significant for conflict onset.

Table 3.6 Consecutive Weather shock, Slave Trade, and Conflict

Dependent Var.	Conflict Incidence		Conflict Onset		# Conflict Events	
	(1)	(2)	(3)	(4)	(5)	(6)
Consecutive growing season SPEI shock	0.216*	0.043	0.315**	0.261*	0.009	-0.018
	(0.127)	(0.150)	(0.133)	(0.157)	(0.016)	(0.021)
Consecutive growing season SPEI shock × Slave		0.219**		0.067		0.030**
		(0.094)		(0.097)		(0.013)
Time varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,436	49,436	49,436	49,436	49,450	49,450

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Another potential concern is that the interaction between weather shock and exposure to the slave trade may coincidently pick up the interactive effect between weather shock and some location or historical characteristic that might be related with the intensity of slave exports. For instance, regions that had fewer slaves exported also had less contact with the Europeans in the colonial period, implying that those regions were less affected by the colonial rule. If it is the case, the interaction between exposure to the slave trade and weather shock perhaps is proxying for an interaction between the exposure to colonial rule and weather shock. A similar reasoning could be applied to other cell-specific characteristics, such as the mountainous terrain, fraction of urban area, malaria index, distance to borders, distance to historical conflict locations, as well as the levels of historical institution and economic development.

We consider these possibilities in Table 3.7, where we include in our estimation additional interaction terms between weather shock and the potential cell-level confounders discussed above. The dependent variable used is conflict incidence. The main effect of weather shock remains positive in most specifications but insignificant. Most importantly, the coefficient of the interaction term between weather shock and exposure to slave trade is robust to the inclusion of alternative interactions. The point estimates for the interaction term of interest are quantitatively close to the benchmark estimation shown in column (2) of Table 3.5. It suggests that the interaction results cannot be explained by other location or historical factors, and it is fully accounted for by the exposure to slave trade.

Table 3.7 Weather shock, Slave Trade, and Conflict, with Alternative Interactions

Dependent Var.	Conflict Incidence							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growing season SPEI shock	0.017	0.037	0.153	-0.145	-0.102	0.087	0.490	0.165
	(0.189)	(0.147)	(0.230)	(0.207)	(0.221)	(0.291)	(0.406)	(0.148)
Growing season SPEI shock×Slave	0.220**	0.239***	0.242***	0.246***	0.264***	0.197**	0.220**	0.242***
	(0.089)	(0.090)	(0.094)	(0.092)	(0.089)	(0.095)	(0.096)	(0.088)
Growing season SPEI shock ×								
× Mountainous Terrain	Yes	No	No	No	No	No	No	No
× Urban Area	No	Yes	No	No	No	No	No	No
× Malaria Index	No	No	Yes	No	No	No	No	No
× Distance to Borders	No	No	No	Yes	No	No	No	No
× Distance to Historical Conflict	No	No	No	No	Yes	No	No	No
× Historical Institution	No	No	No	No	No	Yes	No	No
× Historical Economic Development	No	No	No	No	No	No	Yes	No
× European Explorer Contact	No	No	No	No	No	No	No	Yes
Time varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,436	49,436	49,436	49,436	49,436	39,486	39,486	49,436

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level

One might well worry that the estimation for our interaction term is biased by some other omitted variables that are not included in Table 3.7, or our key explanatory variable—the number of slave exports during 1400 to 1900—may have measurement error. To address this concern, we exploit the exogenous variation in the distance of each cell from its nearest seacoast to construct the instrumental variable. Distance from the seacoast is correlated with the costs of procuring and transporting slaves, and thus our instrumental variable, the interaction between distance from the coast and weather shock is correlated with the interaction between slave trade intensity and weather shock. One potential violation to the exclusion restriction is that the distance from the seacoast may be correlated with the contemporaneous trade openness. However, Blattman and Miguel (2010) survey the literature on the relationship between trade and civil conflict and find it is ambiguous and mixed. This alleviates concerns that modern international trade, which is also affected by distance from the seacoast, may have an interactive effect with weather shock on the prevalence of conflict.

We report IV results for each of the three measures of conflict in Table 3.8. Because the endogenous variable is an interaction term between growing season weather shock and slave trade intensity, the instrumental variable should also be an interaction term between weather shock and distance from the seacoast. Due to the difficulty to program the interaction term with instrumental variable in the mixed-effects logit model, we show the results obtained with a fixed-effects linear estimator. Therefore, the magnitudes of the IV estimates are not comparable with the previous results obtained through the logit estimator. Nevertheless, the second-stage estimates report a positive and highly significant interactive effect between the slave trade and weather shock on the incidence and intensity of conflict. These relationships shown in Table 3.8 are consistent with the findings in the previous section, that is, the legacy of slave trade still matters on the likelihood of current conflict by amplifying the effect of adverse weather-induced agricultural income shock.

Table 3.8 Weather shock, Slave Trade, and Conflict: IV Estimates

Second Stage Dependent Var.	Conflict Incidence		Conflict Onset		# Conflict Events	
	(1)	(2)	(3)	(4)	(5)	(6)
Growing season SPEI shock	-0.015	-0.018	0.008	0.008	-0.092***	-0.085***
	(0.014)	(0.013)	(0.011)	(0.011)	(0.031)	(0.029)
Growing season SPEI shock×Slave	0.044***	0.032**	0.007	0.001	0.145***	0.101***
	(0.013)	(0.013)	(0.010)	(0.010)	(0.028)	(0.026)
Time varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	Yes	No	Yes	No	Yes
Observations	49,450	49,450	49,450	49,450	49,450	49,450
First Stage: Dependent Variable is Growing Season SPEI Shock× Slave Exports						
Growing season SPEI shock × Distance to the Seacoast	-1.6***	-1.5***	-1.6***	-1.6***	-1.6***	-1.6***
	(0.055)	(0.054)	(0.055)	(0.054)	(0.055)	(0.054)
F-stat of excl. instrument	843.74	856.84	843.74	856.84	843.74	856.84

Notes: The unit of observation is a cell-year. The time varying covariates comprise cell-level past conflict dummies and a set of country-level controls, including Polity IV indicators for democracy, indicators for rule and law, log population, and log GDP per capita. Robust standard errors clustered by cell are reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

3.5 Conclusions

In this chapter, we conduct an empirical analysis of the geographical and historical determinants of contemporaneous conflict in SSA. We construct a disaggregated dataset of observations of 0.5×0.5-decimal degrees, by overlaying the geographical information on SPEI drought index, crops land use, monthly cropping calendar, slave exports, as well as the incidence, onset, and intensity of conflict.

The first part of the study investigates the relationship between weather shock and the risk of conflict. We improve the usual measure of weather anomalies using a more comprehensive drought index and focusing on the weather variation during the crop growing season. We also control for the year fixed effects to account for the global time effects, that are often neglected in the literature. The analysis contributes to the debates on the link between climate and conflict by providing evidence that growing season weather shock, instead of whole year weather shock, has a significant and positive effect on the likelihood of conflict. The findings suggest a potential agricultural income channel through which the weather shock works.

The second part shows that the relationship between weather shock and conflict is significantly amplified in conjunction with exposure to the slave trade. The significant interaction effect on the incidence and intensity of conflict remains through a set of robustness checks. Our results shed light on the mechanisms of how geography and history jointly affect the current political outcomes. The legacy of slave trade may act as a “shock multiplier”, and certainly prove its importance in determining the modern development.

CHAPTER IV

HOW NATIONS' WEALTH INTERACTS WITH AID AND PEACE: A TIME AND COUNTRY VARIANT ANALYSIS*

4.1 Introduction

Scholars generally agree that foreign assistance, development, and conflict are interrelated but they are not agreed on the underlying causalities. Foreign aid, conflict reduction strategies and poverty eradication strategies might be made more effective with a better understanding of the causal relationships and consequences among these variables. There have been numerous empirical studies concerning foreign aid, conflict, and development, but none consider these variables together in one model.

Conflict ought to be central in the study of development for developing countries, especially for the poorest countries. In any given year over the last decade, 25-30 countries had internal armed conflict. Collier (2008) calculates that economic growth is reduced by 2.3% per year on average due to conflict. World Bank suggests that conflict is a prevalent global issue, not merely a special case, claiming that state fragility and conflict exact terribly tolls on over 600 million people across the world (World Development Report, 2011). We also find from our sample that almost 80% of conflict-affected nations are among the world' poorest countries. Conflict is portrayed as

* A previous version of this chapter has been presented by myself in the 2016 Agricultural & Applied Economics Association Annual Meeting in August 1st at Boston, Massachusetts. The title of the presented paper is "How wealth of nations interact with aid and peace: A time and country variant analysis". The authors reserve the copyright and permit to include in my dissertation all of the material from the conference paper.

"development in reverse" (Collier, 2008), or "stymieing development and macroeconomic growth" (Stewart et al., 2000).

Conflict events are not distributed randomly across the world. Collier used the term "Conflict Trap" because he found conflict incidences disproportionally occur in a group of about 50 countries, comprising "the bottom billion" population of the world (Collier, 2007). The United Nations also recognized this phenomenon and identified 29 conflict-affected countries. The assumption of conflict trap is that conflict degrades the structural factors, such as infrastructure, commerce, education, and governance, which tends to facilitate future conflict. In other words, the chief legacy of a conflict is another conflict (Collier, 2007). Compared to the "development in reverse" statement, "Conflict Trap" presents a much stronger proposition, implying that conflict-affected countries cannot emerge from poverty and conflict without foreign assistance.

The correlates of conflict are by now well-discussed. Humphreys (2003), Blattman and Miguel (2010) offer comprehensive discussions on the "causes"[4] and effects of conflicts. The correlation between low GDP per capita and higher propensities for conflicts is one of the more robust empirical relationships in the literature. Collier and Hoeffler (1998) argue that increasing income per capita is expected to decrease the probability of conflict when economic alternatives for potential rebels evolve and improve. An alternative explanation of GDP per capita is proposed by Fearon and Laitin (2003). Their point of view is that GDP per capita is a proxy for the state's overall

[4] In many cases it is still not clear whether the correlates actually cause conflict or are merely symptoms of deeper problems.

financial, administrative, police and military capabilities. In other words, the former argument suggests the "opportunity cost" theory to explain the relationship between income level and risk of conflict, while the latter argument employs the "repressive state capacity" as a supplement (Miguel, Satyanath, and Sergenti 2004). Nevertheless, Fearon and Laitin also find that per capita income is a robust predictor of civil war. Another correlate of conflict is infant mortality rates. Urdal (2005) finds high infant mortality rates to be strongly associated with an increased risk of armed conflict onset. Trade is proposed as a potential correlate but showed a less consistent relation to conflict (Blattman and Miguel, 2010). It is noticeable that conflict and development have dual effects. Besides the costs of conflict on development, leading academics (see Sachs, 2005; for example) have also advocated for poverty reduction and socio-economic development in order to reduce violent conflict.

Foreign aid is the least well-discussed correlate of conflicts. Does foreign aid really help the developing countries? Sachs (2005) argues that 0.7% of the GNP of rich countries would be enough to eliminate hunger and endemic disease if devoted to the poor of the world.[5] According to Sachs, with appropriate allocation of the increased aid resources, extreme global poverty of under a dollar per day could be eliminated by 2025. Pessimistic economists suggest that reformation and execution of aid is futile and corrupted. For example, Easterly (2006) states that the chief reason for lack of development progress in modern times is not the lack of aid; instead, he argues it is non-

[5] The world's richest countries provided just 0.33% of their GNP in official development assistance (ODA) in 2005. And the ODA has been declined in the recent years due to financial crisis.

democratic governance and corrupt politics and administration in countries receiving this aid. Through empirical analysis, Burnside and Dollar (2000) discover that aid has a positive impact on growth in those developing countries having good fiscal, monetary and trade policies, while in the presence of poor policies, aid has no positive effect on growth. Svensson (2000) and Easterly et al. (2004) find no evidence that foreign aid brings development. Ree and Nillesen (2009) offer the logic that aid donated to developing countries will help those countries to improve their economic conditions, which in turn impacts upon conflict. That is to say, foreign assistance indirectly reduces conflicts, by directly increasing economic development.

The remainder of this paper is organized as follows. In Section 4.2 we discuss the data set, variable selection and some important observations from the data, and in Section 4.3 we discuss the estimation strategy. Section 4.4 presents our results. Section 4.5 concludes.

4.2 Data

Data is collected from 79 developing countries over 1995-2010. Due to lack of statistical data, Small Island developing countries and developing countries whose populations are smaller than 500,000 are excluded from the sample[6]. The 79-country sample is quite representative for the continental developing countries.

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[6] According to World Bank, there are totally 152 developing countries in the world. We dropped 46 Small Island developing countries and 5 developing countries that have populations no greater than 500,000.

Appropriately choosing conflict variables for the empirical exercise is important. Although we follow previous researchers using the Uppsala University Conflict Data Program (UCDP) database (Gleditsch et al., 2002), we choose different measures of conflicts. UCDP defines armed conflict as “a contested incompatibility that concerns government or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths.” UCDP has two measurements of conflict events based on its definition of conflict. UCDP firstly records the number of battle-related deaths for each country-year; then a secondary measurement is created, called “conflict intensity”. Conflict intensity is measured by grades on a scale based on the number of battle-related deaths, with higher grade indicating more intensive conflict events[7]. The discrete scale measurement of conflict has been popular in the previous studies because of its fitness for econometric models for categorical dependent variables (Ree and Nillesen，2009; Collier and Hoeffler，2002; Miguel, Satyanath, and Sergenti，2004; Fearon and Laitin，2003). For instance, one can set up a threshold such as 1,000 battle-related deaths[8]. If the number of battle-related deaths passes the threshold, then it is regarded as “Conflict Onset”, while conflict fatalities below the threshold is regarded as “Conflict Ending”. In our empirical analysis, we choose to use the actual number of conflict fatalities, rather than the threshold method, for the following reasons. First, the choice of threshold level is subjective. Ree

[7] Conflict intensity is measured in the following way. “0”: battle-related death number is lower than 25 in a given year; “1”: between 25 and 999 battle-related deaths in a given year; “2”: at least 1,000 battle-related deaths in a given year.

[8] Lower threshold is battle-related deaths > 25; higher threshold could be battle-related deaths > 1,000.

and Nillesen (2009) raised concerns that dynamic analysis using either the Probit Model or Linear Probability Model in the previous literature is heavily dependent on the definition of conflict onset and duration. Their results can be changed if the threshold of conflict onset/duration is changed. Second, when transforming conflict fatality into binary states of conflict, information on volatility of battle-related deaths is missed. For instance, if a country's conflict fatalities drop from 10,000 to 1,000, but the number is still higher than the threshold, then the state of conflict intensity remains the same despite of the dramatic decline of battle-related deaths. Therefore, we use the number of conflict fatalities instead of discrete measurements as the main variable because it provides an objective, information preserving and policy-friendly way to analyze conflict-related issues. It is also worth mentioning that conflict fatalities do not include all war-related deaths (Lacina and Gleditsch, 2005). As a result, conflict fatalities are better regarded as an empirical measure of the conflict size, rather than the total exact loss of conflict.

International aid data is provided by the OECD Development Assistance Committee (DAC). Yearly data for each aid receiving country was recorded at constant US million dollars. The foreign aid data reflects the combination of loans, grants and value of technical co-operation given to developing countries. Grants, loans and credits for military purposes are excluded. Previous studies (Collier and Hoeffler, 2002; Ree and Nillesen, 2009; Nielsen et al., 2011) usually employ $\frac{Aid}{GDP}$ (aid-to-GDP ratio). However, this ratio variable ignores population effects and absolute aid changes in the long run (Juselius *et al*., 2013; Lof *et al*., 2015). Following their suggestions, we choose aid per capita as the variable to avoid the limitations of aid-to-GDP ratio. According to the OECD DAC dataset, official development assistance (ODA) includes loans where the grant element is at least 25% of the total loans.

Other primary variables of interest are the following. GDP per capita is frequently used as an indicator for wealth level. We used the PPP (purchasing power parity) -converted GDP per capita data from the Penn World Table (Version 7.1). However, GDP per capita may not reveal the distribution of incomes; for instance, a relatively rich country may have a small minority of population that enjoys the economic advancement. Thus, we also use infant mortality rate to capture the non-income development. We use the World Bank's measure of the probability per 1,000 that a newborn baby will die before reaching age five, in a given geographical area during a given year. We also consider an index of country stability from the Center for Systemic Peace, because a country's stability is closely associated with its state capacity to manage conflict and sustaining progressive development. The index is called state fragility index (SFI), which has a 25-point fragility scale: ranging from 0 "no fragility" to 25 "extreme fragility". SFI is estimated for every country based on effectiveness and legitimacy in four performance dimensions: Security, Political, Economic, and Social. In order to capture the effects of hunger, we used the food inadequacy (FI) index provided by FAO[9]. FI measures the percentage of the population that is at risk of not covering the food requirements associated with normal physical activity.

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[9] FI data is accessible from FAO Statistics: http://www.fao.org/economic/ess/ess-fs/ess-fadata/en/#.WTF9HGjys2w.

To break down the sample by income levels, we follow the World Bank and categorize sampled developing countries according to per capita GDP levels, $4,000 and $12,500. Thus, 47 countries having GDP per capita lower than $4,000 are grouped as low-income developing countries; 30 countries having GDP per capita between $4,000 and $12,500 are classified as middle-income developing countries. Another way to explore the sample in depth is to subgroup the countries by their exposure to conflict. According to United Nations, 29 countries out of the sample are labeled as conflict-prone countries. It is noticeable that there are 16 middle-income countries in the conflict-prone group, accounting for more than a half of the conflict-prone countries. Table 4.1 shows summary statistics for each variable across all sample groups.

Table 4.1 Summary Statistics across All Groups in the Sample

Variables	Overall sample		Low-income group		Middle-income group		Conflict-prone group	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conflict Fatality	262	872	363	1,060	118	447	690	1,331
GDP per capita	3,688	3,300	1,514	996	6,805	2,665	2,239	2,173
Infant Mortality	79	58	110	52	36	35	104	61
Fragility	13	5	16	4	10	5	17	5
Food Inadequacy	29	18	37	17	17	13	40	19
Foreign Aid	51	63	55	62	43	66	43	68

Column (1) and (2) in Table 4.1 present the averages and standard deviations of the primary variables of the overall sample. A typical developing country has $3,688 GDP per capita per year, receives $51 aid per year, has 79 children out of 1,000 die before the age of 5, and loses 262 people in conflict per year. The comparison across income groups shown in columns (3) – (6) reveals that low-income developing countries fall behind the middle income developing countries in every socio-economic index. The average middle-income group's GDP per capita is 4.5 times greater than that of low-income group, and the comparison ratio for infant mortality is 0.33, the FI ratio is 0.46, and the conflict fatality ratio is 0.33. However, people living in low-income countries receive only 28% more foreign aid than those living in the middle-income developing countries. Column (7) and (8) show the summary statistics for the conflict-prone group and, as expected, the average number of conflict fatalities is much higher than any other group. We also observe that all socio-economic indices excluding GDP per capita in the conflict-prone group are worse than the low-income group, even though the conflict-prone group includes several middle-income countries. It also shows that conflict-prone countries receive less foreign aid than any other groups. We make three key observations regarding the data in Table 4.1. First, higher income developing countries appear to have overall better living conditions. Second, there is room for better distribution of foreign aid according to levels of wealth and conflict exposure Third, countries more prone to conflict have lower GDP per capita and suffer from much lower living standards compared to the average developing country.

In order to demonstrate the basic relationships among these variables, we employ 3-dimentional bubble charts, which allow us to present 3 variables simultaneously, to help visualize key trends among our variables. We at first averaged these variables over the time period, then made log transformation on the time-averaged variables. As Figure 4.1 shows, each bubble represents a developing country in the sample. The larger bubble size indicates a higher level of GDP per capita. To classify different income groups, we associate 3 contrasting colors with the income levels.

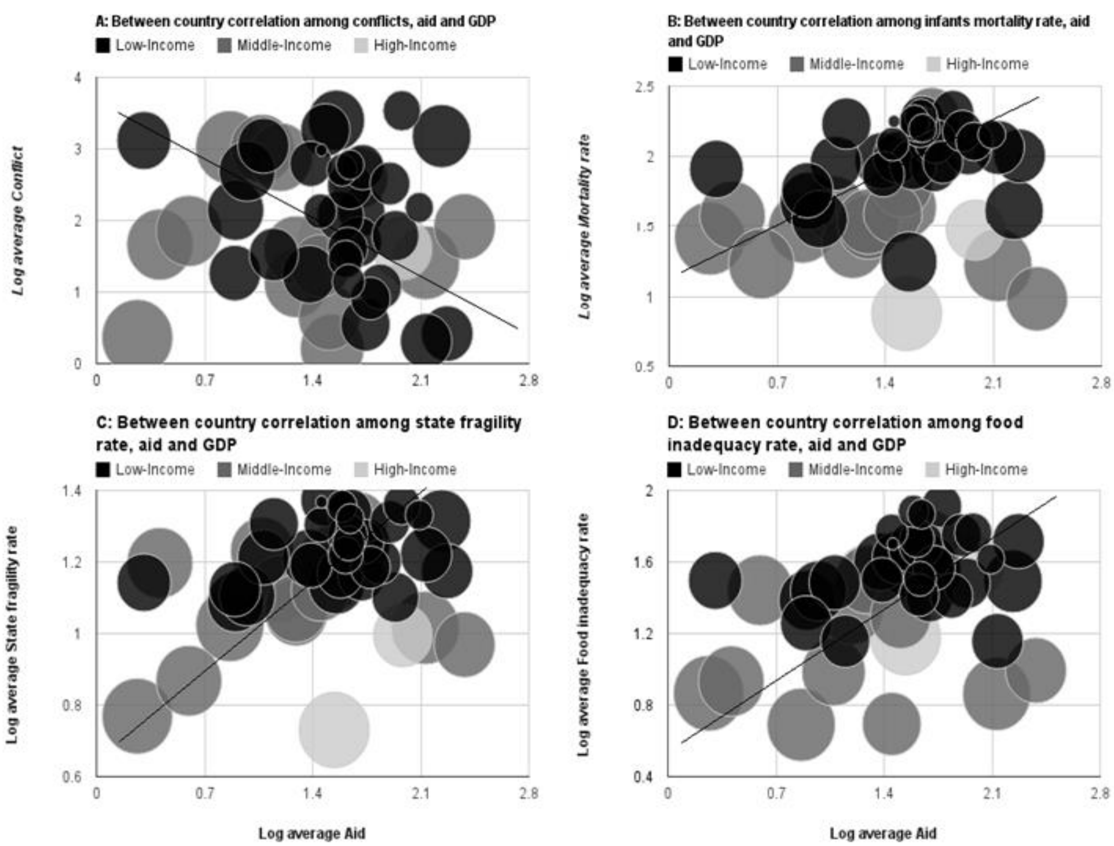

Figure 4.1 Cross Country 3-Dimentional Bubble Charts

Panel A of Figure 4.1 reveals the cross-country correlations among conflict fatality, aid, and GDP per capita. The correlation between conflict and aid seems unclear. However, if we exclude two outliers, Iraq and Afghanistan, in the right-top areas, we find a trend that foreign aid and conflict are negatively related, especially for the low-income group. This observation reinforces our findings from Table 4.1 that, foreign aid seems to flow around the conflict-affected countries. In panel B of Figure 4.1, it is evident that countries with higher mortality rates receive more foreign aid. The exceptions located at the right-bottom corner are Georgia, Lebanon, and Bosnia and Herzegovina, which are hot spots in terms of geopolitical interests and therefore receives substantial amount of aid. Another exception in the left-top corner is Iran that has a high infant mortality rate but does not receive significant international assistance during our sample period. Figure 4.1 panel C clearly shows a trend that more fragile countries receive more aid. The two outliers on the left-top area are Iran and India. Similarly, we find that countries with higher food inadequacy rates tend to receive more foreign aid in panel D of Figure 4.1. The exception on the left-top corner is Iran; while the other two exceptions located at the right-bottom corner are Lebanon, and Bosnia and Herzegovina.

Figure 4.1 provides some information on the apparent correlation among the variables of interest in the paper, but it is not enough to make conclusions about contemporaneous or dynamic causalities. Given the trends shown in Figure 4.1, we expect these variables to play important roles in analyzing the causes and effects among conflict, development, and foreign aid.

4.3 Empirical Methods

We use a panel vector auto-regressive (panel VAR) model to investigate the dynamic interdependence among conflict, development, and foreign aid. Their contemporaneous (instantaneous) causal directions are explored using methods from machine learning. The results are directed acyclic graphs (DAGs) summary of the relationships among innovations from the panel VAR.

The primary econometric model takes the following unrestricted reduced form (Hsiao, 2003):

$$X_{it} = \Gamma_1 X_{i,t-1} + \Gamma_2 X_{i,t-2} + \cdots + \Gamma_p X_{i,t-p} + \mu_i + e_{it} \tag{4.1}$$

where X_{it} is a six-variable vector $\{Conflict,\ GDP, Mort, SFI, FI, Aid\}$; $\Gamma_1, \Gamma_2 \ldots \Gamma_p$ indicate the lag operator, where the optimal lag length p is determined by Schwarz's information criterion (SBC)[10]; μ_i is a vector of unobserved fixed effects, representing country-specific characteristics in our model; e_{it} is a vector of idiosyncratic errors.

Panel VAR model has been widely used in applied macroeconomics. As a combination of the time-series VAR approach and panel data estimation techniques, the panel VAR has several advantages in analyzing the dynamic relationships among variables in the system. For instance, as Sambanis (2002) mentioned, endogeneity is one of the major problems in conflict-related research. Previously researchers attempted to overcome endogeneity by adding lagged variables in the structural model, which has

[10] The optimal lag length p=3. The detailed SBC calculation is provided in the appendix.

underlying assumption that left-hand-side variable is caused by the right-hand-side variables. Yet, the presumed direction of causality in a structural model remains contested (Pearl, 2009). Miguel *et al*. (2004) dealt with endogeneity problems by employing rainfall as the instrumental variable (IV) to study conflicts in Sub-Saharan Africa. In our study, we use the lagged variables as IV and estimate the coefficients by system generalized method moments (GMM). Panel VAR simultaneously models all the variables in the system as endogenous. Moreover, the dynamic relationships among the variables are captured by orthogonalized impulse response functions (IRFs), which is a data-driven tool derived from panel VAR model. IRFs describe the dynamic response of one variable to a one standard deviation shock in another variable, while holding the other variables constant.

As it is well known that, the variables in the panel VAR model ought to be stationary. We employed the second-generation panel unit root test to investigate stationarity. Compared with the first-generation tests, the second-generation tests relax the assumption of cross-sectional independence across different panel units. In fact, we argue that cross-sectional dependence exists in this empirical study due to spatial dependence, which is a result of globalization. Furthermore, we made a test for the presence of cross-sectional dependence in panel data, which is developed by Hoyos and Sarafidis (2006). This test performs well in panel data that is characterized by large N (cross section units) and small T (time periods). And the test results reject the null hypothesis of cross-sectional independence. We then could implement the second-generation panel unit root test. Pesaran (2007) proposed the cross-sectional augmented

Dickey-Fuller (CADF) test, with the null hypothesis of the presence of unit root. The CADF test combined the classical augmented Dickey-Fuller with the approximately lagged cross-sectional mean and its first difference in order to capture the cross-sectional dependence. The results of CADF test are reported in Table 4.2. For variables in level, we find that the null hypothesis cannot be rejected for all variables except for FI; for variables in first difference, the results show that the null hypothesis could be rejected at acceptable level of significance. Therefore, we conclude from Table 4.2 that, the variables are non-stationary in level but stationary in first difference.

Table 4.2 CADF Panel Unit Root Test Results

Variables	Value	P-Value
Conflict	16.67	1.00
Mort	7.22	1.00
GDP	-0.922	0.18
SFI	2.99	0.98
FI	-2.23	0.01
Aid	1.86	0.97
Δ Conflict	-4.44	0.01
Δ Mort	-2.05	0.1
Δ GDP	-2.17	0.08
Δ SFI	-3.36	0.01
Δ FI	-2.52	0.01
Δ Aid	-3.49	0.01

However, it has been noted that the standard first-differencing procedure results in biased coefficients while eliminating fixed effects in Eq. (4.1). Blundell and Bond (1998) showed that the first-differenced estimates tend to be overestimated, since fixed effects are correlated with the explanatory variables due to the dynamic panel data setting. An alternative to the first-differencing procedure is the following orthogonal deviations (Arellano and Bover, 1995):

$$X_{it}^* = \delta_t \left[X_{it} - \frac{1}{T-t}\left(X_{i,t+1} + \cdots + X_{iT}\right)\right], \quad t = 1, \ldots, T-1, \tag{4.2}$$

and

$$e_{it}^* = \delta_t \left[e_{it} - \frac{1}{T-t}\left(e_{i,t+1} + \cdots + e_{iT}\right)\right], \quad t = 1, \ldots, T-1, \tag{4.3}$$

where $\delta_t = \sqrt{(T-t)/(T-t+1)}$. That is, variables in each of the first (T-1) periods are transformed into deviations from their forward means. The weighting δ_t ensures equalized variance and preserves orthogonality in the transformed model. The final panel VAR model is then:

$$X_{it}^* = \Gamma_1 X_{i,t-1}^* + \Gamma_2 X_{i,t-2}^* + \cdots + \Gamma_p X_{t-p}^* + e_{it}^* \tag{4.4}$$

Our objective is to investigate the dynamic interdependence among variables, that is, how one variable of interest reacts to a one-time shock in another variable, while holding all other shocks constant. The approach we applied to orthogonalize shocks is the Cholesky Decomposition, which places some restrictions on variables ordering. It requires variables that come earlier in the ordering should be weakly exogenous with respect to the variables that appear later. For instance, if variable A is listed earlier than variable B, then A would affect B contemporaneously, but not vice versa. However, variables' lagged impacts are not restricted by Cholesky Decomposition.

Often researchers rely on previous literature or economic theory to identify the contemporaneous causal relationships. Since the literature in the area of conflict and development is not well developed, and the opinions are sometimes conflicting, we choose to follow Bessler and Yang (2006) to identify the VAR ordering. The tool we use is called DAGs, which reveal qualitative causal directions through the directed graphs analysis of the covariance matrix of e_{it}^{*} (Pearl, 2009). DAGs could be interpreted as nonparametric structural equation models (NPSEM), since they have no assumption about the functional form of the causal effects or distribution of the variables (Elwert, 2013). In a DAG, directed arrows are used to represent contemporaneous causal flows. If variables are not connected by arrows, then it implies that there is no direct contemporaneous causal effect. Our data is non-Gaussian. Thus, the LiNGAM (Linear, Non-Gaussian, Acyclic causal Models) algorithm developed by Shimizu et al. (2006) is applied here to obtain DAGs. The LiNGAM algorithm is based on independent component analysis (ICA), which is only feasible for non-Gaussian data. Once we find the contemporaneous causal order among variables, we are able to compute IRFs.

4.4 Empirical Results

As explained in the above section, DAGs recover the exogeneity for each variable in order to guide the Cholesky Decomposition in IRF computation. Figure 4.2 demonstrates the contemporaneous causal directions of the overall sample. It shows that foreign aid is not correlated with the others in the contemporary period. We also observe that GDP per capita and conflict fatality are the consequences, while infant mortality, SFI and FI are the causes in the contemporary period. This finding is repeated by the other DAG causality charts of other subgroups, which are placed in the appendix to save space.

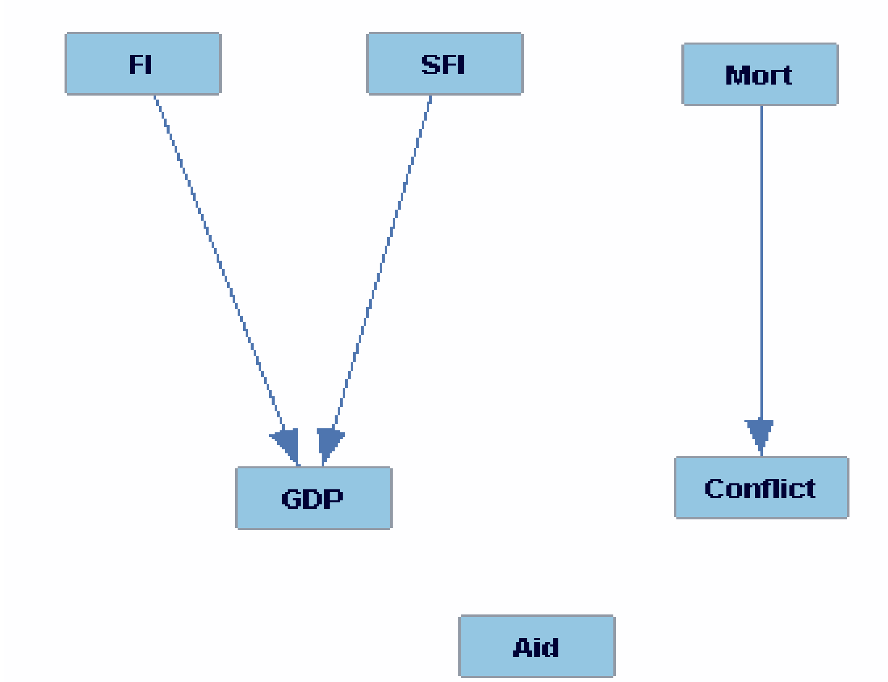

Figure 4.2 DAG Contemporaneous Causality Chart for the Overall Sample

When it comes to the dynamic relationship, it is of great interest to investigate the effects of foreign aid on reducing conflict. Figure 4.3 shows the dynamic response of conflict fatality to a foreign aid shock. The different panels in this figure provide IRFs based on different sample groups. Panel A of Figure 4.3 shows that a positive standard deviation shock to foreign aid per capita (which corresponds to a $3 increase of aid per capita with respect to its baseline) surprisingly leads to an escalation of conflict for all sampled developing countries, although the rising trend of conflict is not statistically significant. The next two panels in Figure 4.3 show similar IRFs for the conflict-prone group and the low-income group. The impact of a shock to foreign aid on conflict becomes significant in the first year for the low-income group, as it suggests in Panel C. However, the effects of foreign aid shock on conflict fatality change drastically for the middle-income group, as shown in Panel D. Comparing panels B, C and D, it appears that aid will only be able to reduce conflict in countries which have better economic infrastructure (either indicating higher opportunity cost for rebels or greater repressive capacity of the government); and for poorer or conflict prone economies an aid shock will even exacerbate conflict, although such amplifying effects are not statistically significant.

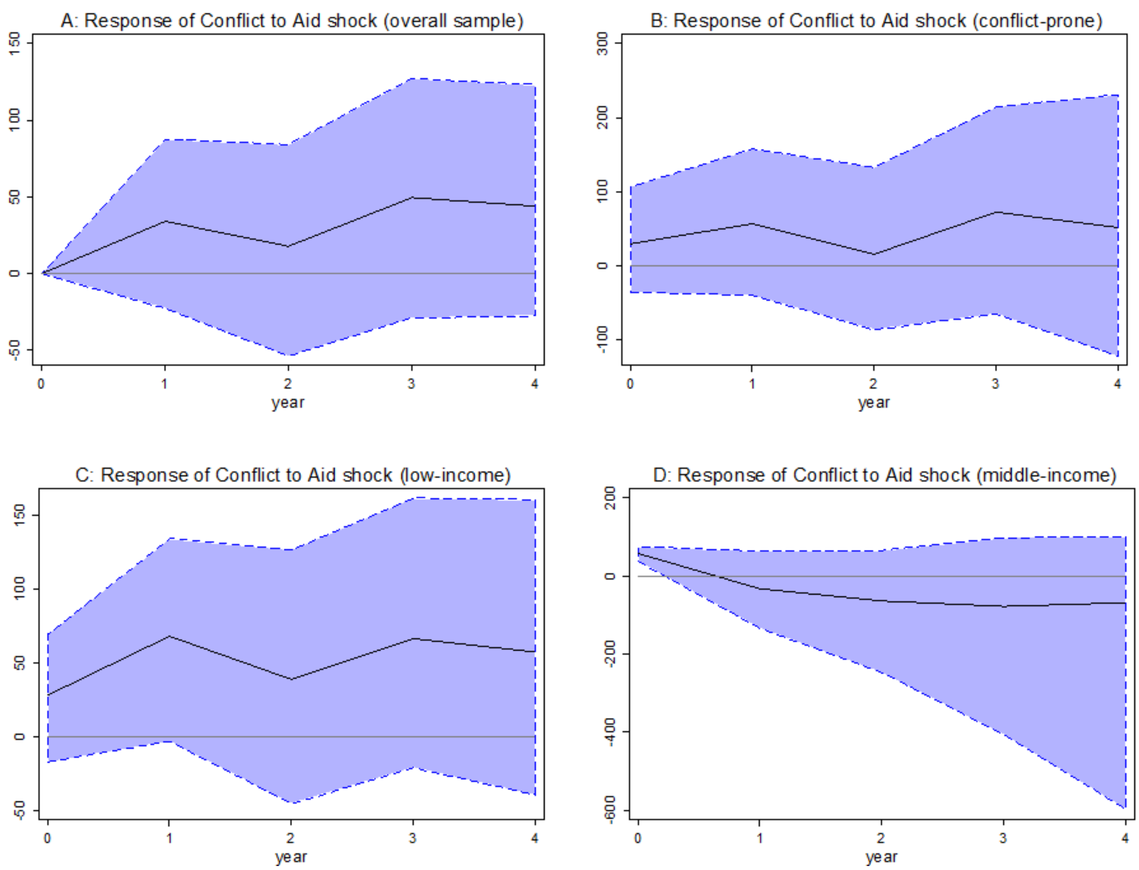

Figure 4.3 Impulse-Response Functions of Conflict Fatality to Foreign Aid

On the other hand, how does foreign aid respond to the changes of conflict? The dynamic response of foreign aid to a one positive standard deviation shock in conflict fatality is depicted in Figure 4.4. As is shown in Panel A, given a conflict fatality shock (which corresponds to an increased number of battle-related deaths by 5), the aid per capita received by a typical developing country is not significant at any period except for the second year. One possible explanation for such lagged response pattern is that most of the aid agencies make the country-specific aid decision every other year. Even the intensification of a conflict is taken into consideration by the aid agencies; their bureaucratic characteristics make them go through many steps to take an action (Easterly, 2002). At the second year, the amount of foreign aid per capita reaches the peak with the magnitude of $10, which implies that the distribution of foreign aid is quite sensitive to the escalation of conflict. The next two panels express similar reactions of foreign aid to conflict shock for the conflict-prone group and the low-income group. Panel D displays the IRF for the middle-income group, exhibiting that the distribution of foreign aid among middle-income developing countries is not sensitive to the sharpen conflicts.

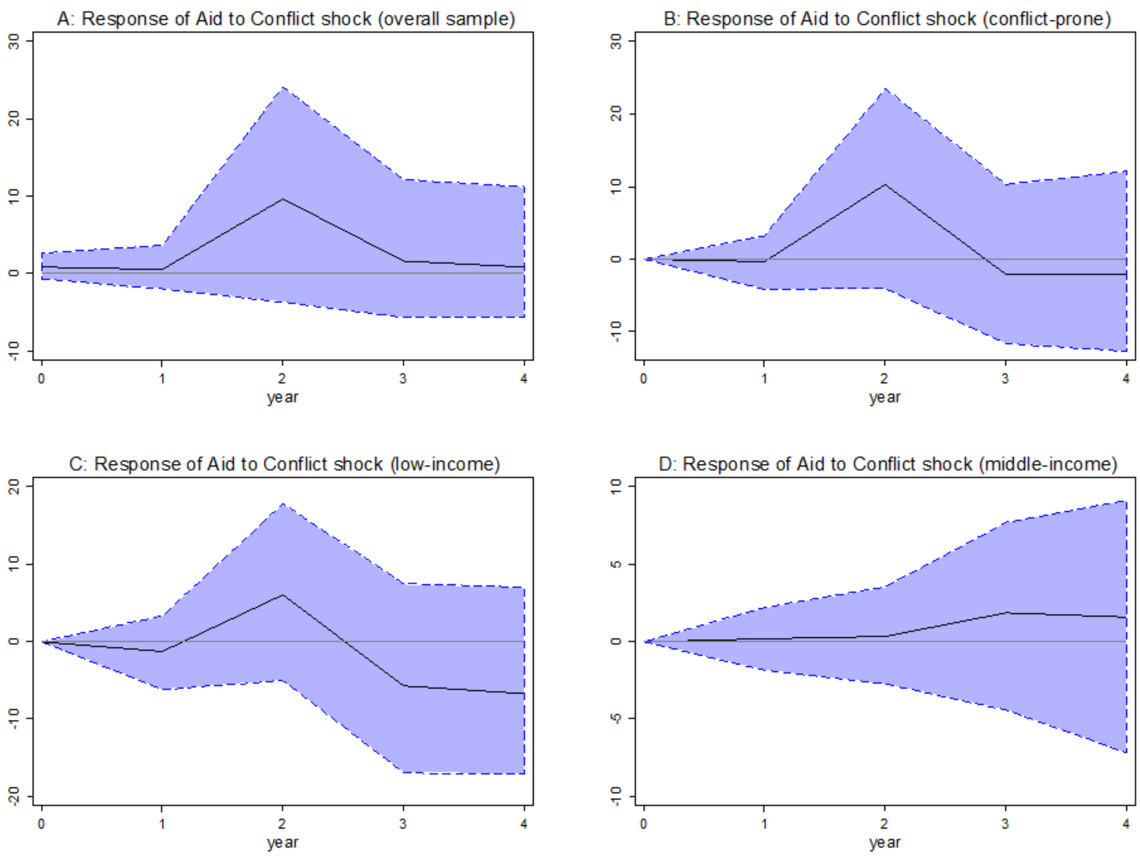

Figure 4.4 Impulse-Response Functions of Foreign Aid to Conflict Fatality

Figure 4.3 and Figure 4.4 together capture the dynamic relationship between foreign aid and conflicts. We find that income levels matter in such analysis. For the middle-income developing countries, although increasing foreign aid would lower conflict fatality, aid distribution is not very sensitive to the degree of conflict. For the low-income and conflict-prone countries, aid delivery is responsive to the degree of conflict in a two-year lag, but the outcome of increasing foreign aid turns out to be weak.

In this part, we examine the dynamic feedback effects between foreign aid and development, while holding all other shocks equal to zero. We note from Figure 4.5 that foreign aid in the conflict-prone and low-income countries is lagged responsive to a one standard deviation shock in GDP per capita. Panel B and C of Figure 4.5 show significant negative effects of GDP shock on foreign aid for the conflict-prone and low-income developing countries. Coincidently, the significant turning point of foreign aid happens at the second year after a GDP shock, which exhibits the same reaction pattern of foreign aid to conflict, as is shown in Figure 4.4. Comparing Figure 4.5 and Figure 4.6 it seems that the distribution of foreign aid relies heavily on the conditions of income development rather than non-income development. Moreover, there is large room for improving the reaction rate of foreign aid.

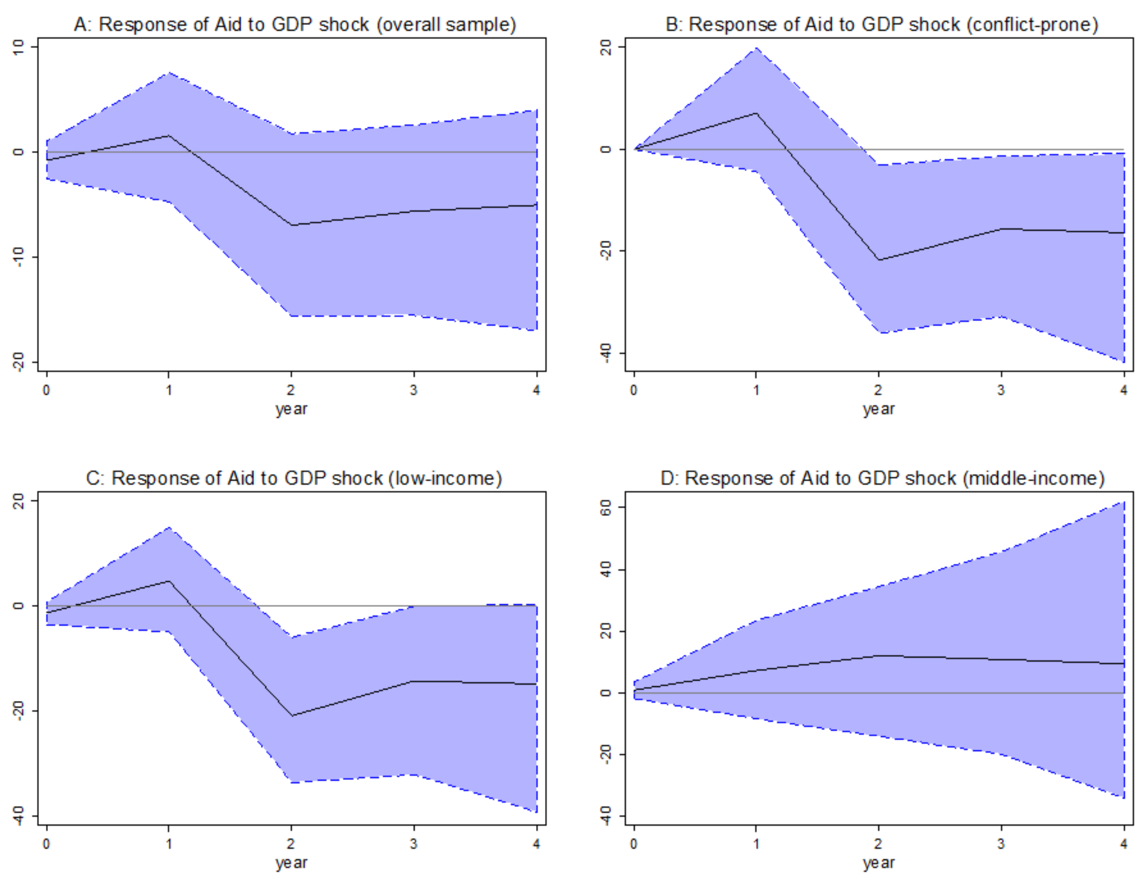

Figure 4.5 Impulse-Response Functions of Foreign Aid per capita to GDP per capita

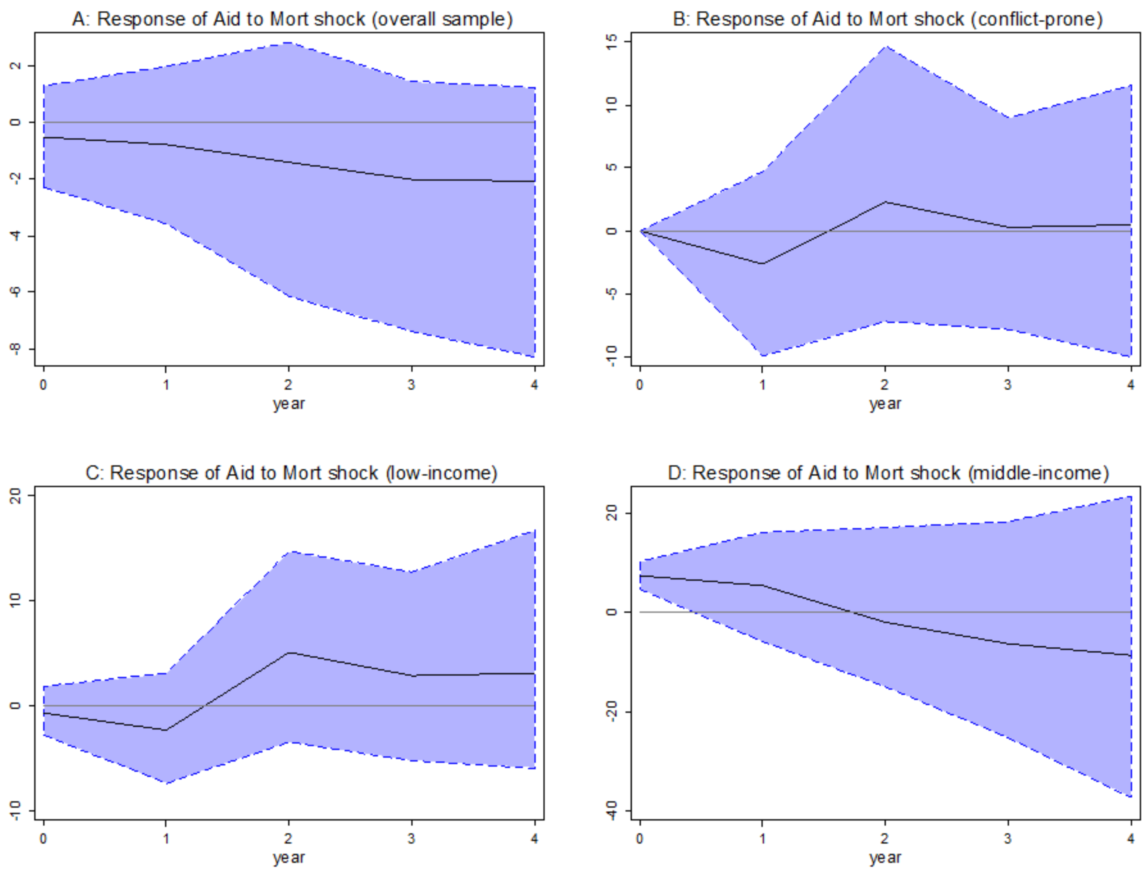

Figure 4.6 Impulse-Response Functions of Foreign Aid per capita to Infant Mortality

Another well-discussed debate is whether foreign aid really benefits the recipients in terms of development. The IRF results also contribute to this issue. Figure 4.7 shows that foreign aid shock to GDP is only positive for the low-income developing countries. Quantitatively, the level of GDP per capita will be increased by $9 with respect to an increase of foreign aid per capita by $3.3. Also, Figure 4.8 shows that infant mortality rates in the conflict-prone and low-income groups negatively respond to the shock in foreign aid. Regarding the middle-income developing countries, the effects of aid on either GDP or infant mortality rate are not significant. Therefore, an increase in foreign aid is shown to be very useful in enhancing the development of the poor and conflict-prone countries.

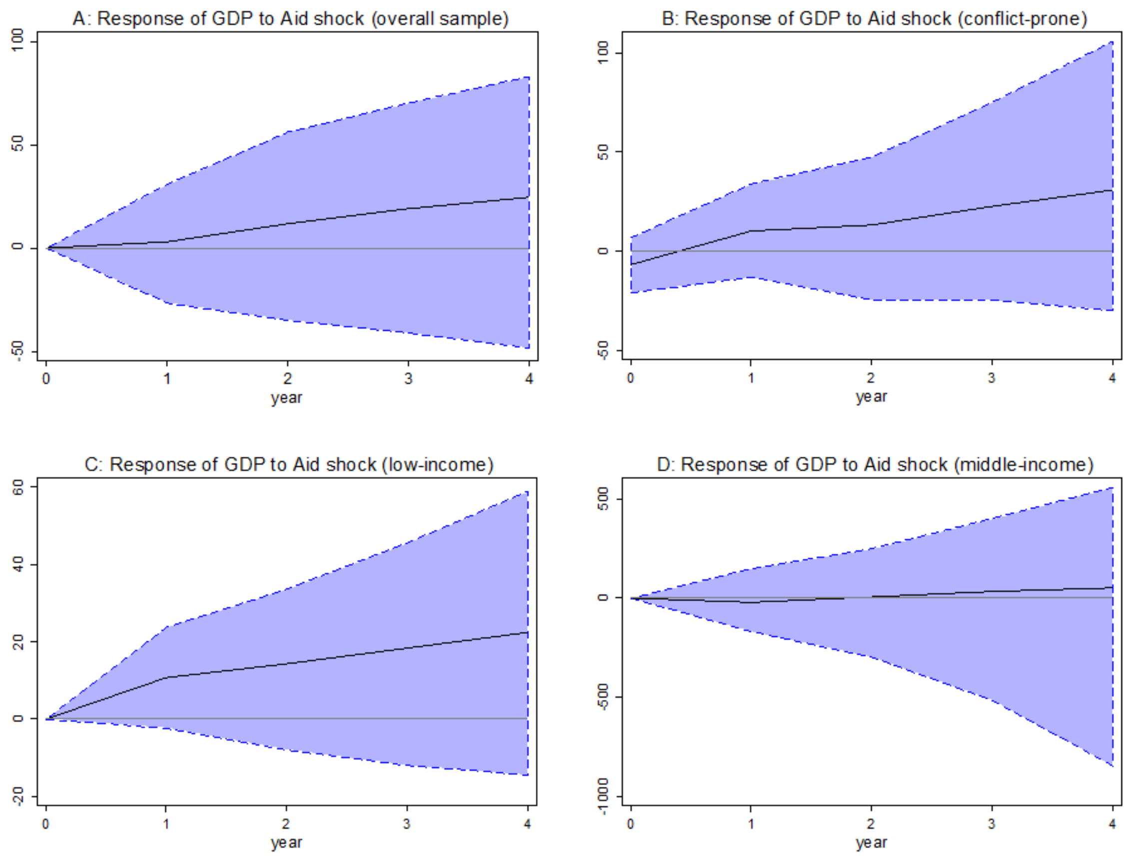

Figure 4.7 Impulse-Response Functions of GDP per capita to Foreign Aid per capita

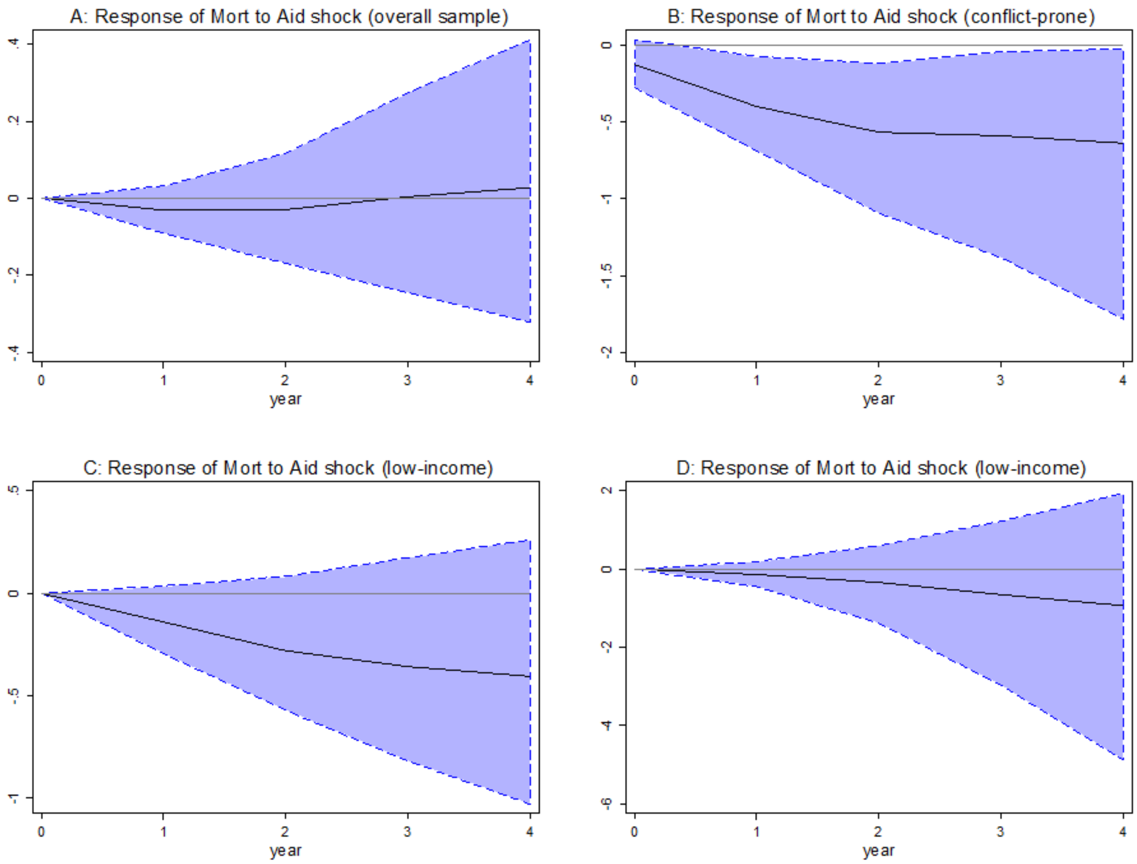

Figure 4.8 Impulse-Response Functions of Infant Mortality Rate to Foreign Aid per capita

4.5 Conclusions

The main purpose of this study is to illustrate how foreign aid interacts with the levels of development and conflict in dynamic patterns. By employing panel VAR model and directed acyclic graphs (DAGs), we are able to demonstrate how a shock (increase) to one variable results in the responding changes of another variable. It shows that the dynamic interdependences among aid, development, and conflict are largely dependent on economic and political contexts. The analysis was conducted using information on 79 nations' relative wealth and conflict proneness over the period 1995-2010. Hence, we divided the overall sample into three sub-clusters: low income countries, middle income countries, and conflict prone countries.

The most important findings of our study are that, foreign aid only appears to reduce conflict in middle income developing countries with relatively higher income level; but foreign aid performs well in enhancing the development of the poor and conflict-prone countries. In addition, we find that foreign aid is responsive to development or conflict shock in a two-year lag. We argue that foreign assistance policies of donors are reactive rather than proactive. The results of this study contribute to neo classical political thought and have policy ramifications.

CHAPTER V

CONCLUSIONS

The objective of this chapter is to summarize the research questions and empirical results of this study. The main purpose of study is to investigate the importance of historic legacy, geography, as well as external assistance shocks on the likelihood of current civil conflicts. Chapter II and III focus on the prevalence of civil conflict in SSA. Chapter IV expands the sample towards to the global developing countries.

Slave trade during 1400-1900 is one the most influential historic event in Africa. Chapter II explores the long-run effects of slave trade on current conflict in SSA. One of the contributions to the literature is that we disaggregate the country level data into hundreds of micro level regions. The first important result is that the more slaves it exported, the more likely a region is prone to civil conflict in the contemporary era. Furthermore, IV approach is employed to confirm that this relationship is causal. Taking advantage of African survey data and geographic information system technique, I also uncover the possible channels through which slave trade affects current conflict. The channels can be categorized into two ways: economic development and non-economic factors. In terms of the non-economic factors, ethnic identities, mistrust, and local institutions appear to be the main channels. I argue that the procurement and trade of slaves lead to mistrust among individuals, weakened local governance and stronger ethnic identity rather than national identity, which in turn increases the likelihood of civil conflict incidence.

Chapter III addresses the question that whether the geography (climate-war) hypothesis holds for the African countries. By constructing the unique agriculture-relevant weather shock indicators at the grid level, I show that weather shock occurred during the crop growing season are strongly associated with the risk of conflict incidence, onset, and intensity. The results provide evidence that weather variability affects the prevalence of civil conflict through agricultural production shock.

Another interesting research question considered in Chapter III is that if the climate-war relationship holds, will it affect the slave trade-war relationship. Proponents of the geography view stress the importance of geographic factors, such as climate, natural resources, and the disease environment in determining the current development and conflict. Although previous studies argue that history also matters in affecting the current economic outcomes, it shows that history influences current economic development through the channels for geographic characteristics. The results from the interaction analysis show that the exposure to the slave trade amplifies the impact of weather shock on contemporaneous conflict risk. It implies the uncovered mechanisms that history and geography can jointly affect the current likelihood of civil conflict events. In other words, the exposure to the slave trade can be regarded as a "weather shock multiplier".

Chapter IV attempts to answer the following two research questions: Can foreign aid reduce poverty? Or can foreign aid mitigate civil conflict? It is assumed that there is no one-size-fits all answer. Thus, I breakdown the sample countries by their wealth levels and conflict proneness. Both contemporaneous and dynamic relationships among foreign aid, development, and conflict are studied in this chapter. One outcome is that foreign aid is responsive to economic or conflict shock in a two-year lag. Another outcome is that the effects of foreign aid are sensitive to the countries' economic and political contexts. On one hand, foreign aid reduces conflict intensity only in the middle-income developing countries that have relatively higher income level and better economic infrastructure. On the other hand, foreign aid performs well in improving the economic and human development for the low-income and conflict-prone countries.

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APPENDIX

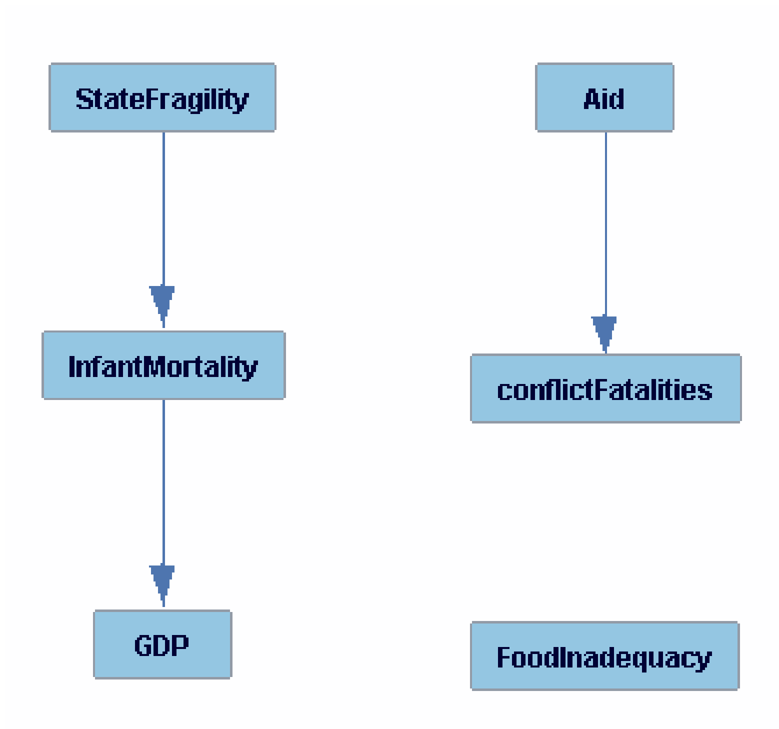

Figure A.1 DAG Contemporaneous Causality Chart for the Low-Income Country Sample

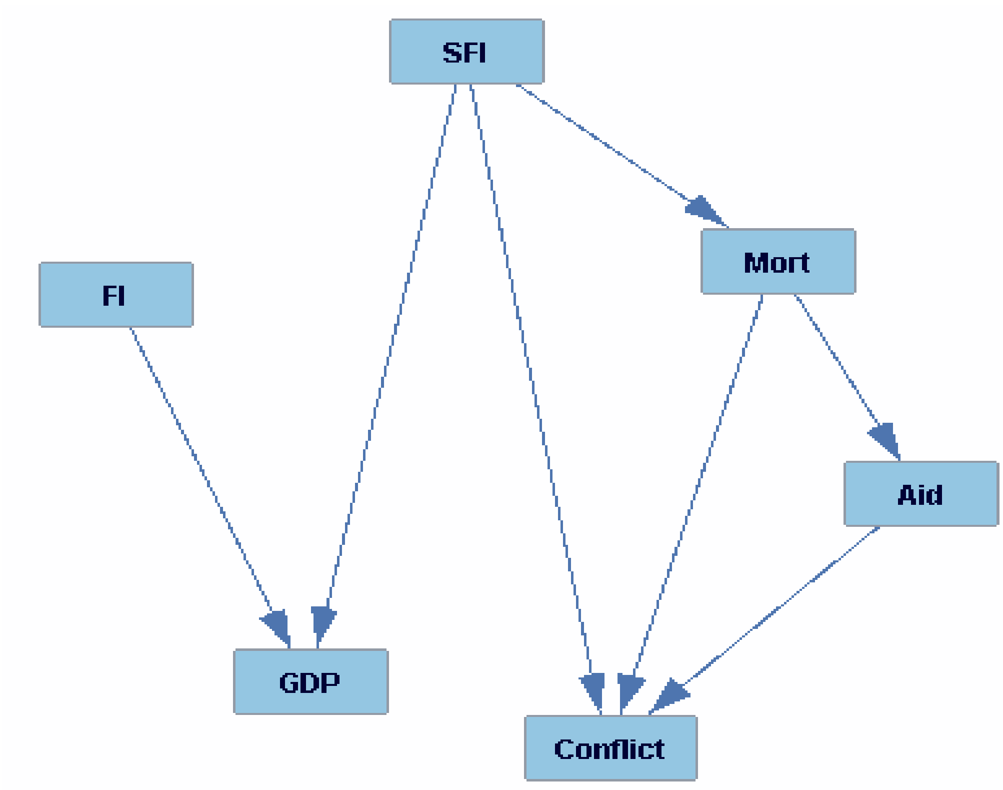

Figure A.2 DAG Contemporaneous Causality Chart for the Middle-Income Country Sample

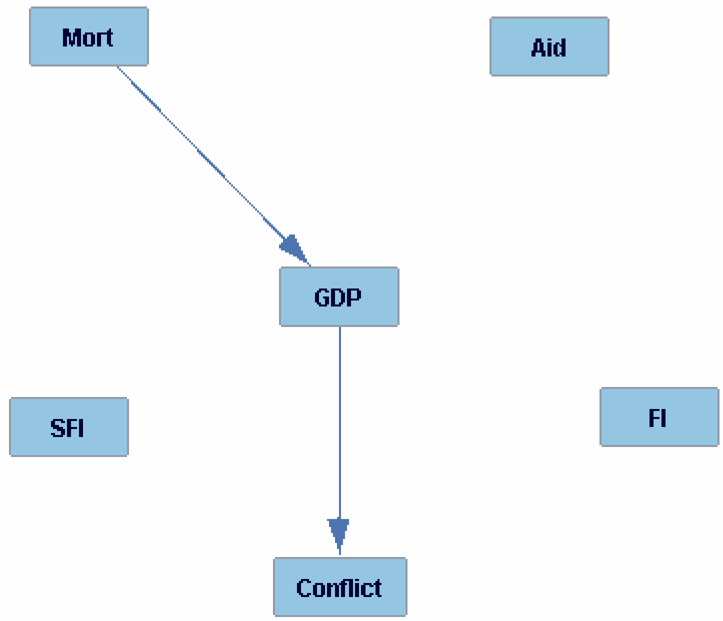

Figure A.3 DAG Contemporaneous Causality Chart for the Conflict-Prone Country Sample