Essays on Civil Conflict in Africa

Submitted by

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Declaration

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

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Signed .... (Stijn van Weezel)

Date:

Abstract

Over the past decade there has been an explosive growth in the research on civil conflict which has lead to a general understanding of the underlying factors that contribute to conflict incidence. Much of the current research results are based on the use of aggregate data, measures, and analyses. This has the disadvantage that it ignores some of the details on conflict dynamics as not all information is retained. This thesis provides four essays that look at civil conflict in Africa, trying to disentangle the complex relation between conflict and factors such as economic performance, food prices, foreign aid, and climate. The findings challenge some of the results in the literature. Focussing on the link between rainfall and conflict, looking at the effect of rainfall shocks in different economic sectors rather than aggregate output, the results show that although rainfall has an effect on agricultural and industrial output, this doesn't influence the outbreak of conflict. Investigating the relation between food prices and the occurrence of civil unrest, using within-year variation, shows that there is a weak link where higher food prices lead to more unrest due to dependence on primary commodity imports. However, these results do not generalise to out-of-sample data. Examining the effect of foreign aid on conflict intensity, the empirical analysis shows no strong proof for an effect in either positive or negative direction contrasting with the literature. Finally, focussing on the forecasts generated by a popular model linking temperature with conflict shows that the predictive power of temperature is low. In summary, the work presented in this thesis provides some new insights into the link between conflict and a variety of economic factors commonly associated with conflict. It also illustrates the use of various disaggregated approaches to study conflict dynamics.

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Chapter 1

Introduction: Civil conflict in Africa

1.1 Trends in African conflict

The research presented in this thesis tries to disentangle the complex relation between conflict and factors such as economic performance, food prices, foreign aid, and climate. Whereas each of the four chapters following this introduction provides an empirical analysis on the link between these particular factors and conflict, this introductory chapter aims to give a more generalised overview of civil conflict in Africa.[1] This chapter will describe some of the broader trends and developments concerning conflict that have taken place across the African continent in the past six decades. Additionally, this introduction also provides a concise outline of what is covered in the other chapters in this thesis.

[1] Note that I focus here on civil conflict as this is the most common type of conflict in Africa. Interstate conflicts are relatively rare: in the past 25 years there have been only 6 such instances. I won't go into detail on the prevalence of interstate conflict in Africa as this is beyond the scope of this introduction.

The African continent has been the focus of a myriad of studies on civil conflict as many African countries have experienced protracted periods of violence over the past 60 years. Figure 1.1 shows the number of conflict-years between 1960-2013. It illustrates that countries without a history of violence, such as Botswana, are relatively rare exceptions. Most countries had some sort of civil conflict, with varying intensity, within their country borders in the past sixty years.

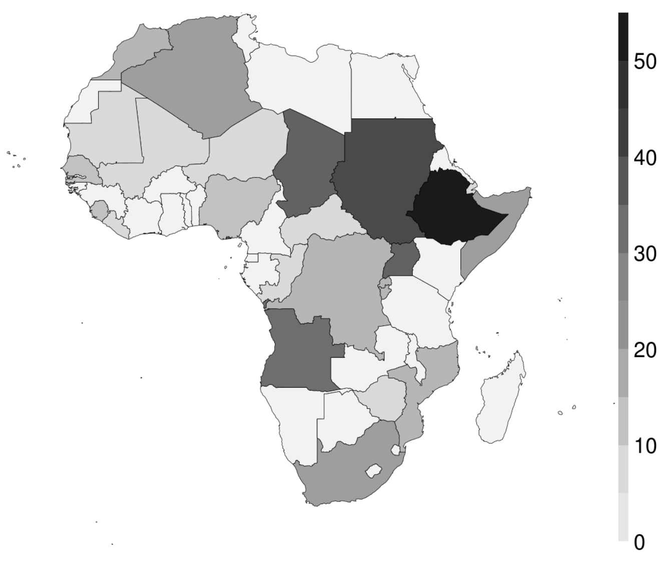

Figure 1.1: Number of conflict-years per country, 1960-2013. Data: PRIO/UCDP

If we consider the trend in conflict over time, comparing Africa to the rest of the world (upper left figure 1.2), we see that over time there has been a steady increase in the number of conflicts. The upward trends seems to coincide with the decolonisation period in the 1960s and the Cold War era. During this period the African trend largely mirrors the world wide increase in conflict.

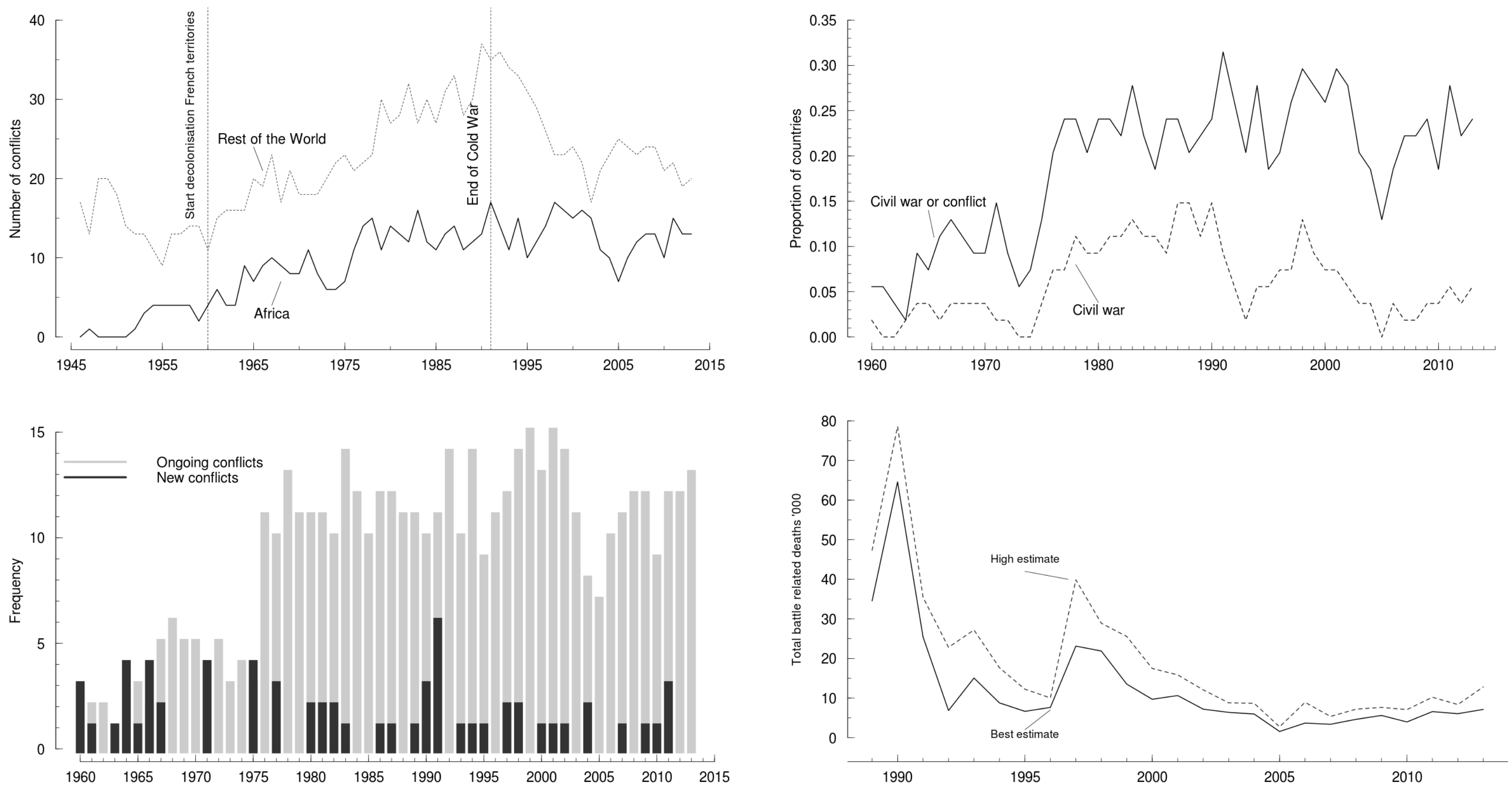

Figure 1.2: *Upper left:* Overview of conflict prevalence in Africa and rest of the world, 1946-2013. Data: PRIO/UCDP. *Upper right:* Proportion of African countries with active civil conflict/war, 1960-2013. Data: PRIO/UCDP. *Lower left:* Incidence and onset of civil conflict in Africa, 1960-2013. Data: UCDP/PRIO. *Lower right:* Battle-related deaths in Africa, 1989-2013. Solid line gives the best estimate, dashed line gives high estimate. Data: UCDP

At least part of this increase can be attributed to exposed rifts between factions in the decolonisation struggle (see Michalopoulos and Papaioannou (2015)) as well as due to the involvement of the superpowers in domestic politics in various proxy wars (e.g. Zaïre, Angola, and Mozambique). It is only after the end of the Cold War and largely peaceful disintegration of the Soviet block that the African trend starts to diverge from world wide conflict trends. In other parts of the world there is a noticeable decrease in the number of conflicts whereas in Africa the number of conflicts at any given year remains almost unchanged compared to the 1980s peak level.
For many, conflict may seem almost like a characteristic feature of Africa which is not entirely surprising given that about 75% of the countries have experienced violent armed conflict since 1946. Since decolonisation in any year around 15 to 25% of African countries experienced civil conflict within their borders (upper right figure 1.2). However, as gloomy as these statistics might seem there are some nuances with regard to Africa's conflict dynamics.

We already saw that conflict prevalence since the 1990s is higher in Africa compared to the rest of the world. This seems to be the results of the fact that while in other parts of the world armed conflicts have terminated since the end of the Cold War (Kreutz, 2010), in Africa we mainly see a continuation of existing conflicts, sometimes only briefly interrupted (figure 1.3). Many conflicts that we observe in Africa today are conflicts that have been going on for some time, such as in Sudan and Somalia, but in general the outbreak of a new conflict is not very common (lower left figure 1.2). There has been some progress though with the end of bloody post-colonial wars in Angola and Mozambique as well as the end of various severe civil wars such as in Ivory Coast, Liberia, and Sierra Leone. This has lead to a steady decline in the number battle-related deaths (lower right figure 1.2), which is also documented in the work by Pinker (2011). Civil wars, which are conflicts with more than a 1,000 battle-related deaths per year, are relatively uncommon (again upper right figure 1.2).[2]

Another important feature of civil conflict is that it tends to be highly localised. For most cases of civil conflict we see that these conflicts occur in particular regions, but that not necessarily the entire country is in engulfed in violence. For example, the statistics show that Ethiopia has experienced more than 50 years of conflict in the past 60 years. However, the conflict intensity if often low and very localised. Focussing on the period between 1989-2010 for which we have good sub-national data (figure 1.4) we can see that although various battle events occur throughout the country, the number of battle events is low and occur predominantly in the Ogaden region near the Somali border.[3] This is just one example where we see that conflict seems to be confined to a particular region. There are similar patterns in other countries. Examples of this include Acholiland in Northern Uganda, the Kivu region in the Eastern part of the Democratic Republic of the Congo, as well as the current unrest in the North of Nigeria.

[2] This figure of course doesn't capture other human suffering that these conflicts often cause such as displaced populations.

[3] These events are likely influenced by the situation in Somalia itself.

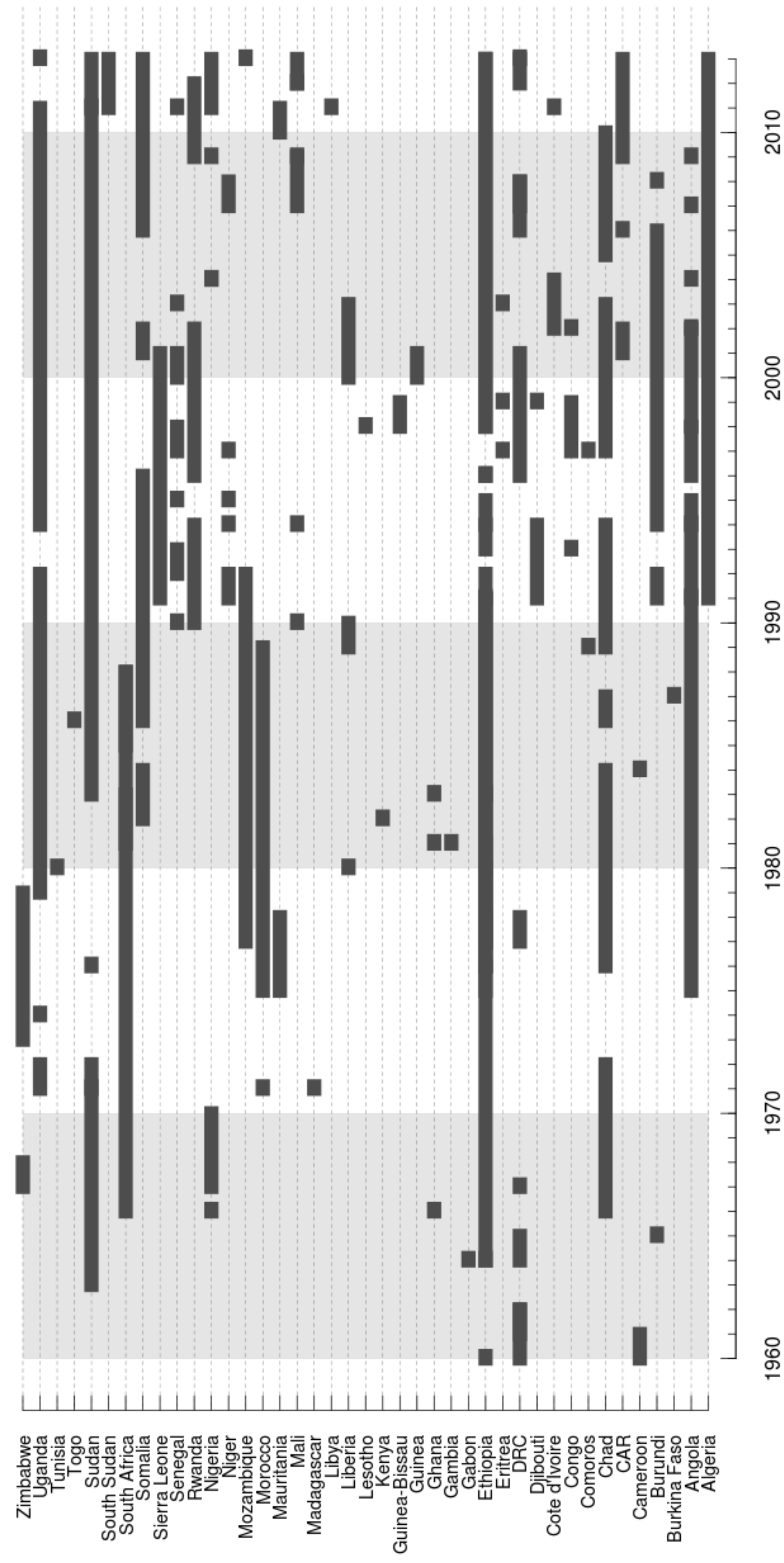

Figure 1.3: Civil conflict-years in Africa, 1960-2013. Data: UCDP/PRIO

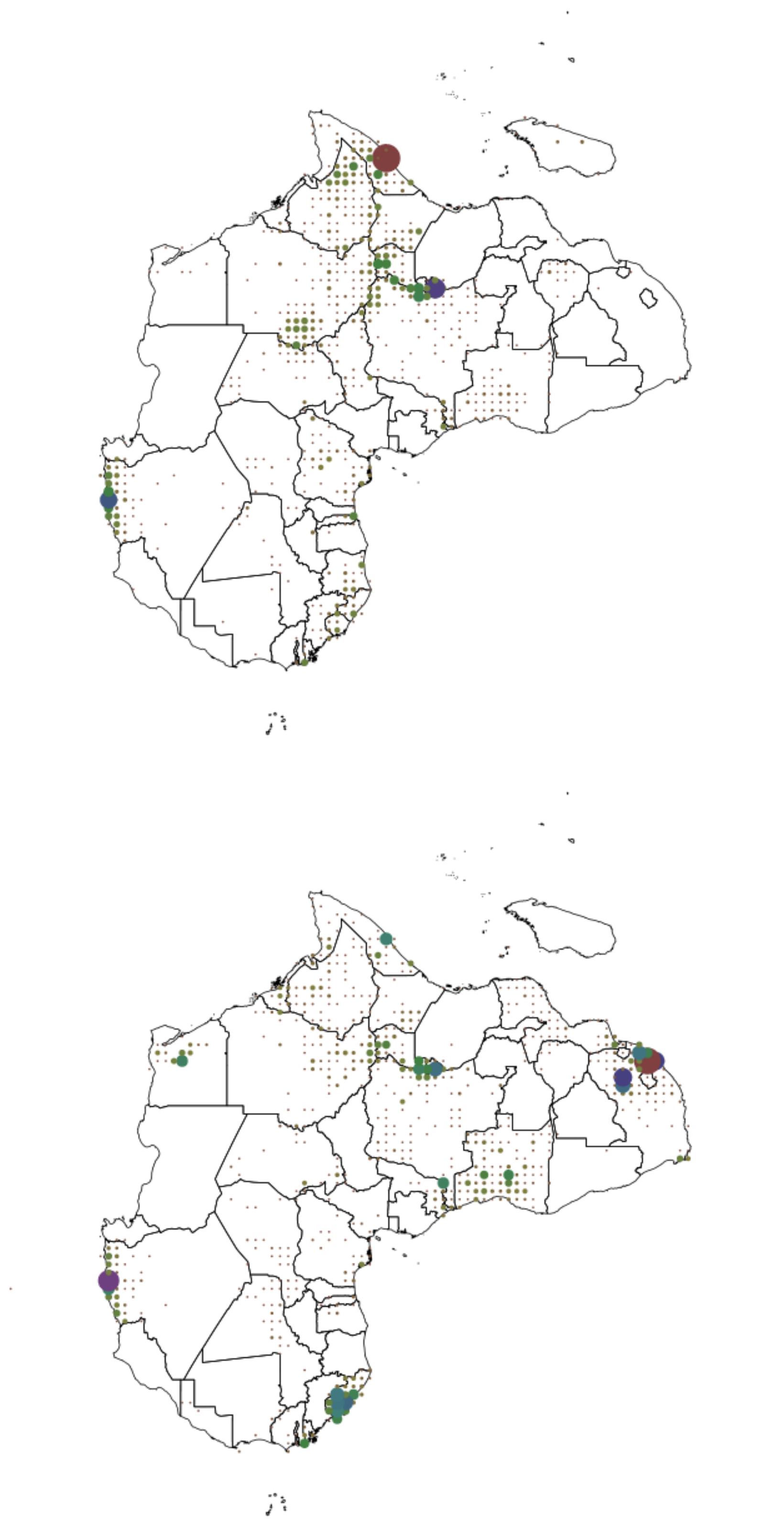

Figure 1.4: Number of local conflict events for 1989-1999 (*left*) and 2000-2010 (*right*). Larger dots indicate larger number of events (events aggregated to 1x1 degree grid-cells). Data: UCDP Georeferenced Event Dataset

1.2 Thesis outline

Over the past decade there has been an explosive growth in the research on civil conflict which has lead to a general understanding of some of the underlying factors that contribute to conflict incidence (see Dixon (2009) and Blattman and Miguel (2010) for an overview). The research presented in this thesis focuses on Africa and consists of four chapters that each provide an empirical analysis of how four factors (economic performance; food prices; foreign aid; climate) are linked to civil conflict.

Chapter two examines the relation between income shocks and conflict in Sub-Sahara Africa between 1981-2010. Income shocks are instrumented by rainfall due to possible endogeneity in GDP data as conflict feedbacks into economic performance. So far the literature on rainfall and conflict has produced inconclusive results. One of the shortcomings in the literature that I address is that rather than looking at the effect of rainfall on aggregate output I estimate the effect in different economic sectors (agricultural and industrial). Using aggregate output might not be appropriate to estimate the effect of income shocks on conflict as rainfall likely affects each economic sector differently. Re-examining the link between income shocks and conflict, accounting for these diverging effects, I find that there does not seem to be strong evidence for a link between rainfall and conflict. Although rainfall affects both the agricultural and industrial sector, its effect on aggregate output is weak and the link with conflict is not robust to different model specifications.

Chapter three provides a study on the effect of food prices on the incidence of violence in Africa between 1990-2012. The real level effect of food prices on violence is estimated using a country-specific food price index based on a country's import pattern of major food commodities based on international food prices as they are a source of exogenous shocks. The regression results show that between 1990-2011 increases in the food price index are associated with higher levels of violence. Moving from low to high values in the price index corresponds, after controlling for economic, social, and political factors, with an increase in violence intensity of 1.3 incidents. This effect seems to be predominantly driven by imports of low-value added primary products. Despite the statistically significant results the predictive power of food prices is relatively low though. To scrutinise the results I use out-of-sample data from 2012 for cross-validation. The results indicate that the model correctly predicts only 36.8% of violent incidents and in general underestimates violence intensity.

The fourth chapter looks at the link between foreign aid and conflict intensity. Although most aid projects are aimed at local development and conflict tends to be highly localised, most research on aid and conflict uses the country-year as unit of analysis. A lot of information is potentially lost due to this level of aggregation. I address this issue by examining the nexus at the sub-national level for three African countries (Democratic Republic of the Congo, Ethiopia, Sudan) between 1999-2008, using a unique dataset with information on local aid projects. The data shows that while aid is generally allocated relatively close to the capital, conflicts occur mainly in the peripheral areas. In contrast with the existing literature the study results do not show a strong effect aid on conflict. The analysis provides relatively little empirical support for a link in either positive or negative direction. However, some of the results do indicate that non-fungible aid, or aid that is not easily diverted from its intended purpose, corresponds with decreases in conflict levels. This might suggest that aid increases the opportunity costs of rebellion, although the magnitude of the effect is very low.

The fifth and final chapter is slightly different in character as it provides a critique on the literature rather than presenting results from new research. It focuses on the research on climate-conflict, although the suggestions made probably also apply to the larger conflict literature. Within the quantitative literature on violent armed conflict we see that there is a heated debate on the effect of climate change on the incidence of civil conflict. This discussion predominantly focuses on the robustness of results to different model specifications and extended datasets. However, there is very little attention for the forecasts generated by the models. Generated predicted probabilities are largely ignored and not included in the analysis. In this chapter I try to illustrate that examination of a model's forecast can be a useful analytical tool to scrutinise a model's performance. The study focuses on the link between temperature and conflict in Sub-Sahara Africa between 1981-2002 and finds that although the regression model has large in-sample predictive power, the performance of the temperature variable is low. Generating out-of-sample predictions for 2003-2013 illustrates that temperature has almost no predictive power.

Chapter 2

Economic shocks and civil conflict onset in Sub-Sahara Africa, 1981-2010

2.1 Introduction

Economic conditions are often singled out as a prime cause of conflict. The empirical literature has, over the years, provided a substantial amount of proof for the claim that low income levels and poor economic performance are associated with conflict (for an overview of the literature see Hegre and Sambanis (2006), Dixon (2009), and Blattman and Miguel (2010)). Within the literature two patterns can be distinguished: firstly that poor countries have a higher propensity to suffer from conflict, and secondly that conflict occurs when countries suffer from negative income shocks (Chassang and Padró i Miquel, 2009). One region in particular has been the focus of much research: Sub-Sahara Africa (henceforth Africa). This region harbours some of the poorest countries in the world and has high conflict prevalence levels, especially compared to similar regions in Asia and the Americas. Although poor countries are disproportionally involved in conflict, the direction of the effect may be difficult to establish (Besley and Persson, 2008). A common problem is that a lot of research suffers from endogeneity issues, particularly reverse causality. There are also other issues such as omitted-variable bias and the fact that data quality for countries of interest is generally poor (Heston, 1994).

To account for these problems Miguel, Satyanath, and Sergenti (2004) (henceforth MSS) use an instrumental variable (IV) approach, exploiting variation in rainfall as a source of exogenous shocks to income. In their seminal work they found that economic growth is strongly related to civil conflict, with low growth rates increasing the risk of conflict.[1] Over the years, a number of other studies have examined the relationship between rainfall variation and conflict, using rainfall as either a measure for changes in climate or to proxy for economic conditions. So far the results have been mixed with no clear consensus on the direction of the effect (Hendrix and Glaser, 2007; Brückner and Ciccone, 2010; Ciccone, 2011; Koubi et al., 2012; Raleigh and Kniveton, 2012; Hendrix and Salehyan, 2012; Fjelde and von Uexkull, 2012; Hodler and Raschky, 2014b).

In this chapter I re-examine the relationship between variation in rainfall, economic shocks, and conflict using the latest data on Africa for 1981-2010 and by focussing on conflict onset in order to identify a possible causal link. In contrast with the existing cross-country literature, I also examine the effect that income shocks in different economic sectors have on the probability of the outbreak of conflict. As Dunning (2008) notes, the likelihood of conflict could be influenced by the sector of the economy experiencing the shock. Dal Bó and Dal Bó (2011) give a theoretical framework arguing that not all positive shocks to the economy will reduce the probability of conflict but that it depends on the sector and its labour intensity relative to the economy. Within

[1] Due to the innovative approach their paper has quickly become one of the standard works in the literature. It has been cited 375 times since it was published in 2004 (according to Web of Knowledge in April 2015)

this framework positive shocks to labour intensive sectors will diminish conflict risk while positive shocks to capital intensive sectors will increase the risk. Dube and Vargas (2013) illustrate this in a study on the effects of exogenous price shocks in international commodity prices on the intensity of violence in the Columbian civil war. Their results show that a fall in prices of labour-intensive agricultural good (coffee) increased violence in regions dependent on income from the agricultural sector due to the fact that lower wages also lowered the opportunity costs of joining armed groups. In contrast, a fall in the price of capital-intensive natural resources (oil in this case) decreased violence as it lowered municipal revenue and thus the value of contestable resources.

This study contributes to this strand of literature by examining the effect that shocks in different economic sectors have on the probability of conflict onset, focussing on the agricultural and industrial sector. Since the agricultural sector in Africa is labour intensive, negative shocks to this sector are expected to increase conflict likelihood according to the analysis by Dal Bó and Dal Bó (2011) and Dube and Vargas (2013). Where Dube and Vargas (2013) provide empirical evidence for the theoretical framework of Dal Bó and Dal Bó (2011), the main contribution of this chapter is that, to the best of my knowledge, it is the first cross-country study that examines the effect of different economic sectors on civil conflict. I solely focus on conflict onset, rather than conflict incidence, as the former is more appropriate to establish a causal link. The main issue with using conflict incidence as the outcome variable is that the assumption that rainfall or economic shocks affect the continuation of conflict in the same way as the outbreak of new conflict is problematic on theoretical grounds and likely to be violated (Ciccone, 2011; Bazzi and Blattman, 2014). Considering the costs associated with initiating a conflict, and those with joining an already ongoing conflict, it is straightforward to see that these costs will be different. Since conflict disrupts the economy and affects economic performance, the opportunity costs for joining an already existing rebellion will be lower compared to those of initiating a new conflict (Collier and Hoeffler, 1998).

Using conflict incidence as the outcome variable neglects the issue of reverse causality between conflict and economic performance and therefore one cannot make any causal claims about the examined link.

In the analysis I find that rainfall is a viable instrument for economic growth although the effect of rainfall on aggregate economic growth becomes considerably weaker after 2000. Moreover, using year-on-year rainfall growth as an instrument gives considerably weaker results compared to using rainfall anomalies. Current shocks in rainfall are significantly and positively linked to economic growth where a standard deviation increase in rainfall corresponds to a 0.5 to 1 percentage point increase in economic growth. This is considerable considering the average economic growth of Africa for 1981-2010. The effect of rainfall on productivity is strongest in the agricultural sector but there is also a positive and significant effect in the industrial sector. This might be due to the importance of hydro-electricity as well as the use of water as a cooling agent in factories (Barrios et al., 2010). With regard to the link between rainfall and conflict the results are very mixed. In a reduced form estimation I find that lagged shocks in rainfall affect conflict onset but the coefficients are only marginally statistically significant and not robust to different model specifications. In a model estimated using IV, with economic growth rates predicted by variability in rainfall, the results are similar with a marginally statistical significant effect for lagged growth rates. If I instrument economic growth with year-on-year rainfall growth I find that lagged growth rates are negatively associated with conflict onset at 90 % confidence level, but the results are again not robust to different model specifications such as using rainfall anomalies as an instrument or using a different outcome variable. Using an outcome variable with a 5-year intermittency period for conflict I do find that the direction of the effect is consistent -though not significant- across the various models: higher levels of rainfall reduce the likelihood of the outbreak of conflict. The estimation results are inconclusive with regard to the effect of shocks in the different sectors of the economy on conflict onset. For both the agricultural and industrial sector it seems that positive shocks are linked to a decreased probability of conflict onset but the estimates are characterized by large uncertainty. Moreover, the coefficients are lower compared to aggregate output and statistically insignificant. I am therefore hesitant to make any strong claims with regard to how different sectors influence conflict likelihood.

2.2 Existing literature

One of the major issues in the conflict literature is that research results are often not robust to different model specifications, the use of different data or hampered by issues such as endogeneity (Hegre and Sambanis, 2006). One of the very few findings that does seem to be robust however is the nexus between economic conditions and conflict (see Dixon (2009) and Blattman and Miguel (2010) for an overview).[2]
Within the literature there are two main patterns: one is that poor countries have a high propensity to experience civil conflict and the second is that civil conflict is more likely to occur when a country suffers from negative income shocks (Chassang and Padró i Miquel, 2009). A prominent example is Collier and Hoeffler (1998) who argue that poorer countries are more likely to experience conflict due to lower opportunity costs for rebellion. When a country experiences disappointing economic growth rates utility maximising arguments prevail over arguments of political marginalisation as an explanation for conflict. Fearon and Laitin (2003) on the other hand argue that poor economic performance is a proxy for weak state capacity. Governmental incompetence, expressed in a weak military apparatus and poor infrastructure, hampers deterrence and capabilities to quell insurgencies. These low repressive capabilities connect poverty and civil conflict.

It can be hard to establish the direction of causality between economic conditions

[2] The paper by Djankov and Reynal-Querol (2010) is one of the few that contradicts the conclusion that poverty is a main determinant of conflict.

and conflict due to issues such as omitted variables bias and endogeneity. The paper by MSS is one of the pioneering works in addressing these issues and has quickly become one of the pillars of the conflict literature. The authors use rainfall growth as an instrument for gross domestic product (GDP) per capita growth and show that positive rainfall growth is strongly negatively correlated with civil conflict. This effect is not significantly different for richer, more democratic, or more ethnic diverse countries. A number of other studies have looked at the link between rainfall and conflict, either examining the direct relationship or by using rainfall to proxy for economic growth.[3] The paper by Hendrix and Glaser (2007) looks at the effect of interannual changes in rainfall and conflict onset in Africa and finds that positive shocks have a pacifying effect and reduce the likelihood of conflict, very similar to the results by MSS. Hendrix and Glaser (2007) argue that short-term shocks in rainfall (yearly growth rate) are a better predictor of conflict than changes in the overall climate over a longer period of time. Hendrix and Salehyan (2012) find that civil war and violent insurgencies are more likely to follow after a year of abundant rainfall, relative to the historical expectation. Thus linking higher rates of rainfall with conflict, contrasting with earlier results. The study by Raleigh and Kniveton (2012) on Eastern Africa finds that the frequency of rebel and communal conflict events increases in periods of extreme rainfall variation and that the effect is present in both cases of negative and positive variation.

This results is somewhat similar to the study by Fjelde and von Uexkull (2012) who use a disaggregated approach combining rainfall data with geo-referenced events data on the occurrence of communal conflict in Africa between 1990 and 2008. The main difference between these two studies is the direction of the effect as Fjelde and von Uexkull (2012) find that only large negative deviations from the historical mean are associated with a higher risk of communal conflict. Rather than focussing on the direct effects of rainfall and conflict, Koubi et al. (2012) examine the causal pathway linking climatic conditions

[3] In this short review I focus on the papers that have looked at the link between rainfall and conflict. For an insight into the relation between rainfall and economic growth I refer to Barrios et al. (2010) and Dell et al. (2012).

to economic growth and violent conflict. In their analysis they find no evidence for the claim that rainfall, or climatic variability in general, affects economic growth.

The MSS paper has also attracted a fair share of criticism based on that the model is agnostic to the sector experiencing the shock (Dunning, 2008), the fact that they erroneously code the outcome variable to include countries participating in civil wars in other states (Jensen and Gleditsch, 2009), and most forcefully by Ciccone (2011) who argues that the results are driven by a positive correlation between conflict in t and rainfall in $t - 2$.

2.3 Data and measurement

2.3.1 Civil conflict

Data on conflict onset comes from the UCDP/PRIO Armed Conflict Dataset, version 4-2011 (Themnér and Wallensteen, 2011) limiting the outcome variable to only instances of intrastate or civil conflict. I include all cases with at least 25 battle-related deaths in a single year.[4] I do not discriminate between conflict and war, the latter typically classified passing the threshold of 1000 battle-related deaths in a single year.[5]

To capture the outbreak of conflict I define a binary onset-indicator for country c in year t that is 1 if there is a conflict in year t but not in year $t-1$ and 0 if there is no conflict in both year t and $t-1$. If there is a conflict in year $t-1$ then the indicator is not defined for t:

$$Onset \begin{cases} 1 \text{ if conflict in } t \text{ but not } t-1 \\ 0 \text{ if no conflict in } t \text{ and } t-1 \\ . \text{ if conflict in } t-1 \end{cases} \tag{2.1}$$

When trying to identify the relation between outcome and explanatory variables, there is a difference whether one uses incidence or onset. As Bazzi and Blattman (2014) note, there are both conceptual and empirical problems with the approach of using

[4]Data is taken from the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002). Civil conflicts are all observations coded as type 3 or 4 in the data set. A type 3 conflict is defined as *"an internal armed conflict that occurs between the government of a state and one or more internal opposition group(s) without the intervention from other states"*. A type 4 conflict is similar only allowing for the intervention from other states on behalf of one or both sides (Gleditsch et al., 2002).

[5]A conflict is defined as: *"a contested incompatibility that concerns government and/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."*.

conflict incidence.[6] Conceptually, using conflict incidence one assumes that rainfall and economic growth affect the continuation of existing conflicts in the same way as the outbreak of new ones (Ciccone, 2011). From the literature we know that violence is associated with shocks as it affects wages (Besley and Persson, 2011), accordingly we would therefore expect that the effect of such shocks is larger in pre-existing conflicts than it is for new conflicts. Collier and Hoeffler (1998) note that starting an insurgency is costly as it brings with it the opportunity costs of rebel labour as well as the costs incurred by the disruption of the economy. A rebellion will therefore only occur if the benefits outweigh the costs. Starting a conflict includes some fixed costs. In the case of an already ongoing conflict this fixed start-up cost is essentially lifted. Meaning that the opportunity costs for joining the rebellion are lower than those of initiating a rebellion. Since the costs are higher for initiating a conflict, this also means that new conflicts are less sensitive to economic shocks compared to existing ones. Estimating the effect of economic shocks on conflict incidence therefore potentially overestimates the magnitude of the effect.

There is also an empirical problem due to the omission of the lagged outcome variable. Conflicts are very persistent over time and often are linked to previous conflicts. Conflicts that occur in t are often affected by both current (t) and lagged ($t-1$) shocks. By omitting the lagged outcome variable one introduces a large correlation in the model between the outcome variable, the shocks, and the error term (Bazzi and Blattman, 2014). Using conflict incidence also doesn't account for the possible reverse causality between conflict and economic growth.

[6] The conflict incidence indicator is coded as:

$$Incidence \begin{cases} 1 \text{ if conflict in } t \\ 0 \text{ if no conflict in } t \end{cases}$$

An example for this is given in table 2.1 where the economic performance (GDP per capita growth) is given for the Democratic Republic of the Congo (DRC) during the First and Second Congo War from 1995 to 2003. It is easy to see that the use of conflict incidence as outcome variable would give misleading results as it doesn't account for the feedback of conflict into the economy. The occurrence of conflict will affect economic conditions irrespective of changes in rainfall, which is used as an instrument to proxy for these economic conditions, thereby introducing a form of endogeneity into the model.[7] I argue therefore that conflict onset is a better outcome variable as it accounts for past conflicts and also is better equipped to deal with the mentioned issues and thus better suited to uncover the causal mechanism between rainfall and conflict.

Additionally, as a robustness check I also estimate the model with a different onset-indicator which uses a 5-year intermittency period in order to account for any mid-term carry-over effects of previous conflict. In this case the onset-indicator is only set to 1 if there is a conflict in year t conditional on that there hasn't been any conflict in the past 5 years.

Table 2.1: DRC during the 1^{st} and 2^{nd} Congo War

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Economic growth(%)	−2.5	−3.7	−7.8	−3.7	−6.3	−9.2	−4.7	0.5	2.6
Incidence	0	1	1	1	1	1	1	0	0
Onset	0	1	–	–	–	–	–	–	0

2.3.2 Rainfall

Time-series data on rainfall comes from the NASA Global Precipitation Climatology Project (GPCP), Version 2.2 (Adler et al., 2003). The dataset provides worldwide

[7] An additional problem is the systematic measurement error in conflict-countries due to the collapse of public institutions that provide the data.

monthly mean precipitation given as a daily average (in mm) and covers 1979-2010. The estimates are the result of the combination of a number of sources, taking the advantage of each data type to get the best possible estimate. Values are based on the information coming from gauge stations as well as microwave, infrared, and sounder data from satellites. The data sources are blended together to produce a global gridded precipitation field with the precipitation data at a 2.5 x 2.5 degree resolution, which corresponds to roughly 250 by 250 Km at the equator.

The two main advantages of this dataset, over the more traditional precipitation data, is that it is less likely to suffer from classical and non-classical measurement error. Data supplied by meteorological institutes comes predominantly from gauge stations and due to the sparseness of operating gauge stations in Sub-Sahara Africa, this might lead to classical measurement error. The number of operating gauge stations might be affected by socio-economic conditions which could lead to non-classical measurement error.

Aggregating the rainfall data from the grid-level to the country-level can produce coarse estimates due to the relative low resolution of the raster (Auffhammer et al., 2013). For some smaller countries aggregation will not produce an estimate at all due to the fact that their national territory does not cover enough space in a grid-box. A way to overcome this problem is by assigning the value of the nearest cell to the particular country as is done by Miguel et al. (2004) and Brückner and Ciccone (2010). Although this is a pragmatic solution it ignores the fact that if this problem affects small-sized countries, it can also affect certain regions of larger countries thereby thus producing skewed estimates for these countries neglecting within-country variation in rainfall.

A simple solution for this problem is artificially increasing the resolution of the raster.[8] Figure 2.1 illustrates this approach for the Great Lakes region. The left panel shows a graphical representation of the grid overlay at the original resolution. It shows that countries like Rwanda and Burundi are too small, in terms of coverage of a grid-cell, to

[8] Many thanks to Robert Hall from the South East Asia Research group at Royal Holloway for suggesting this method.

get an estimate. It also shows that this issue could occur in parts of Malawi and the DRC.[9] The right panel in the figure shows the grid overlay on the national boundaries after I increased the resolution. In this case the resolution was increased from a 2.5 x 2.5 degree raster to a 0.5 x 0.5 degree raster, which is roughly 56 x 56 Km at the equator.[10] Dividing the grid-boxes into smaller boxes is a purely technical solution in order to get a better fit between the raster and the national boundaries resulting in more precise estimates when aggregating the data to the national level.[11] The rainfall data is aggregated to country-year level taking into account the number of days in each month, corrected for leap years, in order to obtain a weighted yearly average for each country.[12] Although this method provides theoretical advantages, in practice the

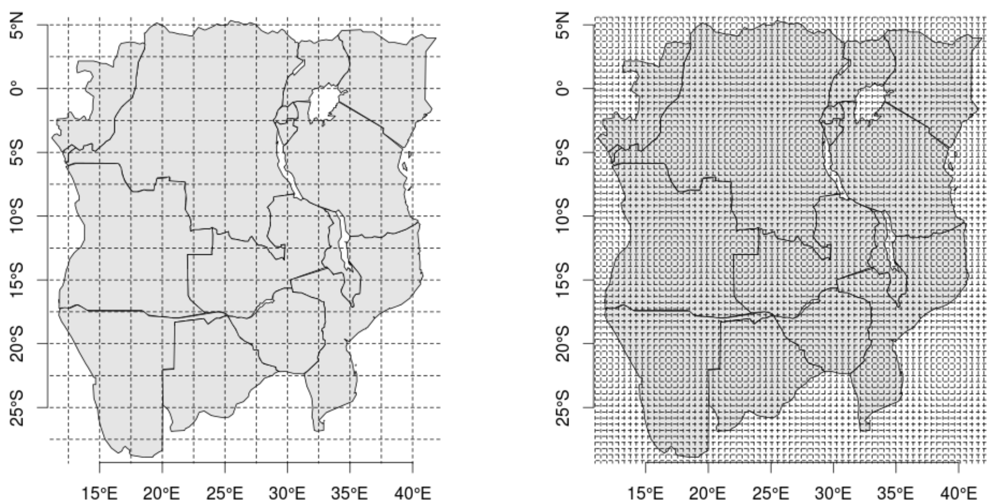

Figure 2.1: Geographic raster for Great Lakes region in Africa at 2.5° x 2.5° *(left)* and 0.5° x 0.5° *(right)*.

difference between the methods of aggregation is small.[13] There are some systematic

[9]At the original resolution aggregating returns no estimates for the following countries: Burundi, Cape Verde, Comoros, Djibouti, Gambia, Guinea-Bissau, Lesotho, Mauritius, Rwanda, Sao Tome and Principe. For the Seychelles the higher resolution aggregation method also does not return an estimate.

[10]Hendrix and Glaser (2007) use a similar method, they refine the raster to 1 x 1 degree resolution and assign cells to countries on the basis of majority.

[11]Note that each of the smaller grid-cells has the same value as the larger original grid-cell. This approach does not change anything about the measurements and therefore does not take into account any within-cell variation.

[12]$Rain_{ct} = dJan_{ct} * 31 + dFeb_{ct} * 28 + ... + dDec_{ct} * 31$

[13]The time-series correlation is 0.99.

differences between the two time-series though, especially for the smaller countries such as Benin, Equatorial Guinea, and Rwanda.[14]

To estimate the effect of rainfall on economic growth and civil conflict I use inter-annual growth and anomalies as a measure for rainfall shocks. Interannual growth is measured as the percentage change in annual rainfall R for country c in year t relative to the previous year $t-1$: $(R_{ct} - R_{c,t-1})/R_{c,t-1}$.

A shortcoming of using interannual growth as a measure is that it tells us little about the relative abundance or shortage of rainfall for a particular country in a given year, compared to the historical expectations. If for a given country c, rainfall in year t was above average it is very likely that rainfall in year $t+1$ will be lower due to the mean-reverting nature of rainfall making rainfall shocks very transitory. Mean-reverting would therefore imply that ΔR_{ct} is negative although the country could still experience above average levels of rainfall (Ciccone, 2011).

[14]The high correlation between the two methods of aggregation can be explained by the fact that most African countries have very arbitrary boundaries. At the 1884-1885 Berlin conference a majority of borders were drawn along meridians and parallels. 44% of African borders follow meridians and parallels while 30% follow other rectilinear or curved lines (Alesina et al., 2011; McCauley and Posner, 2014).

Consider the example in figure 2.2 : the dashed line represents the country average and the spikes are the levels of rainfall for each observation in time. Using year-on-year growth as a measure we would have a negative growth rate at $t = 4$ and a positive growth rate at $t = 6$. Looking at the country average however we can see that rainfall in $t = 4$ is above average and rainfall in $t = 6$ is below average. To better account for both

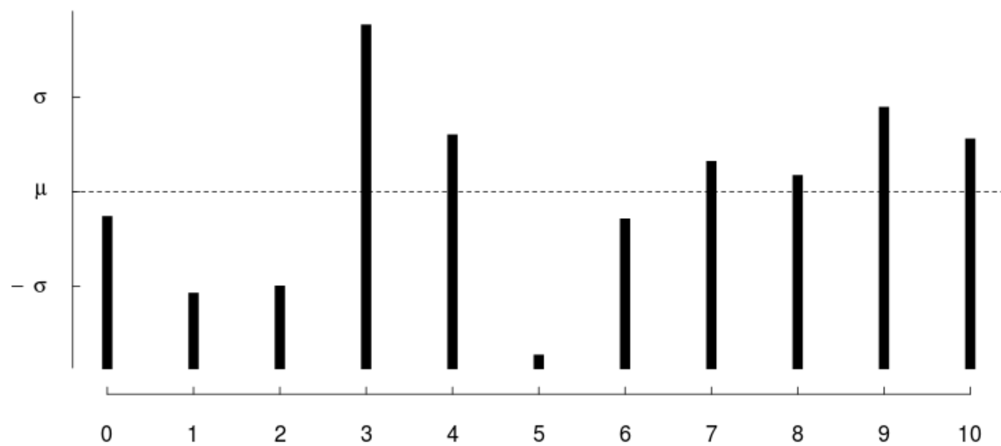

Figure 2.2: Example of precipitation over time, illustrating that negative growth rates could still correspond with positive rainfall levels relative to the mean.

cross-country variation in the mean values as well as within-panel variation, rainfall anomalies are used as an additional measure (Hendrix and Salehyan, 2012). Anomalies are measured as the annual standardized rainfall deviation from the long term panel mean for a given country, $(R_{ct} - \bar{R_c})/\sigma_c$.[15]

The data shows that the majority of observations has the same sign for growth and anomalies. For about a quarter of the observations the signs of the two measures are different though which is a substantial part of the dataset.[16]

[15] Long term is in this case the period from 1979 to 2010

[16] 490 observations (35%) are both positive and 527 observations (38%) are both negative. In 188 observations where anomalies have a positive sign the growth rate is negative (14%) and for 184 observations where the deviations from the panel mean are negative the growth rate is positive (13%). See figure A.1 for rainfall distribution per country.

2.3.3 Economic growth

Data for economic growth is taken from the World Development Indicators (WDI) for 47 countries in Africa between 1981-2010 (World Bank, 2012).[17] The WDI is used as source because of recent concerns with the figures for growth in the commonly used Penn World Tables data (Dell et al., 2012; Johnson et al., 2013). Income growth is measured as the interannual growth rate of real GDP per capita in constant U.S.$ to capture international purchasing power.

2.3.4 Other explanatory variables

A number of other explanatory variables are used to account for specific country-characteristics that are commonly associated with civil conflict in the literature. The model I use is predominantly based on the one used by Miguel et al. (2004).

Peace years are included to account for the fact that the likelihood of conflict strongly depends on the occurrence of previous conflicts. This variable is measured as the number of years that have passed since the last incidence of conflict.[18] The size of the population is often correlated with conflict as larger populations imply difficulties in controlling local level activity and increase the pool from which insurgents can be recruited (Fearon and Laitin, 2003). Another risk of larger populations with regard to resources is that they put additional pressure on the existing resource base which could lead to both relative and absolute scarcity of essential resources such as fresh water. I include the lagged value of the natural log of the total population in the model specification with data taken from the WDI. Empirical evidence shows that there is a curvilinear relationship between regime type and conflict (Hegre and Sambanis,

[17] The dataset is weakly unbalanced due to the fact that Namibia and Eritrea gained independence in 1990 and 1993 respectively. The model estimations include 46 countries due to the lack of data for Somalia.

[18] Peace years are thus measured as the absence of any violence that resulted in at least 25 battle-related deaths in a given year. If there hasn't been any conflict I count the number of years since the country gained independence.

2006). Both extreme autocracies and democracies are less likely to experience civil conflict in contrast with regime types that fall between these two extremes, so called anocracies.[19] The square of the polity2 index from the *Polity IV dataset* (Marshall et al., 2013) is used to control for this relation. The variable is lagged to deal with possible endogeneity issues.[20] Another demographic control is the population's heterogeneity or ethnic composition for which I use the PREG index (Posner, 2004). The PREG index only includes politically relevant groups and allows the values to vary per decade, giving a better representation of the political ethnic composition of a country over time. Most other indices on ethnolinguistic fractionalisation are time fixed and often based on data from the 1960s. Moreover they include all ethnographically distinct groups in a country irrespective of whether they engage in political competition.[21]

Countries with more rough terrain experience higher probabilities of conflict as this terrain provides easier shelter for insurgents and mountainous regions can be difficult to control for governments (Fearon and Laitin, 2003). I measure rough terrain as the percentage of total land area covered by mountains, data taken from Garcia-Montalvo and Reynal-Querol (2005). Throughout the literature, oil-rich countries are strongly associated with conflict onset as the availability of oil can lure insurgents as it provides an extra prize when successfully contesting state power (Fearon and Laitin, 2003; Ross, 2004; Lujala, 2010). The availability of oil revenues can also create a gap between government and population as it provides an easy source of income reducing the need for taxation and thus interaction with the population (Collier and Hoeffler, 2002). This perceived distance can cause frictions if a group has the feeling that the revenues are not being equally distributed. Examples of this include Cabinda province in Angola and

[19] Anocracies are more vulnerable due to political instability, the result of the spread of power among elitist groups constantly competing with each other for power. Kenya, Nigeria, and Zimbabwe are some examples.

[20] Conflict incidence is used in the measurement of regime types.

[21] The PREG index covers 41 of the 47 countries in the panel, data fromAlesina et al. (2003) is used to supplement for the missing countries: Cape Verde, the Comoros, Djibouti, Eritrea, Mauritania, and Sao Tome and Principe.

the situation between Sudan and South Sudan. I use a lagged oil dummy that takes value 1 if oil rents contribute to more than 33% of GDP in a given year, and 0 for all other cases. Data taken from WDI.

2.3.5 Descriptive statistics

Figure 2.3 visualises descriptive statistics for economic growth, precipitation, and conflict.[22] In terms of economic growth, Africa has experienced on average slow growth rates but there has been an increasing trend since 2000. On average GDP per capita growth has been around 1% with a standard deviation of 8 percentage points. 1981-1999 has been characterised by large fluctuations with extremes ranging from -50% to 93%. Since 2000 growth rates have stabilised to an average annual growth rate of 2% and a standard deviation of 5 percentage points.[23] Rainfall variation is enormous (upper right): while the wettest country in the sample (Sierra Leone) has an average rainfall of 2311 mm per year, the driest country (Mauritania) has an annual rainfall of just 118 mm per year. There is no clear trend with regard to shifts in rainfall: on average rainfall has decreased over the past 30 years but there have been unusual spells of relatively wet years such as between 1994-2000.[24]

Compared to similar regions in the world, conflict prevalence is high in Africa although the total number of conflicts has been decreasing. About 1 in 5 observations is coded for conflict while conflict onset is a much rarer occurrence with 1 in 20 observations. Since the 1990s the number of conflicts has decreased.[25] Almost all of the

[22] See table A.1 and figure A.1 for summary statistics.

[23] Some countries perform exceptionally well in comparison to the average; Equatorial Guinea and Gabon, two major oil exporters; Botswana, which has large diamond and nickel deposits; Mauritius which has a successful diversified agricultural economy; and South Africa which has a relatively successful mixed economy.

[24] A period of 30 years is fairly short in climatic terms to distinguish clear trends. However, other research has shown that over a longer period of time rainfall levels in Africa have reduced (Nicholson, 2001; Buhaug, 2010; Barrios et al., 2010).

[25] There has only been a noticeable spike between 2007-2009.

conflicts are minor conflicts, which are conflicts with between 25 and 1000 battle-related deaths in a given year.[26]

[26]Civil wars with more than a 1000 battle-related deaths in a given year are relatively rare. In the dataset only 5 observations are coded for onset of a civil war, 2 of which followed the onset of a minor conflict. In this chapter I focus on intrastate conflict and not interstate conflicts. Between 1981-2010 there were only 7 cases of interstate conflict, and only one which lasted more than a year (Ethiopia vs. Eritrea from 1998 to 2000).

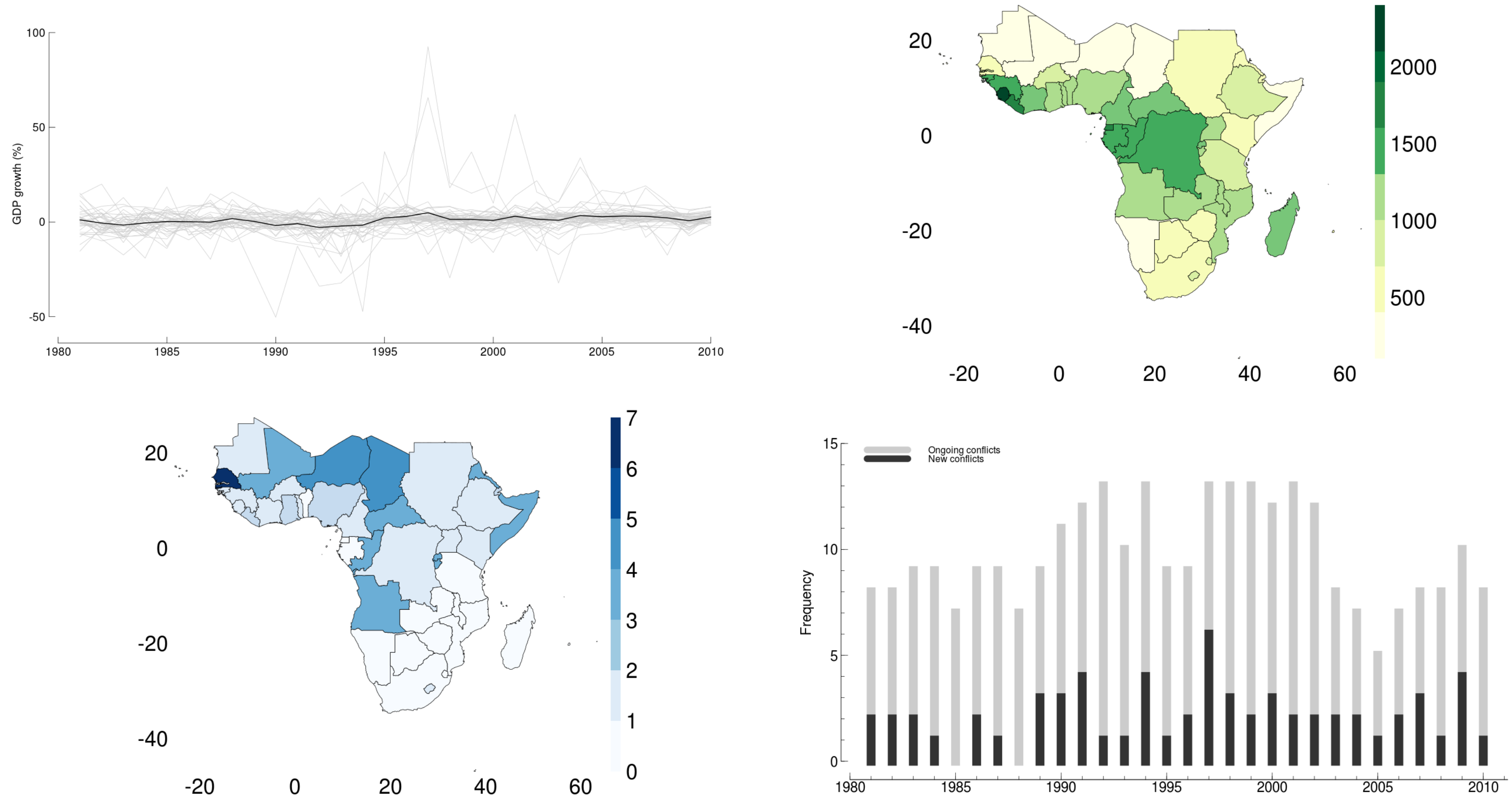

Figure 2.3: Descriptive statistics for economic growth, rainfall, and civil conflict in Sub-Sahara Africa (1981-2010). *Upper left:* Annual growth rate of GDP per capita. The dark line represents sample average, lighter shaded lines represent individual country growth rates. *Source* World Bank Development Indicators. *Upper right:* Mean precipitation in *mm* at country-year level. *Source* GPCP. *Lower left:* Number of conflict onsets per country. *Source* UCDP/PRIO Armed Conflict Dataset v.4-2011.*Lower right:* Frequency of occurrence and onset of civil conflict (with at least 25 battle-related deaths per year), as defined by the UCDP/PRIO Armed Conflict Dataset v.4-2011.

2.4 Estimation framework

The main equation links conflict onset to per capita economic growth and other explanatory variables, where economic growth is instrumented by rainfall.

$$onset_{ct} = a_c + bX'_{ct} + c_0 growth_{ct} + c_1 growth_{c,t-1} + d_c year_t + e_{ct} \tag{2.2}$$

I focus on civil conflict onset in country c in year t, where the principal onset indicator is based on the absence of conflict in the previous year $t-1$. In most specifications country-specific time trends ($year_t$) are included in order to deal with additional variation and a disturbance term (e_{ct}) that is allowed to be serially correlated. The errors are clustered at the country level. To capture some of the time-invariant country characteristics that might be related to conflict, country-fixed effects (a_c) are included in some of the models. I also estimate the model accounting for country characteristics (X'_{ct}).
A reduced-form model is estimated with OLS and Rare Event Logit (King and Zeng, 2001) using the model:

$$onset_{ct} = a_c + bX'_{ct} + c_0 \Delta rain_{ct} + c_1 \Delta rain_{c,t-1} + d_c year_t + e_{ct} \tag{2.3}$$

In the first-stage I regress economic growth in t on changes in rainfall in t and $t-1$, using the same controls as in the main equation. In the first-stage I also estimate the effect of rainfall on the agricultural and industrial sector as opposed to whole economic output. In the second stage economic growth rate is instrumented by the predicted values from the first stage. Changes in rainfall are captured by either the interannual growth rate or anomalies.

$$growth_{ct} = a_c + bX'_{ct} + c_0 \Delta rain_{ct} + c_1 \Delta rain_{c,t-1} + d_c year_t + e_{ct} \tag{2.4}$$

To test the robustness of the results I use a different outcome variable with a 5-year intermittency period for conflict onset.

2.5 Results

2.5.1 First stage results

Table 2.2: Effect of rainfall on economic growth, 1981-2010 (IV−2SLS, first stage)

Rainfall measure	Growth			Anomaly		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall_t	0.02***	0.02**	0.02**	0.01***	0.01***	0.01***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Rainfall_{t-1}	0.02***	0.01**	0.01*	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Peace years			0.00			0.00
			(0.00)			(0.00)
Population_{t-1} (*log*)			0.00			0.00
			(0.05)			(0.05)
Square Polity2_{t-1}			0.00			0.00
			(0.00)			(0.00)
GDP per capita_{1979} (*log*)			0.16			0.08
			(0.94)			(0.96)
Ethnolinguistic fractionalization			−0.06			−0.08
			(0.09)			(0.10)
Rough terrain			−0.01			−0.01
			(0.02)			(0.02)
Oil-exporting country			0.03			0.03
			(0.03)			(0.03)
Country FE	–	Yes	–	–	Yes	–
Country-specific year trend	–	Yes	Yes	–	Yes	Yes
Root MSE	0.07	0.07	0.07	0.07	0.07	0.07
N	1299	1299	1162	1299	1299	1162

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Using the latest data for 1981-2010 I estimate the first-stage model regressing GDP per capita growth on rainfall. Results are shown in table 2.2 where column 1-3 depict the results for the model specifications where I regress economic growth on rainfall growth and column 4-6 for rainfall anomalies. I find a positive and significant relation between economic growth and rainfall similar to the results by MSS.[27] Focussing on interannual growth the effect is robust to the inclusion of fixed effects, country controls, and time trends. A standard deviation increase in rainfall accounts for a difference in economic growth of 0.7 percentage points over years t and $t+1$ which is a substantial effect considering the average growth rate for African economies between 1981-2010. The uncertainty with which we can link rainfall to economic growth increases when introducing controls into the model.[28] Moreover the strength of rainfall as an instrument is severely reduced as the F-statistic drops from 7 to 2.7. As a result the coefficients on economic growth in the second stage estimations will be biased towards OLS-estimates (Bound et al., 1995; Angrist and Pischke, 2008). Estimating the model with anomalies also shows that current changes in rainfall are positively related to economic growth at 1% significance with the magnitude of the effect being similar to the models in columns 1-3.[29] The coefficient for lagged deviations is near 0 and statistically insignificant. I do find that the two coefficients are jointly significant at a 99% confidence level. The results seem to indicate that anomalies are actually a stronger instrument with the F-statistic ranging from 9.4 to 12.2. All country controls show statistical insignificant effects and exhibit small coefficients sizes. The results show that for a longer time period rainfall is still a viable instrument for economic growth, although the magnitude of the effect has diminished over time and in some cases rainfall is a weak instrument.[30] In their original work MSS also found that rainfall was a weak instrument. Moreover, in a

[27] I also re-estimate the MSS model using their dataset and changing their rainfall data with the new rainfall estimates. The results for this are in the annex in table A.2.

[28] When using time-fixed effects to control for common shocks only current rainfall growth rates are significantly linked to economic growth.

[29] The size of the coefficient in columns 4-6 is 0.01 but this is due to rounding as the real coefficient is 0.006.

[30] See table A.2 in the annex for the first-stage estimations per period.

re-examination of their work they found that the first-stage relationship between rainfall and economic growth became weaker after 2000 as neither rainfall growth in year t or $t-1$ was significantly correlated with economic growth in year t (Miguel and Satyanath, 2011). I also find that after 2000 the link between rainfall and economic growth becomes very weak. This trend might be related to the unprecedented economic growth Africa has experienced in the past decade as Miguel and Satyanath (2011) suggest. From 1981 to 2010 the agricultural share of GDP has decreased by about 6 percentage points, from 19% to 13%, with a very sharp decline since 2002. Taking the two economic powerhouses, Nigeria and South Africa, out of the equation the decline is even larger with 12 percentage points. Rainfall is vital to productivity in the agricultural sector due to the fact that in Africa most arable land is rain-fed and irrigation is almost absent. However, the relevance of rainfall to economic performance is not limited to only the primary sector as other sectors also depend on rainfall due to the prominence of water to generate electricity and as a secondary input in the industrial sector (Barrios et al., 2010).[31]

I regress the output from the agricultural and industrial sector on rainfall to determine the separate effects (see table 2.3 for results).[32] As expected the agricultural sector shows the stronger relation between rainfall and productivity illustrated by the relative large coefficient size compared to GDP per capita growth. The sign for anomalies in $t-1$ is a bit counter-intuitive however, indicating that higher rainfall deviations in t reduce output in $t+1$. There is a bit more uncertainty about the link between rainfall and industrial output. For all estimations the coefficient for rainfall in year t is 0 (or near zero) and statistically insignificant. Rainfall in year $t-1$ does seem to be correlated with industrial output in year t according to the majority of the estimations where

[31] According to Barrios et al. (2010) hydro-electricity represents about 47 % of total power generation in Africa.

[32] I used the agriculture and industry value added in constant dollars from the World Bank Development Indicators and calculated a per capita measure to normalize across countries (same approach was used for the service sector).

especially the models using anomalies show a strong link.[33]

[33] I also estimate the effect of rainfall on output in the service sector and find some statistically significant results but in all cases the coefficient has a size near zero and further tests show that rainfall is a very weak instrument with F-values below 2.

Table 2.3: Effect of rainfall on economic growth per sector, 1981-2010 (OLS)

Outcome variable	Agricultural growth				Industrial growth			
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall growth$_t$	0.08***	0.09***			0.00	−0.01		
	(0.02)	(0.03)			(0.01)	(0.01)		
Rainfall growth$_{t-1}$	0.04**	0.03*			0.02*	0.02		
	(0.02)	(0.02)			(0.01)	(0.01)		
Rainfall anomaly$_t$			0.02***	0.01***			0.00	0.00
			(0.00)	(0.00)			(0.00)	(0.00)
Rainfall anomaly$_{t-1}$			−0.01	−0.01*			0.01***	0.01***
			(0.00)	(0.00)			(0.00)	(0.00)
Country FE	Yes	–	Yes	–	Yes	no	Yes	–
Country-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	–	Yes	–	Yes	–	Yes	–	Yes
Root MSE	0.10	0.10	0.10	0.10	0.10	0.11	0.10	0.11
N	1088	964	1088	964	1058	934	1058	934

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p$\leq$ 0.01, ** p$\leq$ 0.05, *$\leq$ 0.1

2.5.2 Rainfall and conflict onset

Examining the between-country differences in rainfall for countries with conflict onset and other countries there is no clearly distinguishable trend concerning rainfall levels or variation and a higher likelihood of observing conflict onset. On average countries that had at least one observation of onset tend to be wetter although the difference with the other countries falls well within the standard deviation of rainfall in the sample.[34] Looking at growth rates and deviations the data shows that countries that had conflict onset have lower growth rates but experience larger deviations.[35]

I estimate the relation between rainfall and conflict using a reduced form estimation, the results for which are shown in table 2.4. The results provide little empirical support for the claim that variation in rainfall contributes to conflict onset at the country-level. Across the various model specifications current variation in rainfall is positively linked with conflict onset. Higher levels of rainfall relative to last year or the panel mean correspond with an increased chance of conflict. However, the estimated coefficients are not statistically significant and come with large uncertainty as all t-values are below 1.[36] Lagged rainfall has the expected sign indicating that lower levels of rainfall increase conflict likelihood. These coefficients come with a bit more certainty as the t-values are consistently larger than 1 and in some of the models the coefficient is one-sided significant at the 10 % level giving some certainty about the direction of the effect.[37] I also estimate the model using a dummy for extreme rainfall deviations ($\sigma \geq 1$ or $\sigma \leq -1$) but did not find any support for the claim that these extreme variations are

[34] 1039 mm versus 993 mm, a margin of only 47 mm.

[35] Countries that had a case of conflict onset on average have a growth rate of 1.6%, a 1.9 percentage point difference with the countries that didn't (3.5%). In terms of anomalies, countries with conflict onset have an average yearly deviation of -0.01 against 0 for the other countries. Countries with conflict onset include 471 observations leaving 918 observations for the other countries.

[36] Z-value in case of the rare event logit estimation.

[37] This is the case for columns 1, 4, and 6. These results are robust at the 90 % confidence level when I control for temperature. Data for temperature comes from NOAA for 1981-2008 and is based on gauge-stations. The downside of using this data is that it could introduce bias into the model due to measurement error (results not shown). Burke et al. (2009) find that temperature is a stronger predictor of agricultural performance and that temperature has a stronger effect on conflict than rainfall.

associated with conflict.[38]

Some of the country characteristics that are used as controls show statistically significant results (col. 3 and 6) indicating that the odds ratio of conflict is reduced by longer peace spells as well as non-hybrid regime types. Moreover, OLS estimation indicates that ethnolinguistic fractionalisation is negatively associated with conflict onset at the 99 % confidence level (col. 2 and 5).

Table 2.4: Effect of rainfall on conflict onset, 1981− 2010 (Reduced form)

Rainfall measure	Growth			Anomaly		
	(1)	(2)	(3)	(4)	(5)	(6)
Specifications	OLS	OLS	RE-Logit	OLS	OLS	RE-Logit
Rainfall$_t$	0.01	0.02	0.38	0.00	0.00	0.03
	(0.02)	(0.03)	(0.69)	(0.00)	(0.01)	(0.13)
Rainfall$_{t-1}$	−0.03	−0.03	−0.49	−0.01	−0.01	−0.17
	(0.02)	(0.03)	(0.87)	(0.01)	(0.01)	(0.11)
Peace years		0.00	−0.05***		0.00	−0.05***
		(0.00)	(0.02)		(0.00)	(0.02)
Population$_{t-1}$ (*ln*)		−0.09	0.01		−0.09	0.01
		(0.14)	(0.14)		(0.14)	(0.14)
Square Polity2$_{t-1}$		0.00	−0.02**		0.00	−0.02**
		(0.00)	(0.01)		(0.00)	(0.01)
GDP per capita$_{1979}$ (*ln*)		1.01	−0.28		1.11	−0.28
		(1.53)	(0.36)		(1.56)	(0.36)
Ethnolinguistic fractionalization		−0.97***	0.07		−0.93***	0.06
		(0.29)	(1.03)		(0.31)	(1.03)
Rough terrain		−0.13	0.01		−0.13	0.01
		(0.11)	(0.01)		(0.11)	(0.01)
Oil-exporting country		−0.01	0.83		−0.02	0.83
		(0.05)	(0.68)		(0.05)	(0.69)
Country FE	Yes	–	–	Yes	–	–
Country-specific time trend	Yes	Yes	–	Yes	Yes	–
Root MSE	0.21	0.21	–	0.21	0.21	–
Conflict observations	63	55	55	63	55	55
N	1101	942	942	1101	942	942

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

[38] Note that in contrast with the studies by Raleigh and Kniveton (2012) and Fjelde and von Uexkull (2012) which both use disaggregated data, the data in this chapter is aggregated to the country level.

2.5.3 Economic growth and conflict onset

Table 2.5: Effect of economic growth on conflict onset, 1981−2010 (IV−2SLS, second stage)

Rainfall measure	Growth			Anomaly		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Economic growth$_t$	−0.48	−0.25	−1.82	1.65	0.87	0.01
	(1.31)	(1.60)	(2.44)	(1.41)	(1.54)	(1.23)
Economic growth$_{t-1}$	−2.12*	−2.16*	−2.37	−1.27	−2.19	−1.31
	(1.22)	(1.21)	(1.42)	(1.32)	(1.53)	(1.21)
Peace years			0.00			0.00
			(0.00)			(0.00)
Population$_{t-1}$ (*ln*)			−0.23			−0.21
			(0.34)			(0.22)
Square Polity2$_{t-1}$			−0.00			0.00
			(0.00)			(0.00)
GDP per capita$_{1979}$ (*ln*)			1.60			1.34
			(5.38)			(2.66)
Ethnolinguistic fractionalization			−1.19*			−0.92**
			(0.69)			(0.37)
Rough terrain			−0.15			−0.14
			(0.12)			(0.11)
Oil-exporting country			0.24			0.08
			(0.27)			(0.14)
Country FE	–	Yes	–	–	Yes	–
Country-specific time trend	–	Yes	Yes	–	Yes	Yes
Root MSE	0.29	0.26	0.30	0.27	0.26	0.23
Conflict observations	63	63	55	63	63	55
N	1032	1032	911	1032	1032	911

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table 2.5 shows the results for estimating the main model using IV-2SLS with economic growth rates predicted by variation in rainfall. For the models where economic growth is instrumented with year-on-year growth in rainfall, the coefficient shows that a 1 percentage point drop in GDP per capita increases the risk of conflict onset in the following year by about 2 percentage points (controlling for country fixed effects and country specific time trends).[39] The model thus predicts that there is a certain lag in the effect of economic growth on conflict where underperformance in year t increase the risk of the outbreak of a conflict in the following year, $t+1$. The direction of the effect of growth at $t-1$ is robust to various model specification as well as using a different measure to capture rainfall shocks (columns 4-6). In the latter cases the results cease to be statistically significant at the traditional levels. Using a one-sided t-test shows that the sign of the coefficient is significant at 90% confidence level in columns 4 and 5 but not for the model including country controls, which is similar to the results in column 3.

Additionally I find that although some of the models show a statistically significant link between economic growth and conflict onset, these results are not robust to the inclusion of time-fixed effects to capture shocks that are common to African countries.[40] The positive sign of current growth rates in columns 4-6 is unexpected, especially considering that this direction only occurs in the cases where I use anomalies to predict growth. None of the country controls (col. 3 and col. 6) seem to have any predictive power except for the variable for ethnolinguistic fractionalization which is statistically significant in both models.[41] The coefficient is significant at the 90% confidence level and indicates that the likelihood of conflict onset actually decreases when fragmentation increases. An explanation for this could be that when a society approaches perfect

[39] MSS found a point-estimate of -1.84 for lagged growth rates which wasn't statistically significant. In their model estimation, current growth rates were negatively linked to conflict onset and significant at the 90% confidence level.

[40] Including time-fixed effects heavily inflate both the size of the coefficient as well as the standard errors. Brückner and Ciccone (2010) also found that the results by MSS were not robust to the inclusion of time-fixed effects.

[41] Something that also occurred in the reduced-form OLS regressions (see table 2.4).

fractionalization (value of 1 in this case) people benefit more from cooperation rather than conflict.[42]

Table 2.6: Effect of economic growth in different sectors on conflict onset, 1981−2010 (IV−2SLS, second stage)

Specifications	(1)	(2)	(3)	(4)
Agricultural growth$_t$	0.02	−0.04		
	(0.88)	(0.58)		
Agricultural growth$_{t-1}$	−1.12	−0.97		
	(1.95)	(0.99)		
Industrial growth$_t$			−0.77	−0.28
			(0.58)	(2.73)
Industrial growth$_{t-1}$			−0.43	−0.99
			(0.52)	(1.68)
Peace years		0.00		0.00
		(0.00)		(0.00)
Population$_{t-1}$ (*ln*)		−0.23		−0.41
		(0.25)		(0.45)
Square Polity2$_{t-1}$		0.00		0.00
		(0.00)		(0.00)
GDP per capita$_{1979}$(*ln*)		0.99		5.76
		(2.56)		(10.14)
Ethnolinguistic fractionalization		−0.56		−0.65
		(0.69)		(1.63)
Rough terrain		−0.13		−0.05
		(0.12)		(0.10)
Oil-exporting country		0.04		0.07
		(0.03)		(0.08)
Country FE	Yes	–	Yes	–
Country-specific time trend	Yes	Yes	Yes	Yes
Root MSE	0.24	0.23	0.23	0.23
Conflict observations	48	41	48	41
N	856	747	826	717

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

[42] As stated in the data section, I use a different index to measure fractionalization taking into account the political relevance of ethnic groups and allowing it to vary by decade. This might explain the difference with the findings in the literature.

Table 2.6 shows the results for the estimations for the effect that different economic sectors (agricultural and industrial) have on the outbreak of conflict using rainfall to predict the growth rates. The estimations are limited to the use of anomalies to instrument for the growth rates as these have shown to be a stronger instrument in the first-stage estimations. According to the literature one would expect that a positive shock in the agricultural sector would have a larger effect on reducing conflict likelihood compared to the industrial sector as it is more labour intensive.[43] The results do not really support this hypothesis as the estimated coefficients are very similar to the main results. Moreover, the estimates come with a lot of uncertainty given the large standard errors and very wide confidence intervals. On the basis of these results I can't tell with certainty if economic shocks in the two different sectors really have a separate effect on conflict onset. Moreover, the coefficients are considerably lower compared to aggregate economic output in the previous table.

As the literature suggests there is a strong link between conflict and economic conditions but the causality may be hard to establish as conflict feeds back into the economy influencing economic performance. To account for this feedback-loop the model is estimated using a more stringent coding of the outcome variable. One that uses an intermittency period after the end of a conflict in order to control for the disruptive effect of conflict on economic performance in the mid-term. I use a 5-year intermittency period meaning that after the last incidence of conflict I code the next 5 years as missing in order to control for any temporal effect of conflict after the conflict ended. The results that were statistically significant, using the standard onset-indicator, do not withstand this test and cease to be significant (see table 2.7 for results). However, I must note that part of this reduction in statistical significance could be due to an increase in imprecision as the number of observations drops with about 14%. Nonetheless, there is also a drop of almost 50% in the point estimates. Another noticeable change is the

[43] In terms of total employment about 44 % works in the primary sector while about 16 % works in the secondary sector (data from WDI for Sub-Saharan Africa 1981-2010).

direction of the effect considering the models where economic performance is predicted by anomalies. Growth rates at t are now negatively, though statistically not significant, related to conflict onset, confirming earlier results in the literature.

It seems that this onset-indicator does a better job in modelling the temporal dependence of conflict and also improves the fit of the model as the mean square errors are smaller, although not by a very large margin. Another interesting finding concerns the country controls where the coefficient for ethnic fragmentation is statistically significant at 95% confidence level and a coefficient size that has increased by 50%. This shows that there is an apparent link between ethnolinguistic fractionalization and conflict onset although not in the direction that was expected. Peace years also enters significantly in one of the models but the point-estimate is near zero.

Table 2.7: Effect of rainfall on conflict onset (*5−year intermittency*), 1981−2010 (IV−2SLS, second stage)

Rainfall measure	Growth			Anomaly		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Economic growth$_t$	−1.42	−0.92	−2.75	−0.13	−0.27	−0.33
	(1.37)	(1.40)	(2.65)	(0.99)	(0.99)	(0.90)
Economic growth$_{t-1}$	−1.16	−1.11	−1.89	−0.48	−1.29	−0.62
	(0.90)	(1.03)	(1.61)	(0.91)	(1.32)	(1.12)
Peace years			0.00			0.00*
			(0.00)			(0.00)
Population$_{t-1}$ (*ln*)			−0.49			−0.25
			(0.72)			(0.27)
Square Polity2$_{t-1}$			0.00			0.00
			(0.00)			(0.00)
GDP per capita$_{1979}$ (*ln*)			3.73			2.93
			(7.01)			(2.86)
Ethnolinguistic fractionalization			−2.12**			−2.15***
			(0.85)			(0.41)
Rough terrain			−0.29			−0.23
			(0.21)			(0.17)
Oil-exporting country			0.26			0.05
			(0.34)			(0.11)
Country FE	–	Yes	–	–	Yes	–
Country-specific time trend	–	Yes	yes	–	Yes	Yes
Root MSE	0.23	0.20	0.28	0.19	0.20	0.18
Conflict observations	34	34	29	34	34	29
N	892	892	795	892	892	795

Notes. FE, Fixed effects; MSE, Mean squared error. Estimates rounded to two decimals. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

2.6 Conclusion

A serious challenge in the empirical literature on conflict is how to deal with the issue of reverse causality. In a study on the effect of economic shocks and civil conflict Miguel et al. (2004) used an innovative approach and instrumented economic performance with year-on-year growth in rainfall and found that there is a positive link between rainfall, economic shocks, and conflict. Their publication has become a standard work in the literature. However, subsequent studies have failed to come to a conclusive result with regard to the link between rainfall and conflict.

In this study I have tried to address some of the issues in the literature that haven't received a lot of attention. Such as the coding of the outcome variable and focussing more on the link between rainfall and different sector of the economy, and their effect on civil conflict probability. With regard to the coding of the outcome variable I argue that using a binary incidence indicator does not identify the causal mechanism of interest. Based on the theoretical contribution by Collier and Hoeffler (1998), the assumption that economic shocks affect the continuation of conflict in the same way as the outbreak of a new one is not viable. Costs associated with joining an ongoing rebellion are lower than those associated with initiating a new one and therefore we should expect that conflict onset is less sensitive to economic shocks (Bazzi and Blattman, 2014). In my analysis I find little support for the link between rainfall and conflict as the statistically significant results that I find are not robust to different model specifications or different measures of shocks. Although the analysis does show that there is some robustness in the direction of the effect. Concerning the different economic sectors I find that rainfall has the largest impact on the agricultural sector which is no surprise given the dependence on rainfall for irrigation. The results also indicate that rainfall has a statistically significant contribution to productivity in the industrial sector but the magnitude of this effect is relatively small and the data does not seem to support some of the strong claims made in other work (Barrios et al., 2010).

Over the past decades the size of the agricultural sector in Africa has decreased although it still employs a significant amount of the total labour force. There is however no strong empirical support for the notion that a negative shock to the agricultural sector significantly increases the risk of conflict.

A caveat with regard to estimating the relationship between rainfall, economic shocks, and conflict is the loss of information due to aggregation when using the country-year as unit of analysis. The yearly aggregates do not give a fair representation of within-country differences for both rainfall and economic performance. An additional problem is the potential mechanical error so to speak in national account data due to the lack of institutions to correctly measure economic performance. A disaggregated approach could be beneficial to answer some of the questions that remain although recent work has shown that also on the local level there does not seem to be a very strong relation between rainfall and conflict (O'Loughlin et al., 2012), something that is also established in this study.

Chapter 3

Food Imports, International Prices, and Violence in Africa

3.1 Introduction

A popular discourse links the incidence of civil unrest to higher food prices, where an increased sense of relative deprivation leads to a higher risk of violent collective action when the staple foods become unaffordable for the masses. Although food riots have become less common in the 20th and 21st century (see Taylor (1996) for an historical overview), some recent events that confronted several countries with severe unrest and political instability have been linked to food price levels (Lagi et al., 2011).

A recent example is the wave of protests, riots, and sometimes lethal violence that followed the 2007-2008 world food price crisis. Developing countries such Haiti, Bangladesh, the Philippines, and several African countries faced severe unrest after food prices peaked. In a reaction to these events the director of the Food and Agricultural Organization (FAO) Jacques Diouf warned that the spread of violence would continue if food price levels would not drop and expressed surprise about the fact that this issue was not on the United Nations Security Council's agenda. He argued that these events showed that higher food prices have dire consequences for peace, security, and human rights (Reuters, 2008).[1] Other societal upheavals have also been linked to food prices: The recent wave of revolutions in the Arab world, which saw political reforms, ousting of various rulers, and in some cases culminated into civil war, followed after record high prices for major foodstuffs such as cereals in late 2010.[2] The escalation of violence in Nigeria has also been partially linked to the price of food consumers pay as the removal of the fuel subsidy increased local food prices due to higher transport costs (The Economist, 2012b).

Despite the anecdotal evidence, the link between food prices and incidence of violence remains speculative due to the paucity of empirical research on this subject. Only recently academics have started to address this gap in the literature beginning with the work by Hendrix et al. (2009) and now including studies by Arezki and Brückner (2011), Berazneva and Lee (2013), Smith (2014), and Bellemare (2015). This study expands the current literature by looking at the predictive power of the real level effect of food prices on violence intensity based on a country's food import pattern, modelled by a country-specific food price index focussing on the effect of a specific basket of foodstuffs. This means that in contrast to some of the existing work, I assume that food prices for the different commodities don't have a homogeneous effect but that the correlation between food prices and unrest is driven by the import dependence on predominantly the low value-added basic foodstuffs. International food prices are used as they are a source of exogenous shocks, whereas using domestic prices could potentially be endogenous.

[1] Since the 2011 meeting of the G20, food security has become a top priority on the agenda.

[2] Food prices might have been a tipping point with regard to the Arab Spring (The Economist, 2012a) leading the population to express their grievances concerning government corruption and the economic decline. A strong precedent for the Arab Spring were the Iranian 2009-2010 election protests.

The regression analysis for 47 countries in Africa between 1990-2011 suggests that higher fluctuations of food prices from the long term trend are associated with higher violence levels. Moving from low to high food prices corresponds to a 0.26 increase in the log count of violent incidents. I find that the correlation between food prices and unrest is predominantly driven by low-value added primary products such as wheat, and the effect is mainly associated with high-intensity types of violence. These results parallel some of the recent findings in the literature.

This study focuses on Africa for a couple of reasons: First, as figure 3.1 illustrates, the large majority of African countries are net-importers of food with an average share of food imports relative to total merchandise imports of 14%.[3] This makes these countries very vulnerable to international price levels. This can be a real burden for these often cash-strapped governments, leading to difficulties in securing an adequate level of food security for their population and by extension in maintaining peace.[4]
Second, the transmission of international food prices to domestic prices leads to inflation and will mainly hit the poor who spend a disproportionally large share of their income on mostly basic foodstuffs (Baquedano and Liefert, 2014; Dawe and Maltsoglou, 2014; Tadesse et al., 2013).[5] Illustrated by figure 3.2, the average African consumer spends around 50% of its disposable income on food alone. As the anecdotal evidence suggests, when staple foods become unaffordable for a large part of the population this might lead to violent collective action. If there is indeed a link between food prices and civil unrest, then we should be able to observe this in African countries due to their import dependency and large shares of consumers who live at the margin, making these countries very vulnerable to changes in international food price levels.

[3] Out of a total of 53 African countries 16 (30%) are net-exporters of food. The average net-imports of foodstuffs relative to total imports, including the net-exporters, is 7%. In 2011, in the top 20 of countries for share of agricultural imports relative to total merchandise 15 were from Africa (FAO Statistical Division, 2013).

[4] See the seminal study by Fearon and Laitin (2003) on how poverty marks weak states which favours political instability and rebel recruitment amongst others.

[5] Despite the relevance of the subject there is little information on the impact of higher food prices on the poor (Ivanic and Martin, 2008).

Third, I use an unique dataset that covers the whole spectrum of civil unrest ranging from strikes and protests up till civil conflict. Unfortunately, this detailed kind of data is not readily available for other regions in the world.

The main contribution of this study is the examination of the predictive power of food prices. So far the literature has predominantly focused on the descriptive power of food prices in explaining past violence without paying too much attention to the accuracies of the generated probabilities of the model. If there is indeed a strong link between food prices and violence, then we should be able to accurately predict these seemingly sudden outburst of unrest. Using the most recent data I attempt to predict violence levels in Africa for 2012. Although the regression results showed that food prices where a strong predictor for violence, I find that the model has poor predictive power only correctly predicting 36.8% of violent events while underestimating the intensity. The out-of-sample correct prediction rate is 11.8 percentage points better than for the in-sample predictions. However, the improvement in accuracy is due to other factors than food prices.

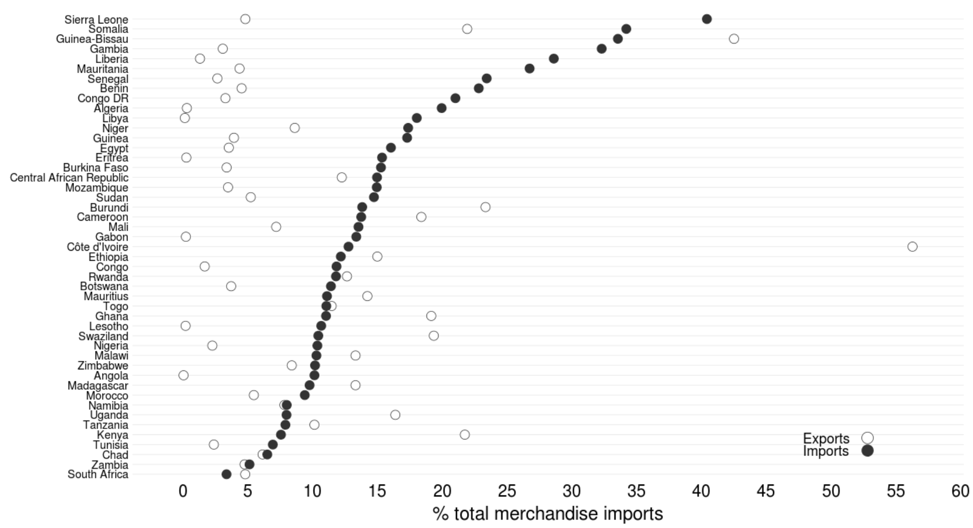

Figure 3.1: Food imports and exports relative to total merchandise imports per country, average for 1990-2010. *Source* : FAOSTAT.

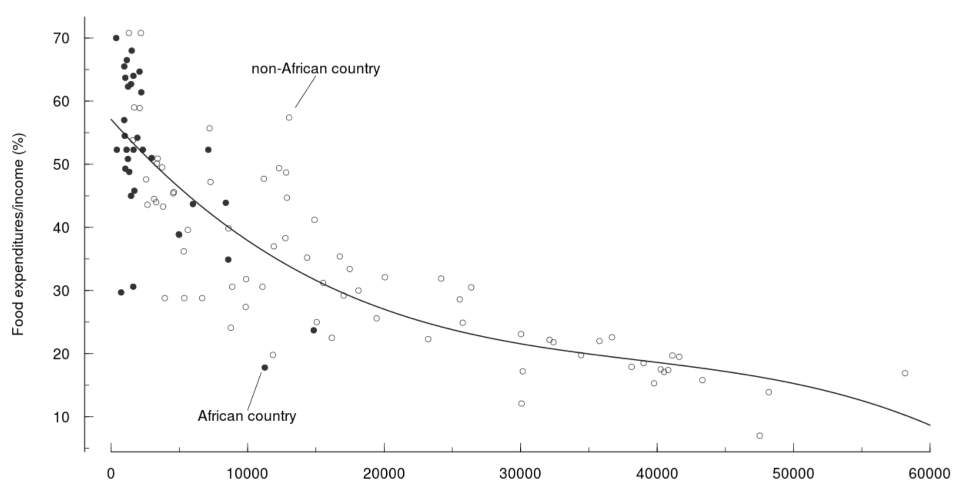

Figure 3.2: Food expenditures as a share of disposable income versus GDP per capita. The third-degree polynomial fit illustrates the decreasing trend in food expenditures as income increases. *Source* : Global Food Security Index (105 countries for 2013).

3.2 Existing literature

This study on the link between food prices and civil unrest fits within the broader literature on food security and conflict. Examples of research within this literature includes work on the effect of malnutrition on conflict onset (Pinstrup-Andersen and Shimokawa, 2008), the link between U.S. food aid shipments and civil conflict incidence (Nunn and Qian, 2014), and the causal relationship between food security and conflict in the Arab world (Maystadt et al., 2014).[6] Within this body of research there is a small but steadily growing strand dedicated to examining the effect of food prices on unrest. This part of the literature can be linked to the emerging literature on conflict and commodity prices which includes a number of studies that also use international prices as a source of exogenous shocks (Besley and Persson, 2008; Brückner and Ciccone, 2010; Dube and Vargas, 2013; Bazzi and Blattman, 2014).

To the best of my knowledge, the first empirical study on the link between food prices and unrest is the paper by Hendrix et al. (2009), who found for a sample of 55 major cities in Asia and Africa between 1961-2006 that international food prices were a significant determinant of the incidence of protests and riots. This effect was contingent on regime type though as hybrid regimes, or anocracies, were driving the results. Their estimation is based on the effect of international wheat prices alone, and this could potentially fail to account for substitution effects between foodstuffs mainly different types of grains. Using global monthly data Bellemare (2015) finds a link between international food prices and unrest, instrumenting food prices with natural disasters. For the 1990-2011 period, he finds that increases in food price levels, and not volatility, are the culprit of more unrest.
Similar to the work presented here, the study by Berazneva and Lee (2013) focuses on Africa and links the occurrence of food riots with high poverty levels and higher

[6]There is also the work by Blaydes and Kayser (2011) who look at the effect of regime type on calorie intake.

levels of political restriction. Their analysis focuses only at events occurring during the 2007-2008 global food price crisis though.

The country-specific food price index used in this study is similar to the one by Arezki and Brückner (2011). They estimate the impact of international food prices on the quality of political institutions and intra-state conflict for 120 countries between 1970-2007. Their results show that increases in international prices correspond with a decrease in institutional quality and increase in the incidence of anti-government demonstration, riots, and civil conflict. The main difference with their working paper is that this study exploits the relatively high-frequency with which data on both food prices and violence is available, using the country-month rather than the country-year as unit of analysis. This more disaggregated approach moves beyond the crude analysis at the annual level and gives a better understanding of the within-year relation between food prices and violence. This study is probably most closely related to the recent work by Smith (2014) who looks at the effect of changes in domestic prices on urban unrest in Africa.[7] Since domestic prices are potentially endogenous he instruments these using international prices (for wheat, rice, and corn) and estimates the effect on urban socio-political unrest at the extensive margin. Because he uses current imports and exports to calculate his trade balanced instrument, it is likely endogenous as these trade flows may be determined by the incidence of unrest. In contrast, the food price index I create is based on the trade-balance before the period in which the outcome variable is measured. Additionally I look at a broader basket of foodstuffs in order get an estimate of the relative importance of food import dependence, something that is generally not addressed in the literature. Moreover, I estimate the effect of food prices on conflict levels in order to get a better idea of the severity of the impact that food prices can have retaining the full information of the conflict data which is often lost when using binary measures. There is now a growing conflict literature that focuses

[7]The domestic prices cover a broader basket of foodstuffs that reflects local consumption but can also include alcohol and tobacco.

on conflict intensity, examples include Hegre et al. (2009), Costalli and Moro (2012), Hendrix and Salehyan (2012), O'Loughlin et al. (2012), Raleigh and Kniveton (2012), and Maystadt et al. (2014).

The biggest departure of this paper relative to the current literature is the analysis that I provide on the effect of food prices on violence focussing on the predicted outcomes and using the model for out-of-sample prediction. Given the recent trends in food prices and the events of the 2007-2008 global food price crisis, having a model with predictive power is particularly relevant. This study therefore adds to the relatively small literature on the prediction of political instability and civil conflict, some examples of which include work by Goldstone et al. (2010), Weidmann and Ward (2010), Gleditsch and Ward (2013), and recently Blair et al. (2014).

3.3 Estimation framework

The regression analysis is based on time-series cross-sectional data from 1990-2011 for all African countries with a population of one million or more.[8] The results from the model estimation are then used to predict the outcome in 2012. Monthly data is used for the outcome and the main explanatory variable in order to capture within-year variability. If there is indeed a strong correlation between food prices and violence then it is likely that this relationship can be observed in a relative short time. The outcome variable is a count of the total number of violent events in a given country-month. The distribution of this variable is slightly overdispersed; of the 12,372 country-months 20.7% are non-zero ($\mu = 0.36$, $\sigma = 0.97$).[9] To model the overdispersion adequately a negative binomial (NB) model is used. (Hausman et al., 1984; Colin Cameron and

[8] This restriction is due to the availability of the data for the outcome variable

[9] The data covers 47 countries over 21 years with the exception of Eritrea which is covered from 1993. South Sudan is not included.

Trivedi, 1986; Allison and Waterman, 2002; Lloyd-Smith, 2007).[10] In general Poisson models are preferred when estimating a model where the outcome variable is a count, but since the conditional mean exceeds the conditional variance such a model would fit the data poorly as it does not account for overdispersion. The NB model is more flexible in this respect. To account for unexplained variation over time and across countries, country and year fixed effects are included in some of the model estimations (Angrist and Pischke, 2008) as well as country-specific time trends. The year fixed effects also control for any possible bias in the outcome variable as the reporting of civil unrest in the earlier stages of the period covered might have been sparser compared to more recent years.

The negative binomial dispersion parameter is estimated using maximum likelihood.[11] A Generalised Linear Model (GLM) is used where the outcome and explanatory variables are linked with a standard link function (i.e. log) to the linear predictor:

$$\eta : P(Y = y \mid X) = \mu = g(\eta) \tag{3.1}$$

This linear predictor is a function of the country-specific food price index and the explanatory variables:

$$\eta_{ct} = X\prime\beta + F_{ct}\gamma \tag{3.2}$$

$X\prime$ is a vector of explanatory variables, fixed effects, and the intercept and F_{ct} is the country-specific food price index (FPI). β is a vector of coefficients associated with the matrix of explanatory variables and γ the parameter of interest measuring the effect of the FPI on the incidence of violence. Due to the use of time-series cross-sectional data

[10]The variance of the NB model is given by $\sigma^2 = \mu(1 + \mu/\theta)$ where θ is the dispersion parameter (decreasing θ correspond with higher levels of dispersion), this model allows the variance to exceed the mean in contrast to the Poisson distribution.

[11]The dispersion parameter θ is estimated in R using the *MASS* package.

the model might exhibit heteroskedasticity, so to asses the statistical significance of the results, robust standard errors are used clustered at the country-level.

3.4 Data and measurement

3.4.1 Food price index

Time series data on food prices is taken from the Global Economic Monitor (GEM) Commodities. This is a collection of monthly commodity prices of the major traded commodities from 1960 to present (World Bank, 2013a).[12] International rather than domestic food prices are used as they are a source of exogenous variation. The literature on price transmission shows that domestic food prices are responsive to international food prices (Demeke et al., 2008; Minot, 2011; Verpoorten et al., 2013; Ianchovichina et al., 2014) and can respond instantaneously (Kalkuhl, 2014). Using domestic prices could introduce endogeneity into the model as civil unrest could also impact the level of local food prices.[13] Like most economic time-series, food prices exhibit a trend over time which needs to be taken into account for estimating the effect as a result of real level differences (Gilbert and Morgan, 2010). To detrend the food prices I apply a penalised splines method to estimate the trend in the data. This methods uses a Generalized Additive Model (GAM) which accounts for the autocorrelation of the data and the error structure, this in contrast to other more commonly used detrending methods (Claeskens et al., 2009; Rosales and Krivobokova, 2012).[14]

[12] Since the data is given in nominal US dollars the Manufactures Unit Value Index, MUV (World Bank, 2013b), is used to deflate and calculate real prices. Values are available from 1960 to 2009, all later years are projections. The MUV is also used by the FAO to calculate their monthly Food Price Index.

[13] Gil-Alana Alberiko and Singh (2013) found no strong evidence for the effect of violence on local food prices in a study on Kenya. It is unclear however if this result generalizes to the whole of Africa.

[14] For commodity i the long-term trend between 1960-2011 is estimated and subtracted from the data. The resulting price series is shifted upwards with a constant to avoid negative values which would distort the country-specific price index when multiplied by negative values due to the use of net-imports.

For each country a specific food price index is calculated based on the country's import pattern. The country-specific index is given as:

$$F_{ct} = \sum_{i=1}^{N=9} P_{it}\lambda_{ci} \tag{3.3}$$

Where P_{it} is the price series of commodity i and λ_{ci} is country's c (fixed-weights) import share of commodity i relative to its initial GDP. Included food commodities for the index are limited to the main staples, such as the major cereals, sugar, and oils. These are the dominant traded agricultural crops (Nelson et al., 2010) and make up the bulk of total food imports as well as to account for substitution effects over time. Moreover, most other price indices contain food items that are of little relevance to the poor (Kalkuhl, 2014). Data on food trade is taken from the FAO Statistical Division (FAO Statistical Division, 2013).[15] I use net-imports to model the wealth effect of trade, and a fixed weight is used rather than periodic shares as short-term changes in the import pattern could reflect socio-political conditions leading to endogeneity (Arezki and Brückner, 2011). Other studies (e.g. Hendrix et al. (2009) and Bellemare (2015)) use individual crop prices rather than a price index, however this could potentially lead to incorrect results as it neglects possible substitution effects, for instance between cereals.

Figure 3.3 provides a visual summary of the FPI per country and illustrates the sometimes large variation in index values across countries.[16] In order to account for cross-country variation in levels and capture the monthly variation I follow the climate-conflict literature and use anomalies as a measure for shocks to food prices.[17] Anomalies are measured as the monthly standardised FPI deviation from the mean for a given country: $\frac{FPI_{ct}-\overline{FPI_c}}{\sigma_c}$, where FPI_{ct} is the current FPI level, FPI_c is the mean for

[15] Food imports make up between 10-25% of total merchandise imports. Cereals make up the majority of food imports (48.7%) followed by oils and fats (15.8%), and sugars (10.4%). Included food commodities are: barley, maize, palm oil, rice, sorghum, soybeans, soybean oil, sugar, and wheat.

[16] Descriptive statistics per country are provided in table B.1.

[17] See Hendrix and Salehyan (2012) for instance.

country c, and σ_c the standard deviation of the FPI for country c.[18]

3.4.2 Violent events

Data for the outcome variable is taken from the Social Conflict Analysis Database, SCAD (Hendrix and Salehyan, 2013). SCAD covers a wide range of so called social conflict events in Africa from 1990 to 2012, and in contrast with other conflict datasets it also includes low-intensity conflict events such as protests, riots, and inter-communal violence. The data is media-based and human-coded with information coming from the news wires from Agence France Press and Associated Press, containing detailed information about the actors and location of the events for a total of around 9000 distinct events. The focus of this study is on violent events such as riots, inter-communal violence, and civil conflict.[19] The outcome variable is the count of the number of incidents in a country-month. Figure 3.4 illustrates per country the number of violent events relative to the total number of events for 1990-2011.

[18]Figure B.2 shows this measure per country over time.

[19]This entails all observations coded as 3,4,7,8,9,10 for either *Etype* or *Escalation* and also includes events from the Uppsala Conflict Data Program dataset on conflict which are included in the SCAD dataset and coded as -9.

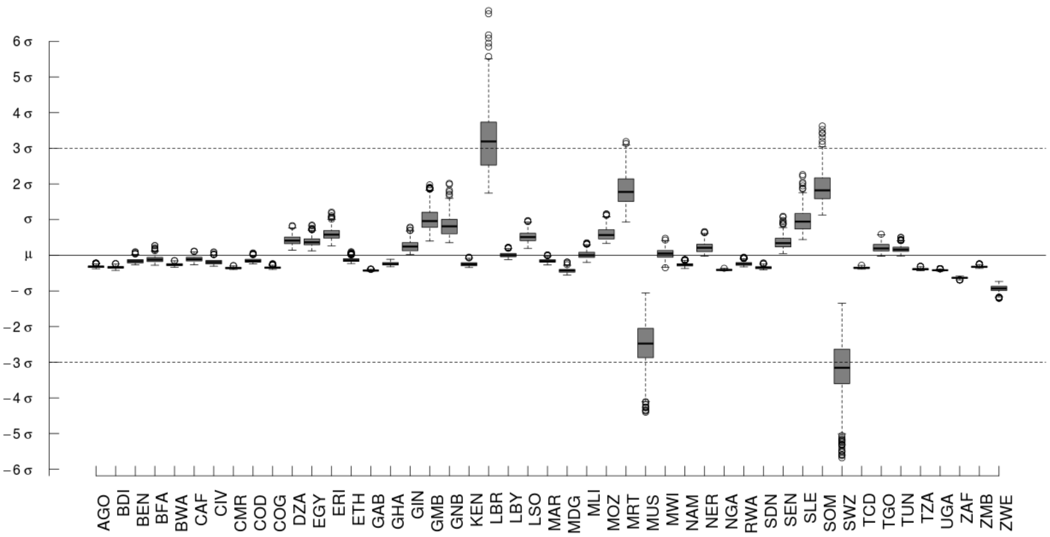

Figure 3.3: Boxplot country-specific food price index for each country in the sample.

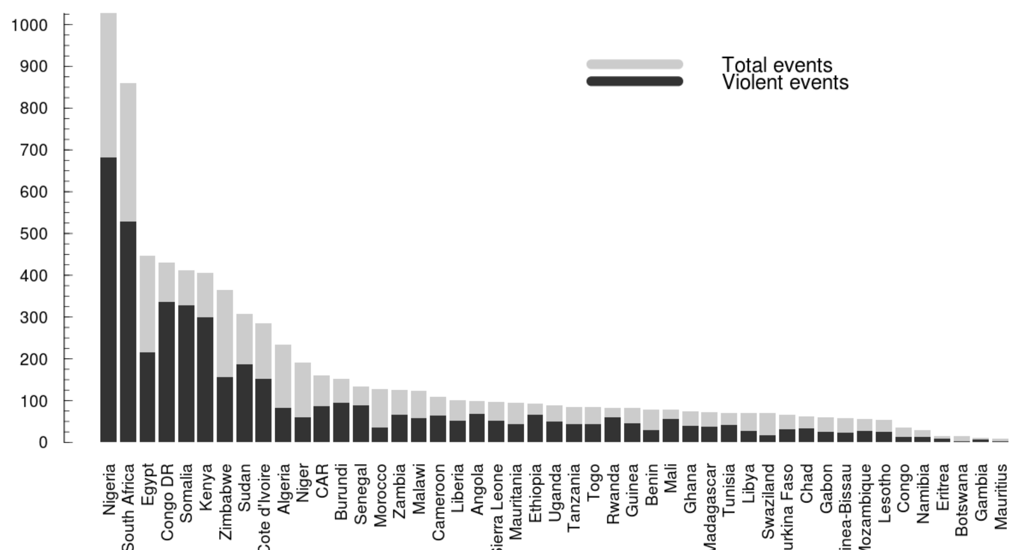

Figure 3.4: Number of total and violent social conflict events for African countries, 1990-2011. *Source* : SCAD 3.0.

3.4.3 Other explanatory variables

The model includes a number of other explanatory variables to control for factors that are commonly associated with instability and conflict.[20] Most of the included variables are based on the work by Goldstone et al. (2010) whose model for forecasting political instability showed good predictive performance.

Civil unrest could be linked to broader issues of political neglect, poverty, and low living standards. Therefore measures are included on income shocks, well-being, population, and regime type.[21] Gross domestic product per capita growth is included to control for income shocks and is measured in purchasing power parity exchange rates in order to compare across countries, the data comes from the World Development Indicators (WDI) (World Bank, 2012). As a broader measure of well-being, compared to GDP per capita, the natural log of the infant mortality rate is included (Goldstone et al., 2010; O'Loughlin et al., 2012), data taken from the WDI . Both GDP per capita growth and infant mortality rate should capture the socio-economic status of a country which is commonly linked to the occurrence of social conflict. The natural log of total population is included as larger populations are more difficult to control (Fearon and Laitin, 2003) and increase food demand.[22] The number of violent events in all other countries is included as a variable in the model to account for the so called demonstration effect (Goldstone et al., 2010) which might set a precedent making violence more likely. To account for regime type I use the categorical measure of Goldstone et al. (2010) who classify regimes on a 5-point scale using data from the polity IV project (Marshall et al., 2013) on the openness of executive recruitment and the competitiveness of political participation.[23] Finally, the lagged outcome variable is included in order to mitigate any

[20]See Hegre and Sambanis (2006); Goldstone et al. (2010)

[21]The data for these variables is annual and lagged by one year to control for endogeneity.

[22]The natural log is used due to scale differences between countries: the smallest country in the dataset has a population around 1 million (Swaziland) whereas the largest country's (Nigeria) population numbers 160 million (the average population is 8.7 million).

[23]Data taken from Polity IV project, (Marshall et al., 2013).

problems that could possibly arise from serial autocorrelation (Beck and Katz, 2011). Descriptive statistics for the main variables are given in table 3.1

Table 3.1: Descriptive statistics main variables

Variable	Mean	SD	Median	Minimum	Maximum	N
Violent unrest	0.37	0.97	0	0	15	12372
FPI_{σ}	-0.06	0.98	-0.20	-2.65	4.07	12372
Violence_{t-1}	0.36	0.97	0	0	15	12326
Violence_{C-i}	16.76	6.70	16	1	47	12372
Δ GDP per capita	0.01	0.07	0.02	-0.50	0.93	11688
Infant mortality rate_{ln}	4.71	0.60	4.81	2.72	5.80	12372
Population_{ln}	15.98	1.20	16.07	13.63	18.89	12372
Regime type	2.39	0.95	2	1	5	11196

3.5 Results

3.5.1 Preliminaries

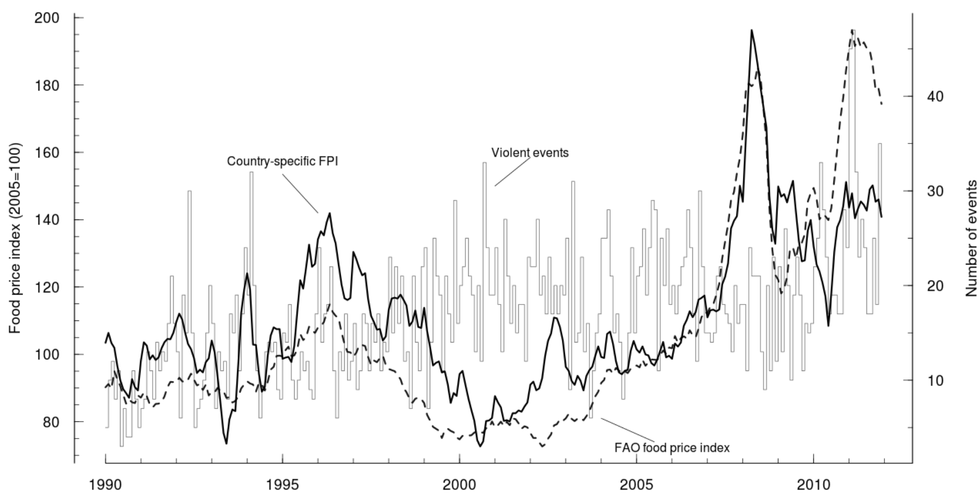

Figure 3.5: Food prices over time plotted against the violence incidence level in each month between 1990-2011. *Source* : FAO Food Price Index, GEM, and SCAD 3.0.

As a preliminary test I plot the monthly time series of violence, the country-specific food price index, and the more generic FAO food price index (shown in 3.5). The time series highlight that the evolution of violence and food prices are in general not very strongly related with each other, although there are some minor trends observable across certain sub-periods. The figure illustrates that between 1990-1998 there is a pro-cyclical movement between the price indices and violence, a trend that also seems to manifest itself in the years after 2010. For both the periods higher index values correspond with higher counts of violence. An example of this is the large spike in food prices around 2010/2011 which seems to perfectly coincide with the large increase of violence around that time.[24]

Interestingly, a similar spike in prices between 2007-2008 as a result of the world

[24]This period corresponds with the start of the Arab Spring which occurred across a number of North-African countries.

food price crisis does not materialise in a noticeable increase in violence levels. Food prices and violence seem to be negatively related in the 1999-2005 period as the time series exhibit a countercyclical movement where food prices increase but violence levels stabilise at around 20 incidents per month.[25] Although a lot of information is lost due to the level of aggregation, this preliminary test does provide some interesting initial insights on the link between food prices and violence showing that on average there is no clear pattern between fluctuation in food prices and violence on the African continent.

[25]More so for the FAO food price index than the country-specific food price index.

3.5.2 Main regression results

Table 3.2: Results negative binomial regression: effect of food prices on violence, 1990-2011.

Specifications	(1)	(2)	(3)	(4)	(5)
FPI	0.22	0.20	0.2	0.21	0.26
	(0.10)**	(0.05)***	(0.1)	(0.06)***	(0.09)***
Violence$_{(t-1)}$		1.29	0.35	0.7	0.41
		(0.06)***	(0.06)***	(0.1)***	(0.07)***
Violence$_{(C-i)}$				0.09	−0.02
				(0.09)	(0.05)
Δ GDP pc.				−0.2	−0.07
				(0.1)*	(0.08)
IMR				0.1	−1.0
				(0.1)	(0.6)
Population				1.4	−4
				(0.2)***	(4)
Regime type				0.1	0
				(0.1)	(0.2)
Residual deviance	6824.8	7328.0	7401.5	5992.2	5998.3
AIC	18638	16980	15157	12671	12133
AUC	0.5381	0.6935	0.8097	0.7551	0.791
N	12326	12326	12326	10722	10722
Country FE	–	–	Yes	–	Yes
Year FE	–	–	–	–	Yes
Country-specific time trend	–	–	Yes	–	–

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. FPI is the country-specific food price index. IMR, Infant mortality rate; AIC, Akaike information criterion; AUC, Area under curve; FE, Fixed effects.

Table 3.2 presents the main results of the effect of shocks in the country-specific Food Price Index (henceforth FPI) on violence using negative binomial regression. Note that throughout this study all input variables are placed on a common scale, centered around the mean and divided by two standard deviations, in order to facilitate easier comparison (Gelman, 2008).[26]

I start with a simple model (col.1) regressing the level of violence on the FPI and find that positive fluctuations correspond with higher violence levels ($e^{0.22} = 1.25$ relative risk ratio).[27] The model has a relatively poor fit though, looking at Area Under the

[26] Due to the rescaling the coefficients can be interpreted as the effect of moving from low to high values.

[27] The log relative risk is assumed to be normally distributed.

Curve (AUC) statistic, the model only correctly predicts violence incidence in 54% of the observations.[28] I include the lagged outcome variable to further account for autocorrelation (Bazzi and Blattman, 2014), which drastically improves the in-sample predictive power. The temporal lag of the outcome variable is a strong predictor for violence, significant at the 1% level and corresponding with a relative risk ratio of 3.6 ($e^{1.29}$).

I change the specification to include country fixed effects and a country-specific time trend (col.3). The country fixed effects account for time-invariant country characteristics, such as ethnic polarisation or mountainous terrain, while the country-specific time trends capture country-specific year shocks such as local droughts. The magnitude of the FPI remains stable but there is an increase in the standard error leading the coefficient to cease being statistically significant within the traditional boundaries (z=1.51, p-value=0.13). Despite the relatively high level of residual deviance, compared to the other models, the descriptive power is relatively good and outperforms the model including the country-specific explanatory variables (col.4). The preferred model (col.5) is specified with the full set of explanatory variables, country fixed effects, and year fixed effects to account for common time shocks. The estimation shows that higher food prices increase the risk of violence after controlling for economic, social, and political factors.[29] Moving from low to high values on the country-specific food price index corresponds with a 0.26 increase in the log of expected counts (the standard deviation of the log of the outcome variable is 0.4).

Estimating the model for different time periods I don't find any evidence for a particularly strong effect in a specific period. The regression results for sub-periods are

[28] As an alternative measure of significance the area under the curve (AUC) is used, which measures the overall prediction accuracy of the model based on the effect of each variable (O'Loughlin et al., 2012). The AUC statistic is measured on a 0-1 scale with the threshold based on the true and false positives ratio. Values closer to one indicate a better prediction rate. Normally the AUC is used for logit models so non-zero values are truncated to one in order to calculate the AUC statistic and determine the predictive power of the model.

[29] $e^{0.26} = 1.40$ relative risk ratio

only significant for 2005-2011.[30] Past violence levels seems to be the main predictor in the model. Including longer lags of violence in the model of up to 12 months does not alter estimated effect of the food prices.[31] The results of the preferred model are also robust to estimations using Poisson, quasi-Poisson, and log-linear models as well as logit and a linear probability model, using a binary outcome variable to account for possible reporting bias.[32] I run a number of robustness checks and find that the results are not sensitive to excluding the two countries with highest violence levels from the sample (Nigeria and South Africa), including an oil price index, including an interaction term with landlocked countries, or accounting for food aid that might mitigate the effects of higher food prices. The results show that besides the lagged outcome variable, the other included variables have very little explanatory power.[33]

3.5.3 Different specifications of the Food Price Index

The estimation results so far have been based on shocks in the food price index based on fluctuations in food prices from the long-term trend, weighted by the share of food net-imports relative to fixed GDP. I now proceed making adjustments to the FPI in order to examine the sensitivity of the results to the specific FPI construction.

I will be focussing on the price series used, included foodstuffs, and the relative weights of the foodstuffs in order to further disentangle the link between food prices, imports, and violence. For each different specification the FPI coefficient along with the 68% and 95% interval are visually summarised in figure 3.6.[34]

[30] See table B.7.

[31] See table B.8

[32] See table B.9

[33] Considering the goodness-of-fit of the model, the Akaike Information Criterion (AIC) shows that the inclusion of fixed effects leads to lower AIC values which indicate a better fit. The dispersion parameter θ is larger than one (1.56) indicating that the data is not highly overdispersed and the use of a negative binomial regression is sufficient (Lloyd-Smith, 2007). The ratio of deviance versus degrees of freedom (0.92) also indicates that the model is a good fit (Allison and Waterman, 2002).

[34] Results for estimated coefficients and models statistics are given in table B.11

The reason for using detrended prices is to account for the trend in food series which allows us to estimate the real level effect. However, the trend in the data might actually matter with regard to violence intensity and therefore I re-estimate the model using nominal and real food prices. The results show that there are some differences where the estimated magnitude for nominal and real prices is about 1.3 to 1.4 times larger than that of detrended prices. Using average net-imports of food relative to GDP for 1990-2011 leads to a 16% decrease in the coefficient size. Using an average weight might account better for shifts in consumption over time compared to a fixed weight, but is also likely endogenous. This coefficient should be therefore interpreted as a sort of lower bound. In this case the relative risk ratio of food price changes is 1.25 ($e^{0.22}$).
Estimating the model using a FPI constructed using only the trade balance gives almost identical results to the main index. Similar to the instrument used by Smith (2014) I

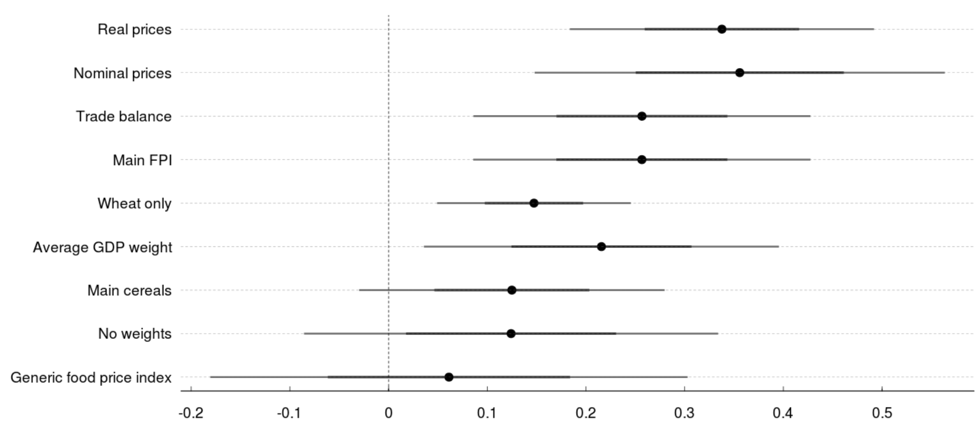

Figure 3.6: Estimates, 68% intervals, and 95% intervals for the food price index coefficient according to different specifications.

construct a price index using only the main cereals: wheat, rice, and maize. Although in this case the net-imports are fixed and relative to GDP in the period before the outcome variable is measured. The results cease to be statistically significant, while also showing a decrease in coefficient size. Focussing only on the impact of wheat prices as Hendrix et al. (2009), do produce a statistically significant coefficient and seems to indicate that shocks in global wheat prices indeed explain some of the observed violence. This partially counters the point I made in the introduction that there could be a potential bias due to unaccounted substitution effects. Although relative to the measures that include the full basket of foodstuffs, it only outperforms the measure that isn't trade-balanced (i.e. only accounting for whether a country imports a particular commodity).[35]

Out of all the food price indices, the generic food price index produces the smallest point estimate accompanied by a large standard error. The explanatory power of this variable is extremely low compared to the other measures. This is potentially due to the fact that it includes foodstuffs which aren't relevant to African countries. In general these results show that the effect of food prices on violence is likely driven by a specific basket of foodstuffs.

3.5.4 In-sample predictive power

The main results and various robustness checks show that in general there seems to be a link between food prices and violence levels. However, we should be cautious relying too much on *p*-values for determining the strength of a particular model (Ward et al., 2010). To assess the in-sample predictive power I re-estimate the model omitting one variable at a time and measure the change in the *AUC* statistic, the results for which are shown in figure 3.7.

The figure illustrates that the main predictor for violence is past violence levels, whereas for instance the inclusion of infant mortality rate actually slightly decreases the predictive power of the model. Following the best fit regression line through 0 the predictive power of regime type and population is about where we would expect it to be, based on

[35]The explanatory power of this measure is similar to the measure only including the main cereals.

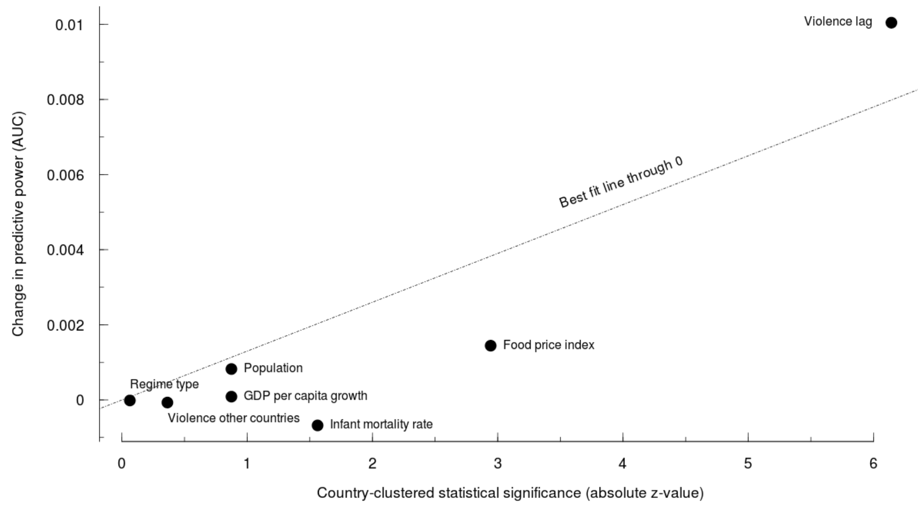

Figure 3.7: Comparison of statistical significance (absolute z-value) vs. predictive power of the variable (ΔAUC), based on model in table 4.1 column 5.

their level of statistical significance. In that respect, although the regression analysis showed that the FPI was a relatively strong predictor of violence based on the magnitude of the coefficient, this doesn't translate into improvements in the model accuracy. To get a better understanding of the model's predictive behaviour I examine the generated predicted outcomes, setting the threshold at 1 to distinguish between predicted events and non-events. Out of the total of 1,969 non-zero observations in the data, the model correctly predicts the incidence of violence in 500 cases which corresponds with a 25% correct prediction rate. This leaves a total of 1,469 false negatives while also generating 184 false positives, the distribution across countries of which is shown in figure 3.8. The figure illustrates that the false positives are almost exclusively generated for countries with high levels of violence prevalence (see fig 3.4) whereas the false negatives cover a wider range of countries. In general the results seem to indicate that the model is able to identify violence in countries with high levels of violence on average but less able to correctly identify specific episodes of violence. This would imply that the effect of food prices is larger in countries like South Africa, which actually has a negative FPI, compared to a country like Senegal which is arguably more exposed to higher food prices due to its large food imports.[36]

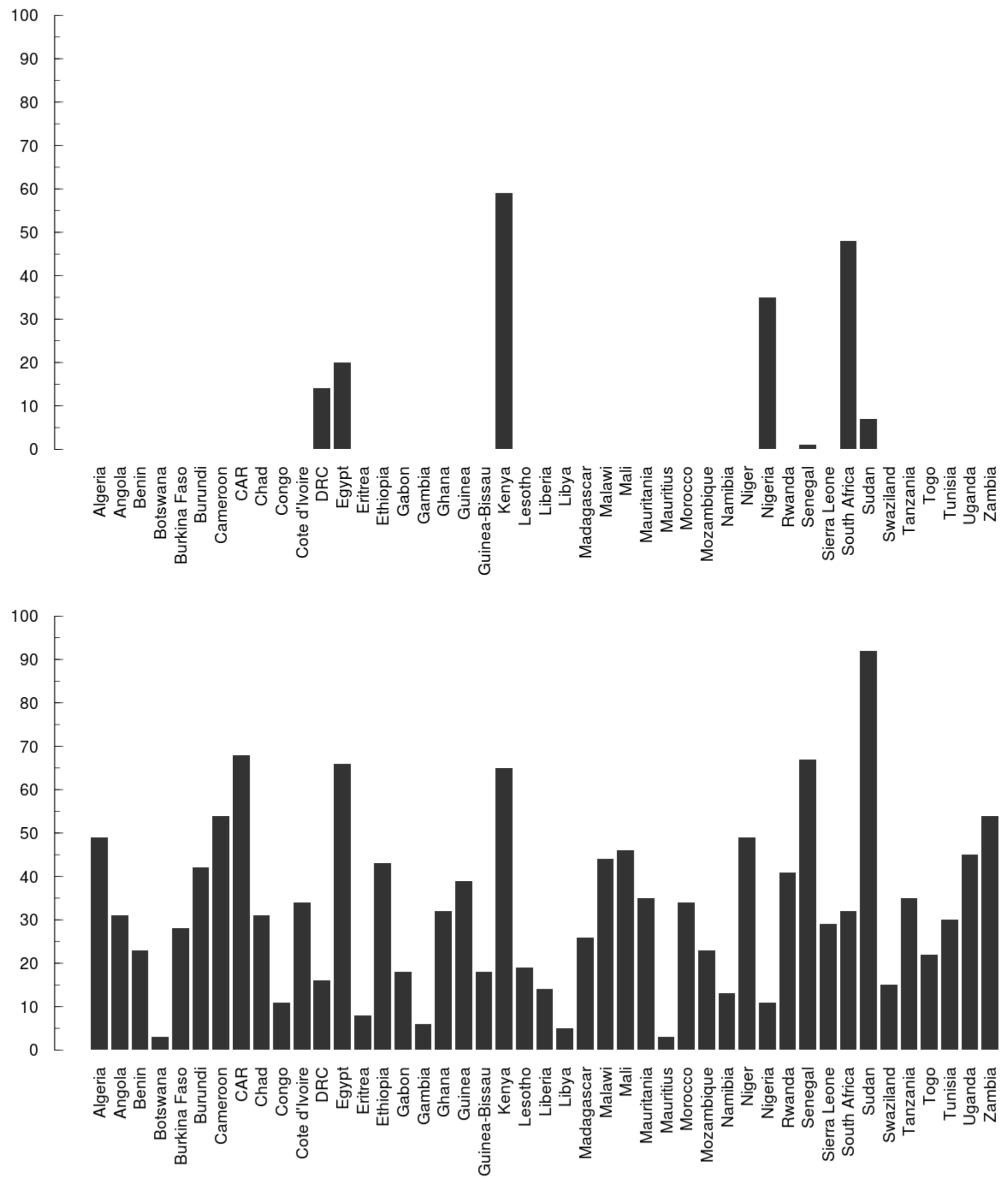

Figure 3.8: Distribution across countries of generated false positives (*top*) and false negatives (*bottom*) for in-sample predictions.

[36]For the false negatives the average shock to the FPI is 0.35 (median is 0.28).

Focussing on the intensive margin, figure 3.9 plots the predicted outcome levels along the observed violence levels which are ordered from low to high where the red line through the plot indicates the true level of the outcome variable. Although in general the model is under-predicting the incidence of violence, it is over-predicting violence in particular countries as illustrated by the figures, both the incidence of violence as well as the intensity of the violence in a country-month. Again, most of these countries appear in the top 5 of violent events. The corresponding shocks to the FPI for these observations are above average with an average value of 0.46 (median 0.62).

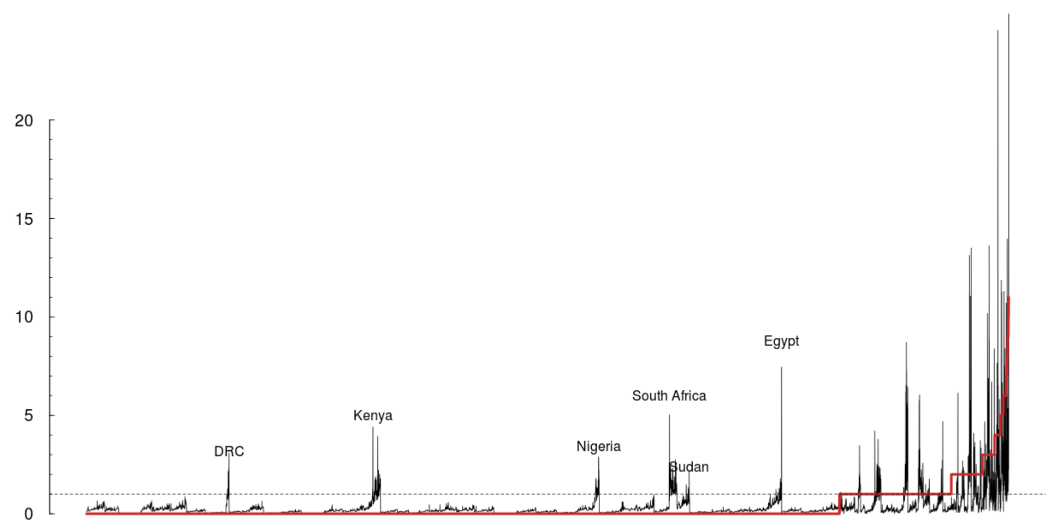

Figure 3.9: Predicted values generated by the model ordered along the observed violence levels from low to thigh, where the red line indicates the real level of violence.

3.5.5 Out-of-sample predictions

I now turn the attention to actual prediction for out-of-sample data using data from 2012, constructing a dataset with 540 observations including 171 cases of violence.[37] One possible exception to my earlier comment that most studies don't pay attention to prediction is the work by Lagi et al. (2011). In their paper they extrapolated the FAO food price index and, based on the increase in the index value, argued that at current prices mid-2012 would be likely point of instability. Figure 3.10 extends an earlier figure (figure 3.5) to include the data on violence and the FPI for 2012 and shows that there indeed seems to be some pro-cyclical movement in both time-series.[38] It would therefore be interesting to see if this trend continues and if food prices can be of value in predicting violence levels. Generating the predicted outcomes using the main model correctly predicts the incidence of violence in 48 observations which leaves 88 false negatives. It seems that the correct predictions have little to do with shocks to the FPI as the average value is negative (-0.18). The in-sample predicted outcomes showed that in general the model was over-predicting the incidence of violence for particular countries and in general over-predicting the intensity of events. The over-prediction of intensity levels has decreased quite sharply. For instance the maximum predicted intensity if just 9.8 versus the actual observed level of 19 (figure 3.12). A positive development is the decrease in the over-prediction for particular countries: the model generates just 8 false positives (7 in Democratic Republic of the Congo and 1 in South Africa, see figure 3.11).

These results are based on the main model which has the FPI specified using de-trended prices while in contrast the prediction by Lagi et al. (2011) was done using nominal prices. As a robustness check I therefore use the FPI constructed with nominal

[37]Due to missing values 36 observations are omitted leaving 504 observations with 136 cases of violence.

[38]The regression analysis results also produced significant results for the estimated effect of food prices on violence in the past 6 years.

prices to generate the predicted outcomes and find that nominal prices perform similarly. The model only generates 1 false positives, but also has less correct predictions with 41 (leaving 95 false negatives). For the main dataset I showed that the predictive power of the FPI was relatively low and this issue seems to be exacerbated for out-of-sample data. Using a baseline model only omitting the FPI variable I find more or less the same predictions as the main model: 50 correct predictions, leaving 86 false negatives (10 false positives). This illustrates that, at least for 2012, food prices are of little use in trying to predict civil unrest.

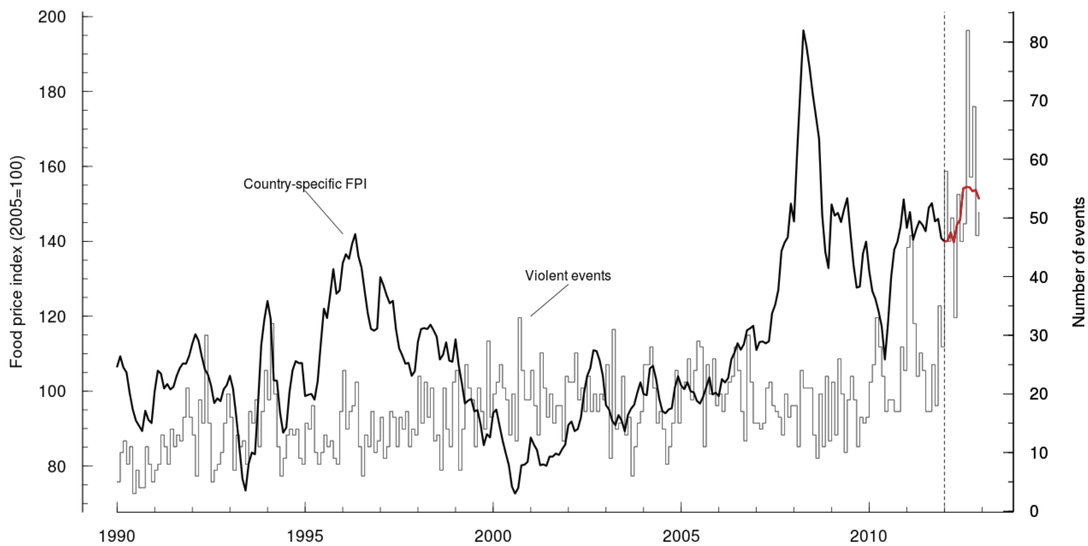

Figure 3.10: Food price index and number of violent events extended to 2012.

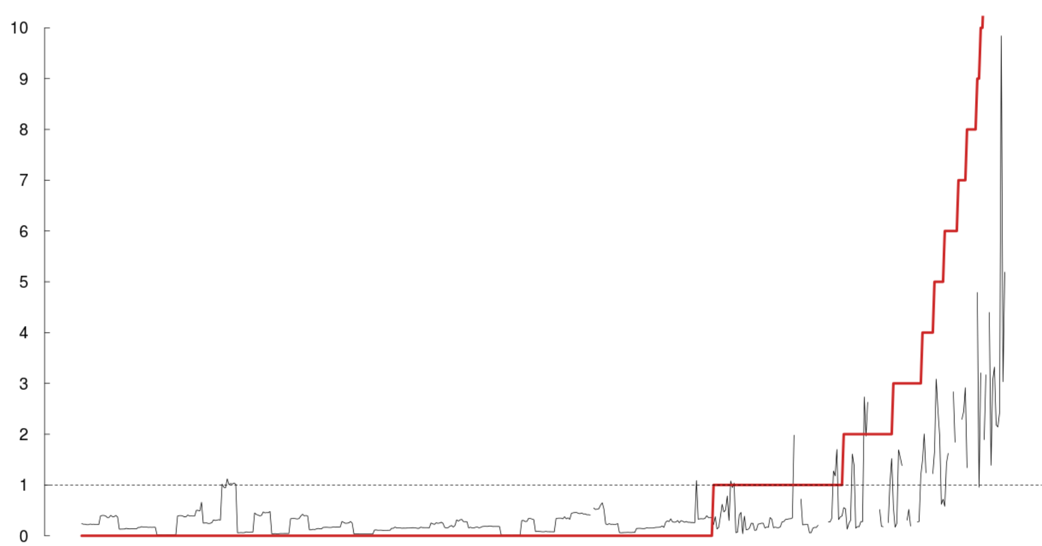

Figure 3.11: Predicted values generated by the model ordered along the observed violence levels from low to thigh, where the red line indicates the real level of violence.

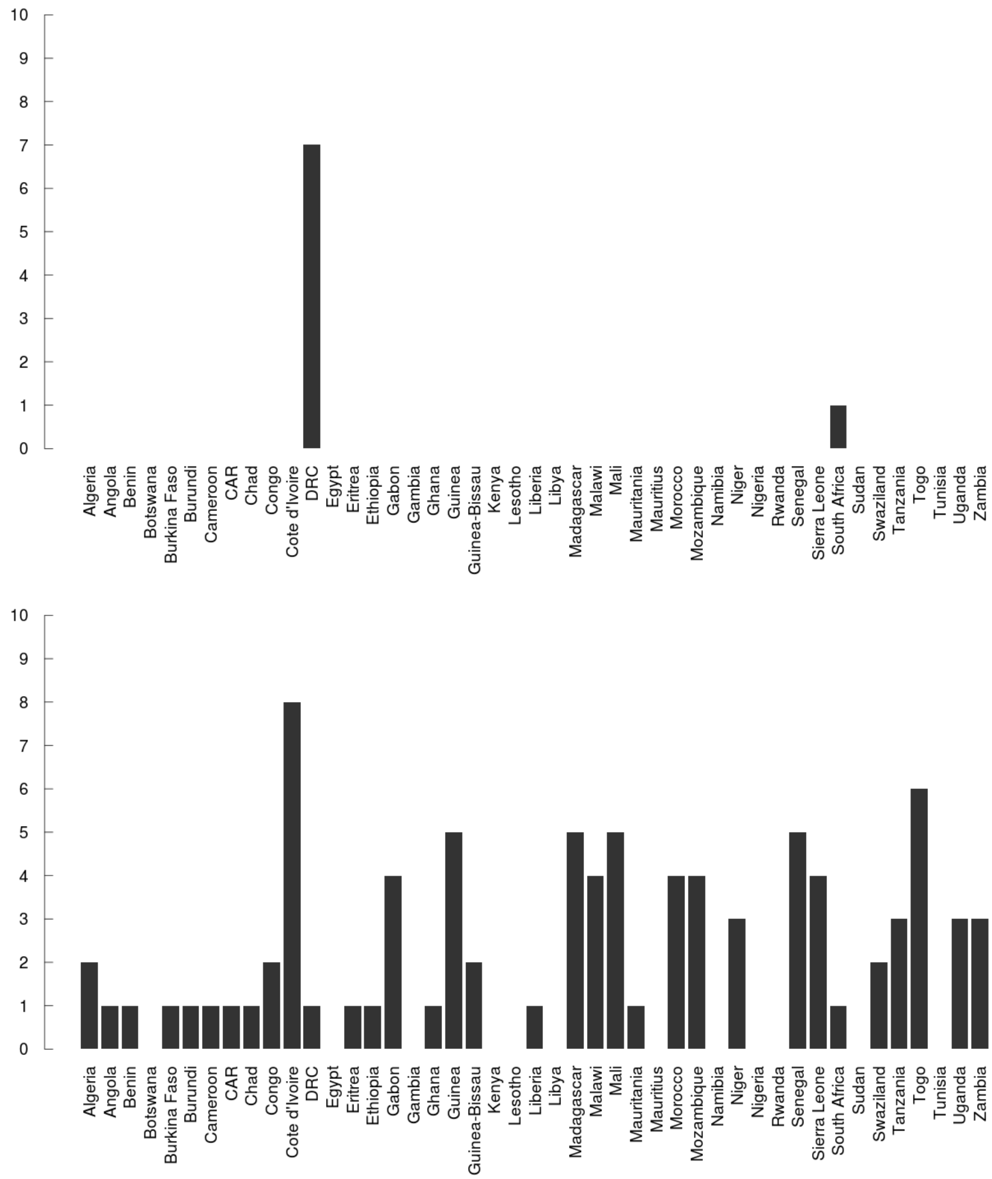

Figure 3.12: Distribution across countries of generated false positives (*top*) and false negatives (*bottom*)for out-of-sample predictions.

3.6 Conclusion

Despite the social relevance of the subject there is still relatively little known about the impact of higher food prices on the poor in the general and on civil unrest in particular, although there has been an increase in research on the subject. Anecdotal evidence on food riots provides some support for the claim of a link between higher food prices and civil unrest, as a scenario occurs where higher food prices create a greater sense of relative deprivation, leading to grievances among the population which could culminate into violence. The empirical research so far has tried to examine this mechanism and found some proof for the claim that higher food prices are associated with an increase in unrest and instability.

Using the latest data I re-examine this claim applying a new method to account for the trend in food prices and construct a food price index based on a country's food import pattern to correctly model the effect of real level differences in food price levels. The regression analysis shows that higher food prices correspond with higher violence levels, an effect robust to different model specifications as well as estimation methods. The results also show that relations seem to be driven mainly by the prices of basic staples (mainly wheat). The magnitude of the effect is relatively low though and despite the statistically significant results I also find that food prices have very little predictive power both for in-sample and out-of-sample predictions. Using data for 2012 I find that the inclusion of food prices in the model is of little relevance to the predictive performance which casts some doubts on the claim of a link between food prices and civil unrest.

Chapter 4

A spatial analysis of the effect of foreign aid in conflict areas

4.1 Introduction

Annually billions of dollars of foreign aid flow from developed to developing countries with the aim to reduce malnutrition, poverty, and increase stability. Concerning political stability, the empirical literature on aid and conflict has produced diverging results with no consensus on the direction of the effect. This might not be surprising given the mixed results on the effectiveness of foreign aid in general (Roodman, 2007; Easterly and Pfutze, 2008; Doucouliagos and Paldam, 2008, 2011).

In this study I do not aim to address the whole debate on foreign aid effectiveness, but rather zero in on the aid-conflict nexus focussing on effects at the sub-national level. This nexus has been studied in the quantitative literature predominantly using the country-year as unit of analysis. Due to this level of aggregation, useful information on the dynamics of aid and conflict is potentially lost as most aid projects are targeted at local development (Findley et al., 2011; Berman et al., 2013) and conflict tends to be highly localised (Raleigh et al., 2010). It is therefore straightforward to see that a more disaggregated approach, that takes into account the local dynamics, could improve our understanding of how aid influences conflict.

There are some examples of recent research that take this approach. These include the study by Berman et al. (2013) on Iraq, Tahir (2015) on Pakistan, and work by Arcand and Labonne (2011) and Crost et al. (2014) on the Philippines as well as the paper by Strandow et al. (2014) that also focuses on Africa. Most of these studies focus on particular conflicts in specific countries which makes their results hard to generalise. This study extends the current literature by providing a cross-country study in which the analysis is focussed on the sub-national level. More specifically I examine the link between foreign aid allocations and conflict intensity in three African countries (Democratic Republic of Congo, Ethiopia, and Sudan) between 1999-2008. I estimate the effect at the provincial and district level based on data from a unique dataset on local aid allocations using Bayesian estimation to produce consistent estimates in the presence of spatial autocorrelation. This work is most similar to that of Strandow et al. (2014), the main difference is that their work focuses on the effect of aid distribution in contested areas whereas I examine the more general effect of aid allocations on conflict. This study also adds to the growing literature on conflict intensity which includes work by Hegre et al. (2009), Costalli and Moro (2012), Hendrix and Salehyan (2012), O'Loughlin et al. (2012), Raleigh and Kniveton (2012), and Maystadt et al. (2014). Focussing on conflict intensity allows us to get better insights in conflict dynamics as we keep the full information of the conflict data, this in contrast with the commonly used cruder binary measures.

The statistical analysis shows that there is little evidence for a particular strong link between aid and conflict. Pushing the results hard I find that at the extremes moving from low to high changes in aid corresponds with 0.2% decrease in conflict intensity. This negative link between aid and conflict is stronger for non-fungible aid compared to fungible aid which likely has no effect in this sample. Given the data availability on aid, which only maps commitments and not disbursements, I am however cautious with drawing too strong conclusions about the causal mechanisms. In the model the strongest predictor for changes in conflict intensity are past changes which correspond negatively with current changes in conflict intensity. This results shows that high intensity conflict events in general are not persistent over time. Considering the spatial effects of conflict the results show that conflict tends to be highly localised and that there is a some risk of contagion across districts but not provinces.

4.2 Existing literature

There is a large schism in the literature concerning the effect of foreign aid on conflict dynamics, specifically the direction of the effect. Theoretically, the perceived positive link between aid and conflict is channelled through rent-seeking behaviour and the potential shift in the domestic power balance as a result of aid allocations.[1]

One strand of the literature argues that aid flows are beneficial and might improve stability. Aid money can be used for social spending which potentially reduces grievances the population might have versus the government. It also increases opportunity costs of conflict, making it more difficult to recruit insurgents, and additionally aid money could be diverted to increase military expenditures which provides a strong deterrent (Collier and Hoeffler, 2002, 2007). In all these cases foreign aid will bolster government capacity and reduce conflict risk, an effect for which Collier and Hoeffler (2002) offers three routes.

In the direct route i) aid augments the government budget and relaxes budget constrains

[1] An important concept in this regard is the issue of state capacity as described by Fearon and Laitin (2003) who argue that bureaucratically weak states have an increased risk for insurgency. See Petřík (2008) for an overview on the literature on the role of development assistance in ongoing conflicts and its influence on violent tensions during times of peace.

while indirectly ii) aid affects economic growth (although this is heavily debated) and iii) diversifies the economy making it less dependent on primary commodities. According to Collier and Hoeffler (2002) these three factors combined make conflict less likely as a result of foreign aid flows.
de Ree and Nillesen (2009) provide empirical evidence for the direct channel, where aid relaxes the budget constraints. They find that higher levels of foreign aid are correlated with a reduction in conflict duration, possibly due to increased government capacity according to the authors.[2] In similar vein, Savun and Tirone (2011) show that stability improves in countries during a democratic transition when receiving foreign development assistance. So called democracy aid helps reduce the commitment problems of the government that occur during this democratisation process as the authority of the central government weakens and uncertainty increases. Subsequently the likelihood of conflict decreases due to this democracy aid.

In contrast, the other strand of the literature is more negative in tone and argues that aid increases conflict risk. In a seminal paper, Grossman (1992) describes how the insurgents' objective is to capture the state for financial advantages. More aid will make this objective more lucrative and thus increase incentives, something also echoed by Addison and Murshed (2001). The empirical proof for this hypothesis is based mainly on the uncertainty or volatility in aid flows. For example Arcand and Chauvet (2001) find that although aid can have a stabilizing effect, the uncertainty of aid flows will actually increase conflict likelihood. Aid flow volatility leads to higher uncertainty levels which fosters instability. In turn, large negative shocks will lead to a shift in the domestic power balance which increases conflict likelihood as shown by Nielsen et al. (2011). Focussing on state capacity, Djankov et al. (2008) find that negative aid shocks can lead to a deterioration in institutional quality. They also find that the magnitude of the effect of aid rents is larger compared to that of natural resources such as oil.

[2] They are unable to establish a causal link however.

Besides this volatility, there are other parallels between natural resources and foreign aid. For instance local aid allocations, like humanitarian aid, provide a lootable resource similar to natural resources. Aid can be appropriated by insurgents (Blouin and Pallage, 2008) in order to supplement their income or help support their operations, both of which will potentially increase conflict duration (Findley et al., 2011). Anecdotal evidence includes the theft by al-Shabaab in Southern Somalia of about $500,000 worth of humanitarian materials and supplies between late 2011 and early 2012 (Department for International Development, 2013). Similarly Nunn and Qian (2014) find in a study on the effect of U.S food aid on conflict that increases in food aid correspond with increases in both the incidence and duration of civil conflict.[3]

There are a number of papers that have tried to disentangle the relation between aid and conflict at the local level.[4] Berman et al. (2013) look at the effect of per district development spending by the U.S. military in Iraq and find that aid potentially reduces violence. This effect mainly occurs in district with small aid projects (below $50,000) combined with high levels of troop strength, and the availability of development expertise. This paper provides an interesting insight in the effect of aid spending in a conflict situation, highlighting some of the factors required for aid to have a beneficial impact on the local community. Two other examples focus on the effect of local development programmes in the Philippines. Arcand and Labonne (2011) use a rent-seeking model for conflict and show that between 2003-2006 increases in the intensity of violence around aid projects are related to the insurgents' ideology and not just an effect of the level of aid itself. Similarly Crost et al. (2014) examine the effect of a large development programme on conflict intensity between 2002-2009 and find that municipalities that are barely eligible for receiving aid from this programme experience large increases in

[3]This effect tends to be more pronounced in countries with a recent spell of conflict. Collier and Hoeffler (2002) argue that food aid is the only type of aid that can be appropriated by insurgents during a conflict.

[4]Böhnke and Zurcher (2013) study the impact of aid on perceived security in Afghanistan and is therefore not directly comparable with the other works discussed here or this paper in general.

fatalities as the authors argue the insurgents try to sabotage the project. Focussing on Pakistan, Tahir (2015) finds that aid increases conflict risk as it erodes the fiscal capacity of the state.

Most similar to this study is the work by Strandow et al. (2014) who examine the effect of aid distribution in contested areas during ongoing wars in Sub-Sahara Africa. They find that concentrated aid increases the likelihood of conflict.

From the literature the following mechanism emerge, linking foreign aid and conflict (as discussed in Findley et al. (2011)) that is of interest to this study. Larger aid flows will increase the prize associated with capturing the state, an effect that provides rent-seeking opportunities which increases the risk of insurgency. However, simultaneously higher aid levels potentially decrease conflict risk as it improves state capacity. Following this mechanism, in the local context we would expect to observe more conflict in remote regions of the country. In these peripheral areas at a distance from the capital the central government has arguably less authority and is also less visible compared to regions closer to the seat of power. Considering the effect of local development projects we would expect that higher levels of regional aid allocations intensify conflict as it has the potential to weaken insurgents on the long term as local economic development increases opportunity costs and popular support for the government (Crost et al., 2014). Additionally, since aid is a resource that can be appropriated it potentially provides incentives for conflict at the local level as well. Aid appropriation can become a key objective for local insurgents in order to supplement income and accordingly, at the local level, we would expect to observe regions where aid and conflict tends to cluster.

4.3 Data and measurement

First and second level administrative divisions are used as unit of analysis as they capture the social heterogeneity that follows sub-national boundaries (Østby et al., 2009; Aas Rustad et al., 2011).[5] I use two different levels as the statistical results could be driven by the level of aggregation as a result of modifiable areal unit problem (MAUP) (Gehlke and Biehl, 1934; Openshaw, 1983; Fotheringham and Wong, 1991) and also to account for possible displacement effects (Maystadt et al., 2014).

4.3.1 Foreign aid

Measurements on local foreign aid allocations are taken from the UCDP/AidData dataset constructed by Findley et al. (2011) which includes detailed information on the location of aid projects for the period 1989-2008 and is currently the most comprehensive geocoded aid dataset available.[6] This dataset is based on AidData (Tierney et al., 2011) which contains detailed information on development finance (loans or grants) allocated to developing countries with the intend to promote economic development. It includes data on finance by governments, official government aid agencies, and inter-governmental organisations but not from non-governmental organisations, the private sector or military assistance. The information in the dataset is compiled from a wide range of sources such as annual donor reports and project documents from bilateral and multilateral aid agencies as described in Tierney et al. (2011).

For each region aid allocations, measured in constant U.S. dollars, are aggregated to region-year level and lagged by one year.[7] The lag is taken for two reasons.

One is to account for simultaneity bias as aid commitments could be the results of

[5] Data source: GADM database of Global Administrative Areas v.2.0 (GADM, 2012). First and second level administrative divisions correspond with provinces and districts respectively.

[6] See also Strandow et al. (2011).

[7] To account for scale differences, the natural log is taken.

donors' reaction to violence levels (de Ree and Nillesen, 2009). Donors could decide to increase aid commitment to an area experiencing conflict to help reduce the adverse effects of violence or reduce commitments as risk mitigation. However, it is very unlikely that donors are able to anticipate conflict as there is very little known about how aid, and donors behaviours, influences conflict (Strandow et al., 2014).[8]

Second, a shortcoming of the dataset is that it only contains information on commitments and does not track disbursements.[9] To deal, at least partially, with this problem the aid commitments are lagged since there is likely a delay between commitments and the actual disbursement in the intended region. This also implies another constraint concerning the estimation of the effect of aid on conflict. Due to the absence of information on disbursements I can't account for longer delays than one year between aid commitments and disbursements or for cases where there is not a one to one relation between commitments and disbursements. This means that ultimately I rely on the assumption that aid commitments will have short term effects on conflict intensity.

Although this is the most comprehensive dataset available it is unclear, and also impossible to know, whether it includes the total number of aid projects.[10]

An inspection on data availability shows that potentially missing data might not be random in terms of temporal coverage. The number of aid projects per year in the earlier year (1989-1997) is considerably lower (only 16% of the total) compared to the later period from 1998 onwards. A more serious source of bias is the country selection. Only Sub-Saharan African countries with conflict between 1989-2008 are sampled, and predominantly conflict-years are included. This leads to gaps in data availability as shown in figure 4.1. To account for these problems I focus the analysis on the period with relatively good coverage (1999-2008) and only include countries that have no gaps

[8] Additionally Strandow et al. (2014) argue that in the unlikely case that donors do anticipate conflict, this will probably lead to an increase in variation in aid commitments meaning that there is no systematic effect across donors and aid types that biases the results.

[9] This data is not available.

[10] This is also acknowledged by Strandow et al. (2014).

in their records. I therefore limit the sample to 3 countries: the Democratic Republic of the Congo (DRC), Ethiopia, and Sudan. These three are included as they are roughly comparable in size, also in terms of the sub-national administrative units, and additionally have substantial within-country variation in both conflict levels and aid allocation.[11]

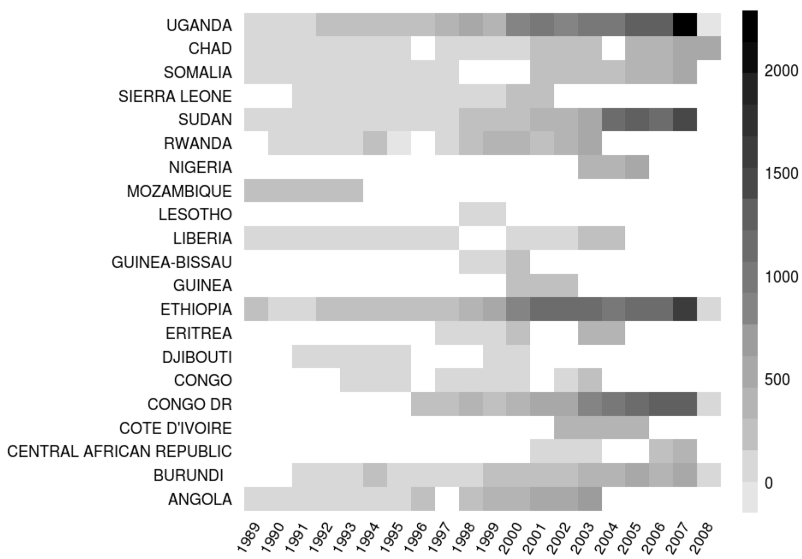

Figure 4.1: Overview of the coverage of aid allocations per country for the period 1989-2008. Darker shades indicate a higher number of aid projects included for the corresponding country-year. *Sources* : UCDP/AidData, Findley et al. (2011).

4.3.2 Civil conflict

Data for the outcome variable is taken from the UCDP Georeferenced Event Dataset v.1.5-2011 (Sundberg et al., 2010; Sundberg and Melander, 2013). This is the most accurate geocoded dataset on conflict available (Eck, 2012). An additional advantage is that it uses the same geocoding methodology as the aid dataset (Strandow et al.,

[11]For these reasons I do not include Uganda and Burundi as they are not comparable in size at national and sub-national level.

2011).[12]

A conflict event is defined as "a phenomenon of lethal violence occurring at a given time and place" and each event is given as a point with longitude and latitude coordinates, time of occurrence, and the number of fatalities. This point data is aggregated to the regional level to create the conflict measure: the total number of fatalities in a year.[13]

Conflict at the local level might exhibit particular spatial patterns which leads to spatial autocorrelation in the outcome variable.[14] This means that the observed value for conflict intensity in region i could depend on conflict levels in nearby regions, rather than only the covariates in region i itself. To account for this interdependence a spatial lag of outcome variable W is included in the model. This spatial lag is a spatially weighted conflict measure based on conflict intensity in the k neighbouring regions of i. W is calculated using a binary spatial weights matrix based on first order contiguity, i.e. only including the direct neighbours of i.[15] The spatial weights matrix is not row-standardised as row-standardisation would imply that the influence of region j on i decreases when the number of neighbours increases. This would entail that the effect of conflict in neighbouring areas is larger when a region has relatively few neighbours which is not theoretically justifiable in this case.[16]

[12]This ensures that the precision of the two datasets is identical, in contrast with other available datasets where the precision of the geocoding is less clear, and thus facilitates accurate matching.

[13]As a robustness check the model is also estimated using a binary indicator for conflict incidence. This indicator takes value 1 if there is a conflict in region i at time t and 0 otherwise.

[14]This could mean diffusion where conflict in region i could spread uniformly to other regions in the geographic space or clustering where region i and its k neighbours have very similar levels of conflict. Spatial autocorrelation is similar to temporal autocorrelation with the main difference that spatial autocorrelation can move in either direction.

[15]Direct neighbours irrespective of national borders. Contiguity is used rather than a distance based measure because of the variability in size of the regions.

[16]Note that according to LeSage and Pace (2010) the estimates and inferences from the regression model should not be sensitive to particular specifications of the spatial weights structure.

4.3.3 Other explanatory variables

In some model specifications a number of additional explanatory variables are included to account for specific factors that could be linked to civil conflict.

I include regional total population with yearly data derived from the Gridded Population of the World v.3 dataset (CIESIN, 2004). Local income shocks are linked to conflict (Hodler and Raschky, 2014b), but since comparable income data at the sub-national level for developing countries is almost non-existent I follow Henderson et al. (2012), Michalopoulos and Papaioannou (2015), Hodler and Raschky (2014a), and Besley and Reynal-Querol (2014) by using satellite night light density data as a proxy for economic activity. Data is taken from the National Oceanic and Atmospheric Administration's Earth Observation Group. Some recent studies have provided empirical evidence for a link between ethnic heterogeneity and the prevalence of conflict (Cederman and Girardin, 2007; Weidmann, 2009; Kuhn and Weidmann, 2013), therefore a ethnic polarisation measure (Garcia-Montalvo and Reynal-Querol, 2005) is included, data taken from the GREG dataset (Weidmann et al., 2010). Similarly, total population (Hegre and Sambanis, 2006) and lootable resources (Ross, 2004, 2006; Lujala et al., 2005) are linked to conflict. Natural resources are accounted for by a dummy indicating the presence of oil or diamonds.[17] Finally, as a proxy for government capacity the natural log of the distance from the national capital is included as peripheral areas far from the capital could be more likely to experience conflict as government power is weak in these regions.[18]

[17]Data source: Gilmore et al. (2005) for diamonds and PRIO Petroleum Dataset v.1.2 for oil (Lujala et al., 2007)

[18]The distance is measured in kilometres from the centroid of the administrative division.

4.4 Estimation framework

The effect of foreign aid on conflict is estimated using Bayesian regression which has the advantage of producing consistent estimates in the presence of spatial interdependence (LeSage, 2000). This in contrast with classic methods like OLS, used by Berman et al. (2013) and Crost et al. (2014)), which suffers from omitted variable bias if the spatial structure is not modelled, or simultaneity bias when the spatial lag is included as the errors are no longer independent. To identify the effect of aid on conflict I use the same approach as Berman et al. (2013) and use a first-differences design. I regress changes in conflict levels on changes in lagged aid allocations controlling for changes in conflict in neighbouring areas and lagged changes in conflict as given in the following model specification (Eq.1):

$$\Delta C_{it} = \rho\Delta\sum_k W_{ikt}C_{kt} + \beta\Delta C_{it-1} + \gamma\Delta A_{it-1} + \theta_t \tag{4.1}$$

Outcome variable C_{it} is the change in the log count of the number of fatalities in region i at time t. The sign and strength of the interdependence in the outcome variable is estimated by $\rho\sum_k W_{ikt}C_{kt}$, where W is the autoregressive term and ρ the spatial autoregressive parameter.[19]

The temporal lag of the outcome variable is included as in the model as this effectively captures common trends and accounts for temporal dynamics (Plümper and Neumayer, 2010). Year indicators (θ_t) are included in the model to account for common shocks. γ represents the effect of changes in aid levels on changes in conflict intensity.

[19]The inclusion of the spatial lag controls for contemporaneous correlation in the outcome variable and allows me to estimate the sign and strength of the correlation. I refer to the work by Beck et al. (2006); Plümper and Neumayer (2010); Franzese and Hays (2007) for an extensive overview of model specification in the presence of interdependence. Annex B presents results for the Moran's I test for autocorrelation which establishes that there is spatial autocorrelation in the outcome variable.

Although less informative, I also consider changes on the extensive margin using a conflict onset indicator and estimating the model with logit as a robustness check. The conflict onset measure is a binary indicator for region i in year t which equals 1 if there is a conflict in year t but not in year $t-1$ and 0 if there is no conflict in both year t and $t-1$. If there is a conflict in year $t-1$ then the indicator is not defined for t. To estimate the effect I use a multilevel model similar to the one used by Danneman and Ritter (2013). The advantage of using a multilevel model is the ease with which it can handle the time-series cross-sectional structure of the data and account for differences across the units of analysis (Gelman and Hill, 2006).[20] I use the following estimation framework:

$$C_{it} = \alpha_i + \rho \sum_k W_{ikt} C_{kt} + \beta C_{it-1} + \gamma Aid_{it-1} + \theta_t \tag{4.2}$$

$$\alpha_i = \alpha_0 + \eta_i \tag{4.3}$$

Where $\eta_i \sim N(0, \sigma_i^2)$ and X is a vector with other explanatory variables. The model is estimated using a partial pooling procedure which means that intercept α_i is an outcome in the model, where α_0 represents the average intercept across the regions and η_i is the unique effect of region i on α which is assumed to be a random shock from the normal distribution (Shor et al., 2007).

The models are estimated using a Gibbs sampler, which is a Markov Chain Monte Carlo (MCMC) algorithm, in order to construct the posterior distribution for the parameters from which the coefficients and their uncertainty interval are calculated.[21] Parameters

[20] The unit of analysis, the region-year, is nested within the regions so the data has a clustered structure with two levels or hierarchies: the regional level and the time component. The multilevel model recognises the existence of this hierarchy by allowing residual components at each level in the hierarchy.
For a more extensive theoretical elaboration on the use of Bayesian multilevel models with time-series cross-sectional data I refer to Shor et al. (2007).

[21] JAGS is used for the Gibbs sampler (Plummer, 2014).

in the model, such as γ and ρ, are modelled using vague or non-informative priors with distribution $N(0, 10)$ (Gelman et al., 1995).[22] To construct the parameters I run 3 parallel MCMC chains each with 40,000 iterations with the thinning rate set at 5 in order to account for the autocorrelation in the chains. For each of the chains the first 10,000 iterations are discarded as burn-in in order to have some more certainty that the coefficient estimates are taken from the posterior distribution (Brooks and Gelman, 1998; Brooks et al., 2011). The coefficients and their uncertainty intervals are constructed as averages across the remaining iterations (18,000 in this case).

4.5 Results

4.5.1 Preliminaries

Figure 4.2 shows the spatial distribution of aid allocations (aggregated to 0.5 degree grid cells, larger circles correspond with larger aid flows) and civil conflicts (individual events) for the three sampled countries covering the period 1999-2008 (the black diamond indicates the national capital). Large aid allocations are concentrated around the capital of DRC, Darfur and South Sudan in Sudan, and the central region of Ethiopia. In contrast, conflict tends to be highly localised in DRC's Kivu region, Somali in Ethiopia, and Darfur in Sudan. In general the data does not seem to show a high degree of overlap between aid and conflicts, save for a few regions such as Darfur and Kivu.

[22]These priors should add nothing to the analysis and not influence the posterior. As a result of using non-informative priors the estimated coefficients will be similar to maximum likelihood estimation.

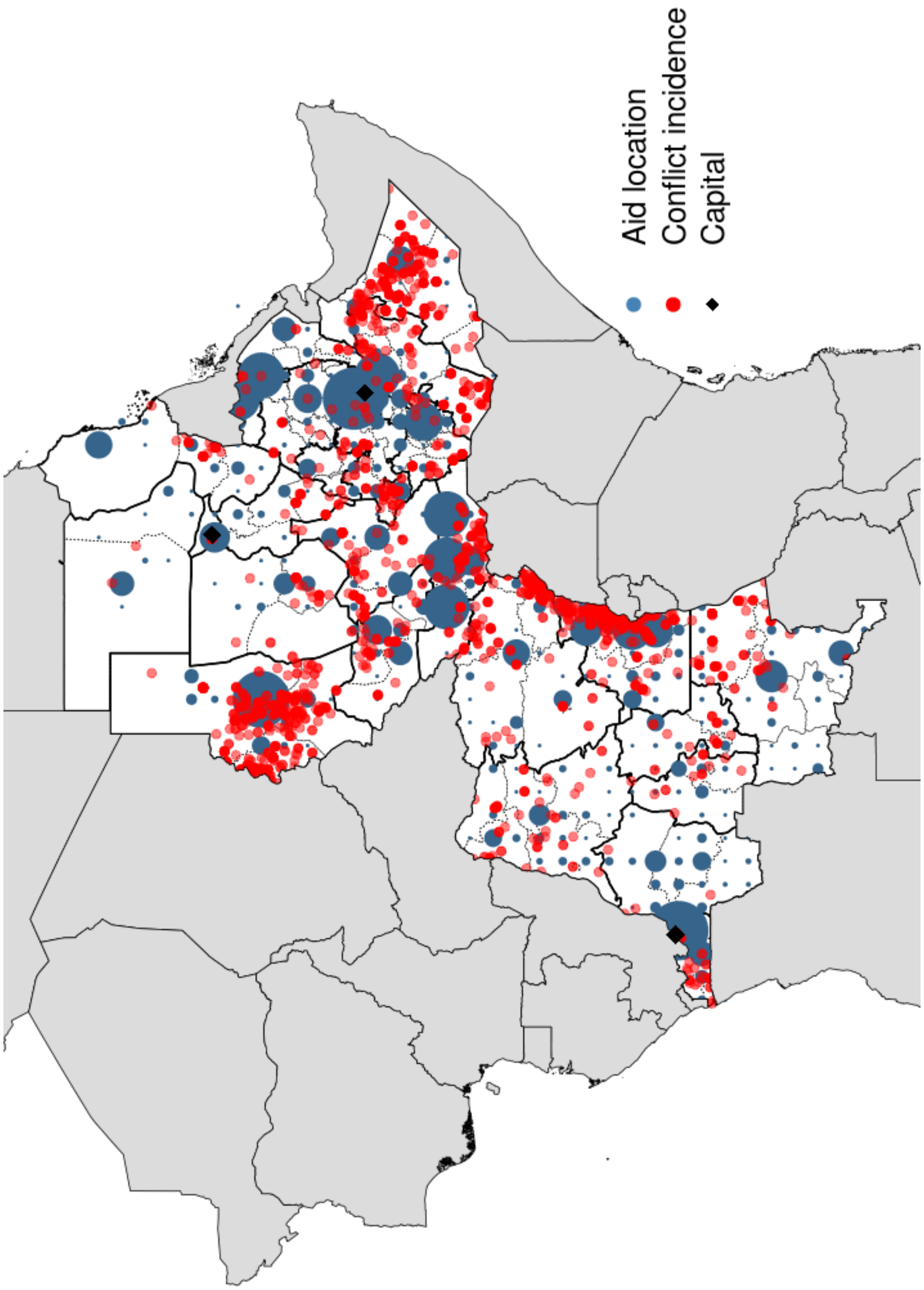

Figure 4.2: Unique observations of conflict incidence and aid locations between 1999-2008. *Source* UCDP/AidData.

As a preliminary test I examine the spatial patterns in aid and conflict using the non-aggregated data, retaining all the information there is on location. Based on the results in the literature we would expect to observe conflict at distance from the capital and close to aid sources.

Figure 4.3 maps the location of aid and conflict relative to the capital, where larger circles represent larger aid flows or higher conflict intensity. It illustrates that conflict tends to occur relatively far away from the capital, but aid in general is allocated closer to the capital. On average the distance between the capital and conflict is about 1000 Km (1016 Km $\pm$ 492 Km) which is relatively large. Since this number is an average across the three countries, I account for the size of each country standardizing the distance dividing it by the distance between the capital and the furthest point in the country relative to the capital.[23] I find that for both DRC and Sudan conflicts occur at large distances from the capital, with average ratios of 0.72 and 0.70 respectively. This could mean that for these two countries the central government has difficulties in controlling the peripheral areas or that the government is stronger in the central areas pushing conflict to these other areas. For Ethiopia the average ratio is considerably smaller at 0.44 which could be explained by the fact the Addis Abeba is located much more central compared to Kinshasa and Khartoum. For foreign aid the distance ratios are smaller at 0.50 (DRC), 0.31 (Ethiopia), and 0.55 (Sudan).

The data suggests that aid is mainly allocated in the central areas whereas conflict tends to occur in the peripheral areas. There are a number of possible explanations for this pattern. It could be, as suggested by the literature, that aid strengthens the position of the government. Aid projects will foster local development which increases the opportunity costs of insurgency. In the peripheral areas there are less aid projects meaning that these regions lag in their economic development and are therefore more

[23] $\bar{D}_{capital \rightarrow conflict}/max\, D_{capital}$. $max\, D_{capital}$ is 1945 Km for DRC, 1035 Km for Ethiopia, and 1364 Km for Sudan.

likely to harbour insurgencies. Additionally, aid donors could be risk averse and allocate money to locations where the government is relatively strong again depriving the peripheral areas from aid.

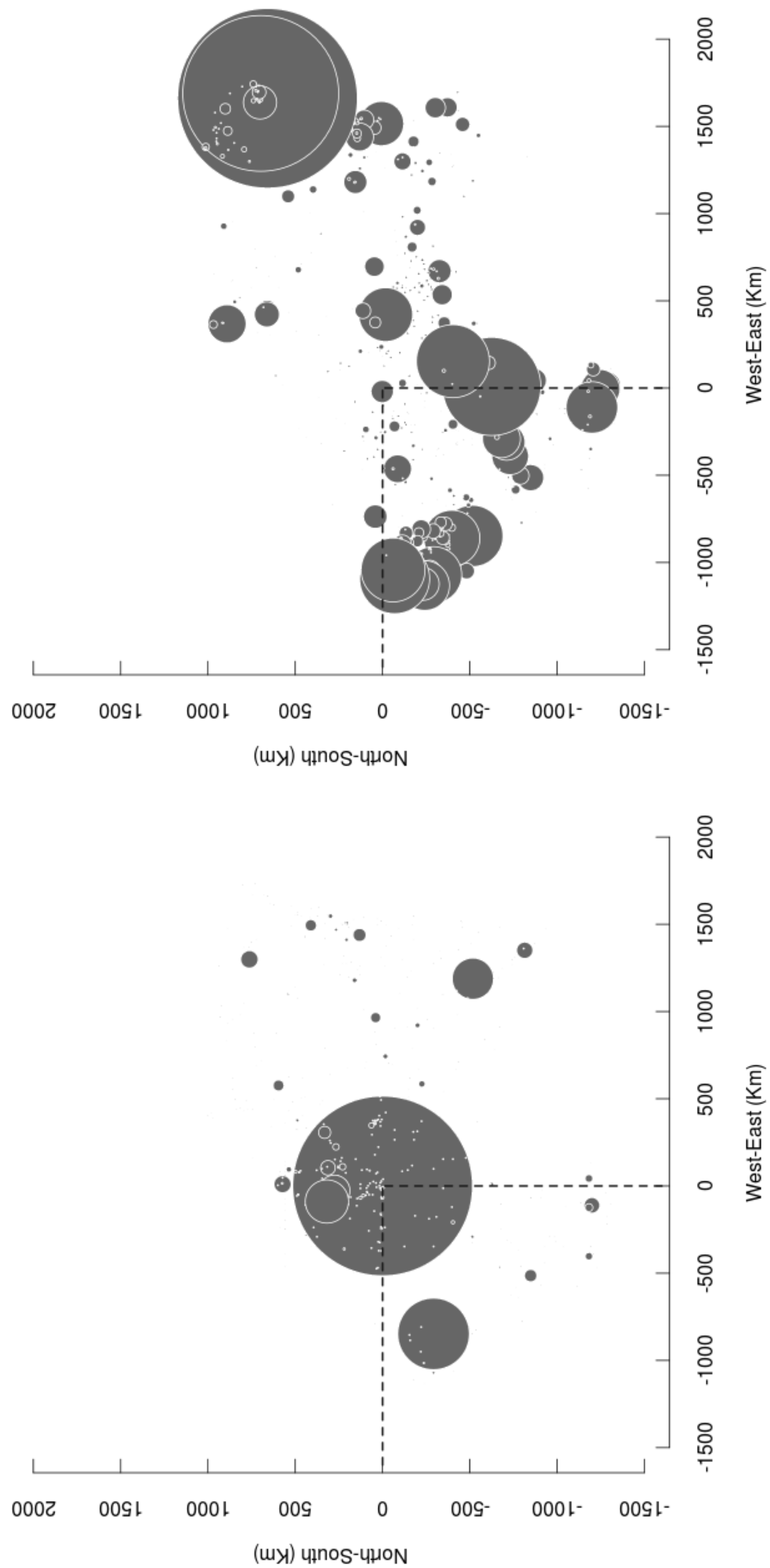

Figure 4.3: Spatial distribution of aid *(left)* and conflict *(right)* relative to the capital. The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

To test whether aid and conflict cluster in localised areas I examine the interdependence between observations measured by the Nearest Neighbour Distance (NND).[24] The NND is calculated as the distance between an aid project and the nearest conflict event for each year between 1999-2008, where the aid allocations are lagged by one year to account for simultaneity. The results are presented in figure 4.4.

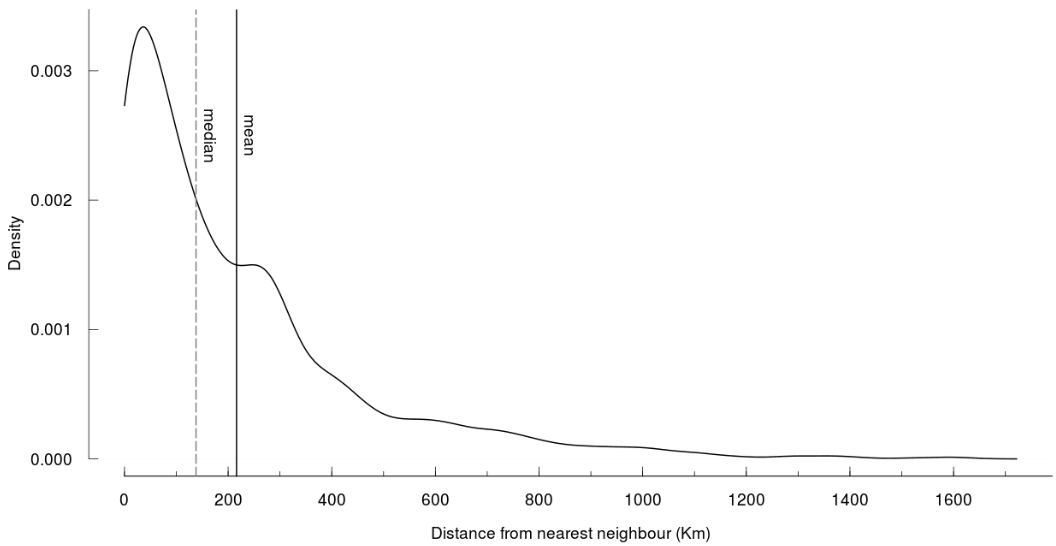

Figure 4.4: Density of nearest neighbour distance between conflict and aid. Solid vertical line indicates the mean value, dotted vertical line indicates median value.

[24]I also examine the intensity of the number of aid and conflict observations using the kernel density. Results for which are briefly discussed in the appendix C.

If aid provides incentives for conflict, because it is a prize that can be appropriated or the subject of sabotage, then we would expect that the distance between aid and conflict is small. Smaller distances correspond with stronger interdependence, but as illustrated by the figure in general there is a large spread in distances and interdependence appears to be weak. The mean NND is 218 Km and median NND is 141 Km. These are relatively large distances compared to the NND values for aid and conflict separately where the average distance between observations is around 100 Km.[25]

For 27% of the observations (435 cases out of a 1651 observations) the distance between an aid project and conflict is below 50 Km.[26] This indicates some stronger interdependence and provides some support for the notion that aid might provide incentives for conflict in some individual cases. This corresponds with some of the results found by Strandow et al. (2014) where aid distributed to areas which were contested increases the likelihood of violent armed conflict.

4.5.2 Regression results

Table 4.1 presents the estimated coefficients along with their 95% interval (in parentheses) at both levels of aggregation.[27] Since the input variables are all placed on a common scale centered around the mean and divided by two standard deviations, in order to facilitate easier comparison, they can be interpreted as the effect of moving from low to high values (Gelman, 2008).[28]

Model 1 is the preferred model and specified according to Eq.1. Some results in the literature (Arcand and Labonne, 2011; Nielsen et al., 2011; Crost et al., 2014) show

[25] Adjusting the sample to only include observations with the highest level of precision in geocoding does not alter these figures much: mean NND=257 Km, median NND=150 Km. The NND for the full sample is 110 Km and 98 Km for conflict and aid respectively. See also see figure C.9.

[26] 24% (275 out of 1135 observations) using the sample with higher precision levels.

[27] All models converged based on a visual inspection of the traceplots for the parameters of interest and the values for the $\hat{R}$ statistic which was below the 1.05 threshold in all cases.

[28] The dummy for natural resources was also standardised because the input was skewed.

Table 4.1: Predicting changes in conflict intensity

	Province level (*N=203*)			District level (*N=952*)		
Specifications	Model 1 (1)	Gov. (2)	Sector (3)	Model 1 (4)	Gov. (5)	Sector (6)
Foreign aid	−0.2	−0.2		0.01	0.01	
	(−0.7; 0.3)	(−0.7; 0.3)		(−0.17; 0.19)	(−0.17; 0.19)	
Foreign aid to government		0.2			−0.1	
		(−0.4; 0.8)			(−0.3; 0.1)	
Fungible aid			0			0.02
			(−0.5; 0.5)			(−0.16; 0.20)
Non-fungible aid			−0.5			−0.07
			(−1.0; 0)			(−0.25; 0.11)
Spatial lag	−0.2	−0.2	−0.2	0.12	0.13	0.11
	(−0.7; 0.2)	(−0.7; 0.2)	(−0.7; 0.4)	(−0.06; 0.29)	(−0.05; 0.30)	(−0.07; 0.29)
Temporal lag	−1.4	−1.4	−1.4	−1.32	−1.32	−1.31
	(−1.9, −0.9)	(−1.9, −0.9)	(−1.9; −0.9)	(−1.50, −1.14)	(−1.50; −1.14)	(-1.49; -1.14)

Notes. Table presents point estimates with their 95% intervals between parentheses. All models estimated with year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

that larger amounts of foreign aid should increase conflict risk due to the creation of rent-seeking opportunities and possible attempts by insurgents to sabotage local development projects. At the province level I find that the estimated effect at the province level (table 4.1 col.1) has the opposite sign, indicating that positive changes in aid correspond with changes to lower conflict intensity levels. The magnitude of the effect is not very large: moving from low to high changes in aid levels corresponds with just a 0.2% decrease in conflict intensity.[29] Although the 95% interval shows that the effect is not statistically significant, the results indicate a negative link with about 0.82 probability.[30]

The province level results contrast with the district level (col.4) where the magnitude of the estimated effect is near 0 and the probability of a negative link is just 0.46. This large difference in probability could be due to the fact that at the district level there is no link between aid and conflict. There could be a case of an ecological

[29] These results are robust to the inclusion of country-specific time trends.
[30] There is some variation between 0.80 to 0.83 based on the model specification.

fallacy here, where we would assume that the relation found at one level of aggregation (provinces) would also be true at another level of aggregation (districts).[31] Although in both cases there is basically a null result based on the magnitude of the estimated effect. The results also contrast with those of Berman et al. (2013) and Crost et al. (2014) who use a similar level of aggregation, although they only look at a conflict in one particular country. This discrepancy could also be partially explained by attenuation bias as a result of measurement error. The use of a finer resolution means that some observations are lost due to the precision of the geocoding. For the conflict events the loss is not very large, just a 18.5% reduction in the number of observations. It is considerably larger for the included number of aid projects, reducing the sample by 53.6%.[32]

At both levels of aggregation the strongest predictor for changes in conflict intensity is the lagged outcome variable. Moving from low to high levels of intensity corresponds negatively with current changes. Potentially this is due to some kind of mean-reversion process as conflicts are relatively rare events, and even rarer are conflict events with very high fatality counts.[33] The estimated effect of the spatial lag also differs across provinces and districts. This seems to indicate that the spillover effects of conflict are confined to the smaller administrative units. It is easier for insurgents to move from one district to another district than it is to move between larger provinces.[34] As provinces are the larger administrative units they might therefore not pick up the sub-national variation the way districts do when conflict is highly localised.

Aid that goes directly to the government could increase state capacity and reduce the probability of conflict onset and shorten conflict duration as found by de Ree and Nillesen (2009). I therefore include a variable for government aid in the model

[31] See also Maystadt et al. (2014) for an example on mining and conflict in the DRC.

[32] Number of unique events per level of aggregation, at province level there are 7,381 conflict events and 6,586 aid projects whereas the district level includes 6,008 conflict events and 3,052 aid projects.

[33] Conflicts, like other forms of human behaviour, exhibit universal patterns that approximate power-law distributions (Bohorquez et al., 2009).

[34] Katanga in the DRC for instance is about 16 times the size of Belgium.

(col.2) and find that at the province level positive changes in foreign aid going to the government corresponds with an increase in conflict levels (75.6% probability). The magnitude of this effect is almost identical to the negative effect of aid at the local level, thereby offsetting each other. Again the results show a different effect at the district level which is rather puzzling in this case given the fact that there are no changes in the measurement of the variable.

The main aid variable is agnostic about the fungibility of aid, the ease with which it can be diverted from its intended purposes. The reason for estimating the model with a pooled aid variable is that in general aid is likely to become fungible if the donor is not able to monitor the actual disbursement (Devajaran and Swaroop, 1998), which is a reasonable assumption in this case.[35] Rather than increasing net-expenditures in particular sectors it could be that aid money is actually substituting government spending. Feyzioglu et al. (1998) find that aid money is not necessarily fungible at the aggregate level but that it depends on the sector for which the aid money is destined. Development loans or grants for agriculture, education, and energy lead to a reduction in government spending in these sectors whereas money earmarked for the transport and communication sector are fully spend on the intended purposes. This entails that at the local level aid going to these fungible aid sectors might be easier to appropriate by insurgents as well (Findley et al., 2011). [36] I estimate the effect of aid accounting for the potential fungibility. Following Feyzioglu et al. (1998) and Findley et al. (2011) aid going to agriculture, education, energy supply and generation (as well as general budget support) are coded as fungible whereas aid going to transport and communication is coded as non-fungible.

The results show that at both the province and district level there is a likely no

[35]There is some debate in the literature whether aid is fungible or not. See the literature review in Feridun (2014) for a synopsis.

[36]This effect is similar to what Dube and Vargas (2013) find for the capturing of rents from the oil sector in Colombia.

effect between fungible aid and conflict. Non-fungible aid is more strongly negatively linked with conflict. The magnitude of the effect for non-fungible aid is smaller at the district level which again could be due to previous mentioned reasons such as attenuation bias. The interpretation of the negative effect of non-fungible aid is that this aid type improves local welfare and therefore increases the insurgents' opportunity costs. In this case we don't see an increase in violence as a result of insurgents trying to sabotage the project as was suggested in the Crost et al. (2014) study.

In general the estimations provide very little support for a link between aid and conflict in either direction and this is consistent across a number of different robustness checks. Including additional variables to account for changes in population and economic activity (proxied by satellite night lights) doesn't alter the results.[37] Rather than using inter-annual changes I estimate the model using aid shocks following Nielsen et al. (2011). Again the results provide no strong support for a link between aid and conflict in this sample.[38] The results are also not specifically driven by the estimation method as estimating the model with a more orthodox methods such as OLS produces very similar results. [39]

4.5.3 Comparing estimates with outcomes

The regression results only provide some very minor evidence for a link between aid and conflict. In any case the magnitude of the potential effect is very minor. The estimated coefficient in the main model is based on the assumption that the effect is homogeneous across regions. There could be the possibility that aid actually has a different impact

[37]See table C.3 and C.4 for results.

[38]Shocks are defined as standardised deviations from the region mean: $(Aid_{it} - \overline{Aid_i})/\sigma Aid_i$. See table C.9 for results.

[39]See table C.5 and C.6.

depending on the region. The estimated effect in the main model therefore could be averaged out, missing region-specific effects. To account for this I re-estimate the model allowing separate coefficients per region, both for the aid variable as well as the variables that control for the temporal and spatial effect of conflict. Figure 4.5 shows the estimated coefficients for each region and illustrates that most region-specific coefficients fall within a one standard deviation range of the estimated regression line of the main model. Only at the district level there are some district located more remotely from the main model's regression line but still within two standard deviations. The figure indicates that in general the main model seems to capture the effect of aid on conflict accurately.

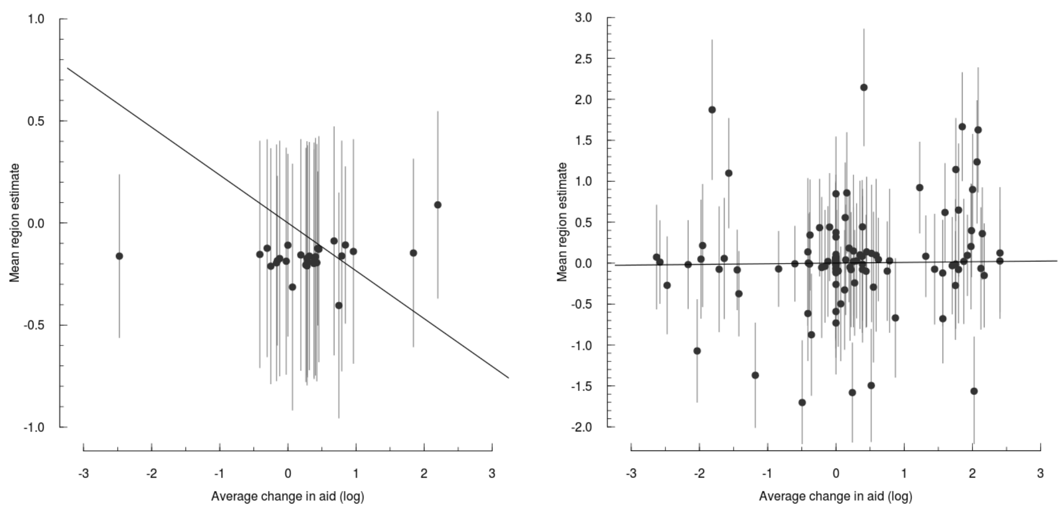

Figure 4.5: Estimated coefficient for each province (*left*) and district (*right*) along the regression line from the main model. The grey lines for each coefficients indicate the standard deviation.

Figure 4.6 shows the actual change in conflict intensity compared to the estimated change in conflict intensity generated by the pooled and the varying slope model. There does not seem to be a systematic bias in the estimates and to some extent the model seems quite capable matching the estimated changes with corresponding actual changes. The model slightly underestimates the magnitudes of the changes in the outcome variable. Also the zeroes in the outcome variable pose difficulties as there is a lot of scatter around these observations where there are no changes in conflict intensity. Based on the difference between the estimated outcomes at the provincial and district level, the model unsurprisingly performs better with more data points as illustrated by the difference in fit. Also the varying slope model fits the data marginally better than the pooled regression model. Indicating that the region-specific coefficients for the variables better capture the local conflict dynamics in contrast with the more generalised approach.

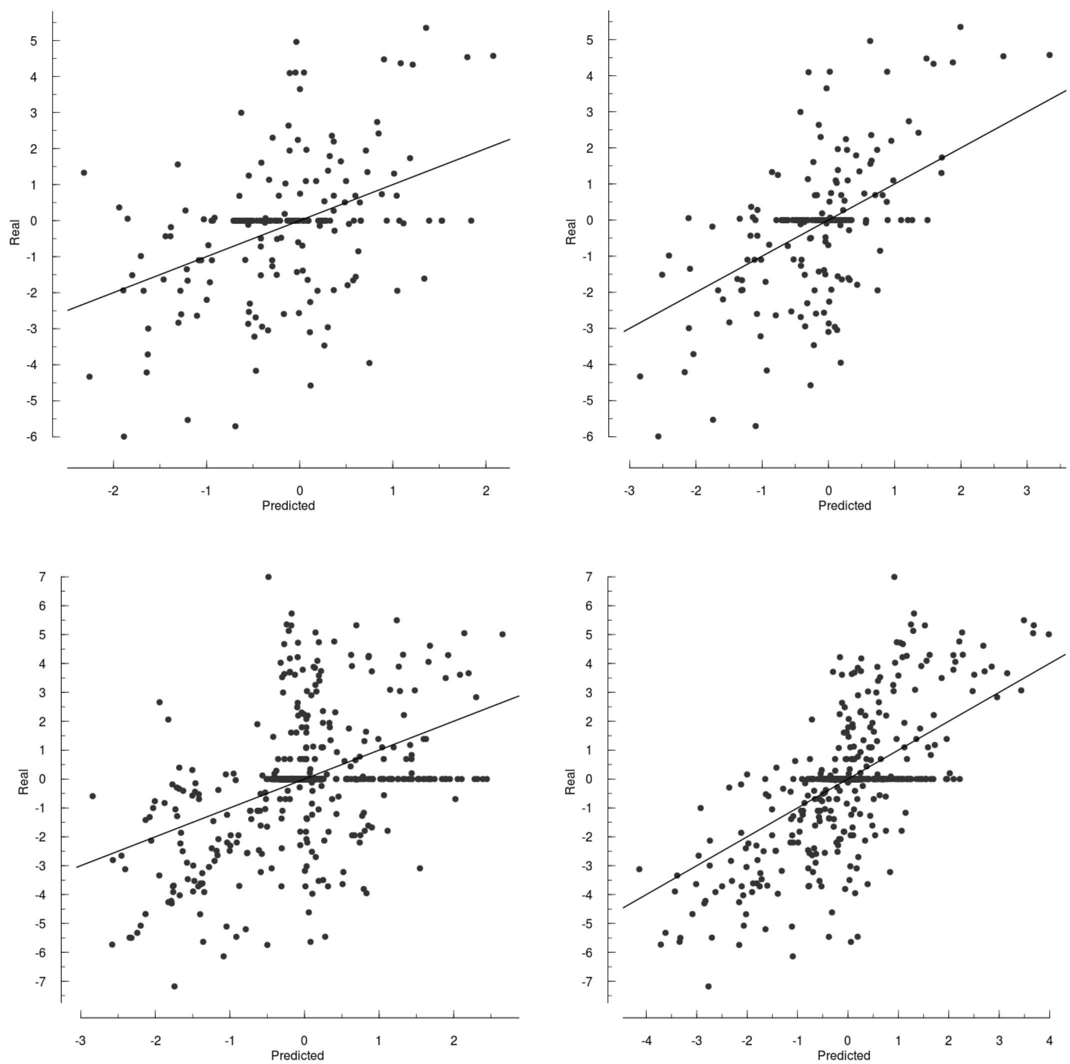

Figure 4.6: Actual changes in conflict intensity compared to estimated changes at province (*top*) and district (*bottom*) level using pooled regression (*left*) and a varying slope model (*right*).

4.5.4 Interaction effects

Besides the direct effect of aid on conflict I also consider the effect of interactions between aid and other possible influential factors. These include the temporal and spatial lag, distance from the capital, and ethnic polarisation, results for which are summarised in figure 4.7.[40]

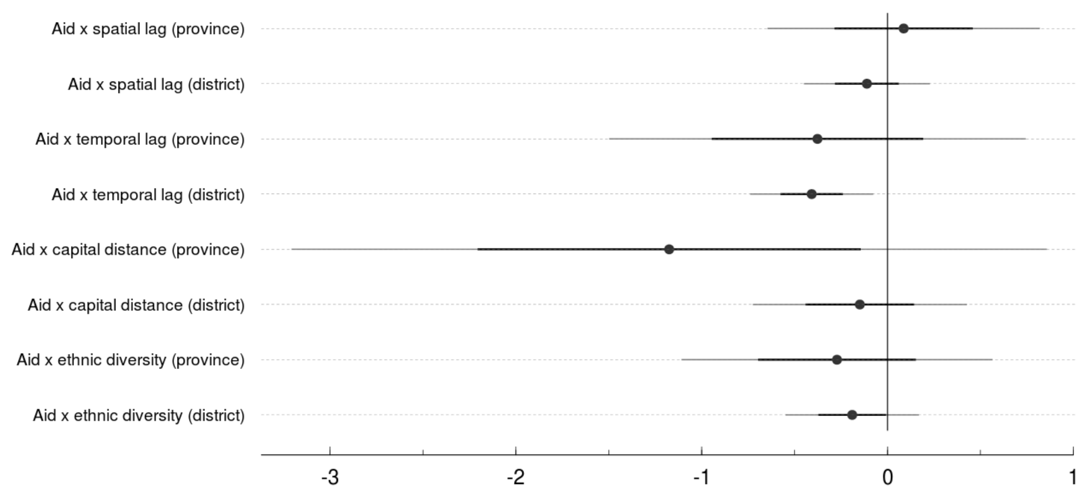

Figure 4.7: Estimates with 68% and 95% intervals for various interaction effects with foreign aid.

[40]See table C.7 and table C.8 for results.

In general all the interaction terms are skewed towards negative values. Consistent with the main results the estimated effects are close to zero or have zero in their 95% interval. The only exception to this is the interaction between the temporal lag and aid at the district level. This effect is likely to be largely driven by the temporal lag. The main results showed that higher levels of past conflict correspond with a reduction in current conflict levels. Hodler and Knight (2012) show that foreign aid is more effective in promoting economic growth in ethnic homogeneous countries. This might imply that as aid is less effective in ethnically polarised regions as opportunity costs for insurgency remain low and the aid itself provides rent-seeking opportunities. As a result these regions might experience higher levels of conflict. The estimation result do not provide support for this hypothesis as the effect of aid on conflict in regions with higher levels of ethnic polarisation is not different from the main result. Similarly, the estimated effect of aid is also not different in regions further away from the capital and regions in conflict ridden neighbourhoods.

4.5.5 Effect of aid on conflict onset

So far the estimations have focussed on the effect of changes in aid on changes in conflict intensity, i.e. looking at the intensive margin. I now consider the extensive margin examining the effect of changes in aid on conflict onset, results are summarised in figure 4.8.[41]

Most variables have relatively low predictive power, especially at the provincial level, and is therefore not adequate in predicting the outbreak of conflict.[42] Although at the district level there seems to be a slightly stronger relation between foreign aid and conflict onset. However, the strongest predictors for the outbreak of conflict are ethnic polarisation and the presence of natural resources which have opposite effects. Ethnic polarisation increases the probability of conflict onset which resonates with a number of

[41] This is the model specified according to Eq.2. Full results are reported in table D.1.

[42] See figure C.12.

other studies (Buhaug and Gleditsch, 2008; Weidmann, 2009; Bosker and de Ree, 2014). The presence of natural resources is negatively associated with conflict onset, but this could be the result of a displacement effect where conflict actually takes place in the surrounding areas as argued by Maystadt et al. (2014).

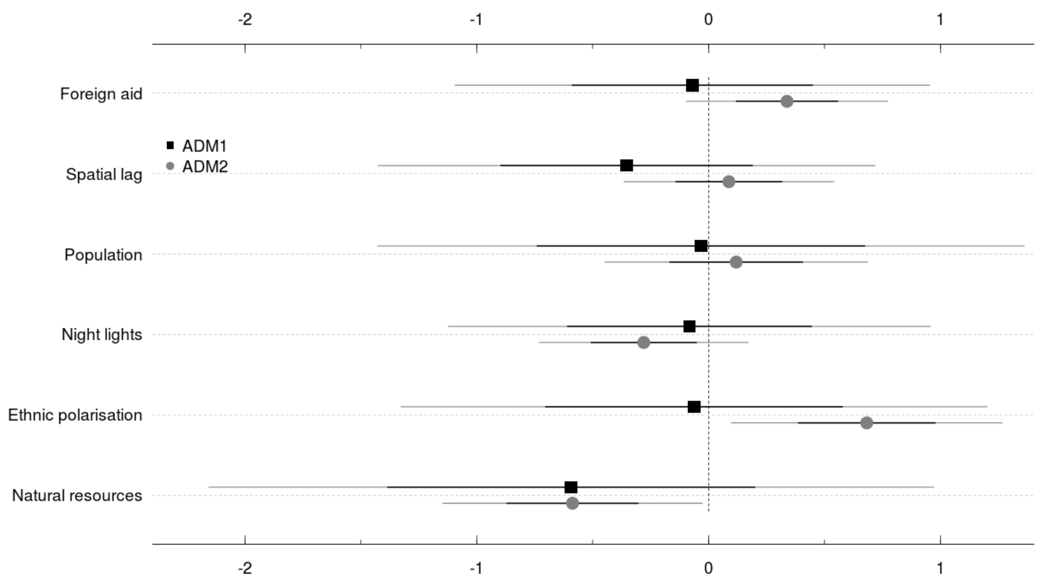

Figure 4.8: Logit estimates with 68% and 95% intervals at province (ADM1) and district (ADM2) level.

4.6 Conclusion

This study extends the aid-conflict literature by focussing on the link at the sub-national level across different countries. This means that the full information on local development projects and sub-national variation in conflict is retained. In contrast with the existing work I find no strong effect of aid on conflict in either positive or negative direction. The spatial analysis shows that although both aid and conflict cluster in localised geographic areas there does not exist a strong interdependence. In the regression analysis I find no strong empirical proof for an effect of aid on conflict levels or conflict onset. I do find that non-fungible aid corresponds negatively with conflict intensity but the evidence is not very strong. The strongest predictor for conflict levels is the change in past conflict levels where the analysis showed that current conflict levels decrease after a previous year with very high levels. This shows that high levels of intensity are relatively rare and not sustained over time. At the district level there is spillover effect of conflict where districts in violent neighbourhoods are more likely to experience violence. This effect is highly localised though as the analysis at a higher aggregation level does not produce the same results.

Chapter 5

Climate-conflict in Sub-Saharan Africa: Examining predictive power

5.1 Introduction

There is an expanding literature that attempts to disentangle the factors that contribute to the incidence of violent armed conflict. Within this research area much attention is given to the robustness of results in terms of replicability, subject to the use of more recent data and different model specifications. However, surprisingly little attention is given to testing and analysing the predictive power of the models. Although for some scientific research having a model with good descriptive power is sufficient, considering conflict predictive power is particularly relevant given the damaging consequences of war and its long lasting effects (Abadie and Gardeazabal, 2003; Chamarbagwala and Morán, 2011; Serneels and Verpoorten, 2013). It is therefore remarkable that within this body of research seemingly so little effort is made at prediction (see Schrodt (2013) for a comprehensive critique).

Despite the increase in research effort, which has lead to a general understanding of some of the main factors that underlie conflict (Hegre and Sambanis, 2006; Blattman and Miguel, 2010), there seems to be no record of improvement in the accuracy of predictions in the conflict literature. As Ward et al. (2010) observe:

> too much attention has been paid to finding statistically significant relationships, while too little attention has been paid to finding variables that improve our ability to predict civil wars

Predictions generated by models are often ignored while they provide useful information on the model's performance as shown in O'Loughlin et al. (2012) for instance. There are some other notable exceptions to this trend, such as the recent studies by Goldstone et al. (2010), Weidmann and Ward (2010), Gleditsch and Ward (2013), and Blair et al. (2014).

This study contributes to this literature by attempting to predict war focussing on the link between climate and conflict. There is a growing body of research examining how climate influence economics outcomes and affects human well-being (see Dell et al. (2014) for an overview). There are large concerns about the human impacts of global warming and it is therefore important to understand the relation in order to assess the risks (Stern, 2006; German Advisory Council on Global Change, 2008). I focus on this particular field as it is of great interest due to climate change forecasts (IPCC, 2014) and because of the potential climate-conflict nexus. I say potential here because within the academic community there is an ongoing debate on the scientific evidence for a link between climate change and the risk of violent armed conflict (see for instance Scheffran et al. (2012a); Hsiang and Burke (2013); Hsiang et al. (2013); Klomp and Bulte (2013); Buhaug et al. (2014); Hsiang and Meng (2014); Hsiang et al. (2014); Raleigh et al.

(2014)).[1]

From this literature I use the model from the seminal work by Burke et al. (2009) who found that higher temperatures are linked to increased probabilities of war in Africa. Simulation based predictions of their model show that, conditional on historical patterns, by 2030 there will be a 54% increase in armed conflict incidence relative to the 1981-2002 baseline. This increase could even be an underestimate according to a more recent study (Burke et al., 2014). The reason for focussing on this particular model is because of its central place in the literature as well as the simplicity of the model, which should be beneficial to generating accurate predictions.[2] There has been some debate with regard to the robustness of the results, where the critiques have predominantly focussed on sensitivity to model specification and re-estimation using more recent data (Buhaug, 2010; Sutton et al., 2010; Burke et al., 2010; Hsiang and Meng, 2014). The reply from Buhaug (2010) seems to be the most forceful critique on the original study, claiming that climate variability is a poor predictor of armed conflict and that African civil wars can be explained by other more structural and contextual factors such poor economic performance for instance.

Hsiang and Meng (2014) disagree with this conclusion arguing that there is no statistical difference between the model specifications used by Burke et al. (2009) and Buhaug (2010).[3]

[1]Edward Miguel, one of the leading scientists in this field of research, likened the research on climate-conflicts to the research on smoking about 50 years ago, arguing that we figured out that climate causes conflict but don't know how to prevent it (TEDxBerkeley, 2014).This analogy seems a bit premature given the lack of consensus in the literature. Other overview articles, not mentioned in the text, include Bernauer et al. (2012), Gleditsch (2012),Scheffran et al. (2012b), Meierding (2013).

[2]Their research has been cited 385 times since its publication in 2009 (according to Google Scholar, 18 April 2015).

[3]Hsiang and Meng (2014) found that Buhaug's results are not different from those in Burke et al. work based on the implementation of various statistical test, but do not attempt to verify whether the findings of Burke et al. were correct. See O'Loughlin et al. (2014) for a critique on the Hsiang and Meng (2014) study and Buhaug (2014) for Buhaug's reply.

To the best of my knowledge, no study has attempted to use the model for generating predictions for real out-of-sample data. This study is probably most similar to Buhaug (2010), who use the original data of Burke et al., shorten the time period for model estimation to 1981-1998 and generate predictions for 1999-2003. In contrast, using the original model estimations I generate predicted probabilities for conflict using the most recent available data covering 2003-2013 which is a more extensive cross-validation of the model.[4]

The regression analysis shows that the model seems to do exceptionally well for in-sample prediction and in general has high descriptive power based on an Area Under the Curve (AUC) value of around 0.98.[5] These results seems to be an overfit however as examining the results in closer detail I find that the predicted values are almost entirely contingent on the inclusion of the country fixed effects and country-specific time trends.
For the out-of-sample predictions the model produces a large number of false positives (for countries with high levels of conflict prevalence), while at the same time failing to correctly predict war incidence in countries with slightly lower levels of past conflict prevalence. It seems that the in-sample performance on the training data exaggerates minor fluctuations in the data where the results do not generalise beyond the cases studied. Both the regression and prediction results show that the performance of the model is mainly driven by the inclusion of country fixed effects and country-specific time trends, whereas the inclusion of variables capturing climate variability adds little to no predictive power.

[4]This study thus provides a replication of the original work and an extension according to the proposed terminology of Clemens (2015).

[5]This is the AUC of the Receiver/Operator Curve (ROC) which measures the false positive rate versus the true positive rate. AUC values closer to 1 indicate a more accurate model. The AUC values for the three models are: model 1, 0.981; model 2, 0.981; model 3, 0.936. Omitting all explanatory variables and estimating the LPM with only country fixed effects and a country-specific time trend, the results still report a high AUC statistic of 0.980 which is a reduction in predictive power of just 0.09% compared to the preferred model (model 1).

5.2 Results

5.2.1 In-sample predictions

I start with replicating the results in order to check the in-sample predictive power of the model. As I try to argue in this paper that cross-validation should be part of the analysis, it could of course be that for some reason this isn't possible due to lack of data. When data is sparse one can always examine the in-sample predictive power of the model as I will illustrate in this section. Additionally, in most quantitative studies there is a lot of focus on the statistical significance of the estimated parameters based on the traditional p-value thresholds. This litmus test, so to speak, was never meant to be a definitive test when it was introduced by Fisher but intended as an indicative test for evidence worth a second look (Nuzzo, 2014). Again, looking at the predictive power of the parameters can give us a better insight into the relation of interest.

The original data covers 41 countries in Sub-Saharan Africa for the period 1981-2002. The preferred model (model 1) has the following functional form:

$$War_{it} = \beta_1 Temperature_{it} + \beta_2 Temperature_{i,t-1} + c_i + d_i year_t + \epsilon_{it} \tag{5.1}$$

The regression equation links civil war to current and lagged temperature levels ($Temperature$), conditional on country fixed effects (c_i) and time trends ($d_i year_t$).[6]

Although War is a binary outcome variable, the model is estimated using Ordinary Least Squares (OLS). It seems to make little sense fitting a continuous regression to an outcome variable that can only take two values (Gelman and Hill, 2007). However,

[6] Additional models include measures for current and lagged rainfall levels (model 2), and explicit lagged country controls for income per capita and regime type (model 3). Model 3 also includes year indicators rather than a country-specific time trend. Model 1 and 2 do not include year indicators meaning that they do not account for worldwide changes (Couttenier and Soubeyran, 2014). Civil wars are conflicts with >1,000 battle-related deaths, temperature is measured in Celsius.

due to the use of time-series cross sectional data and the inclusion of fixed effects, a Linear Probability Model (LPM) might be preferred over non-linear models (Angrist and Pischke, 2008).[7] Nonetheless, there are some concerns with using a LPM such as heteroskedasticity due to the binary outcome variable and the fact that the predicted probabilities are not constrained by the 0-1 interval.[8] Figure 5.1 shows the predicted probabilities for each model and illustrates that there are indeed predicted values outside the unit interval. This might not be of too much concern as long as not too many values fall outside of the interval. However, in this case the results are a reason of concern: Examination of the preferred model (model 1) shows that the predicted probabilities for 39% of the observations have a value smaller than 0 or larger than 1. As a result, the estimates can be biased and inconsistent (Horrace and Oaxaca, 2006).[9]

Given that warming increases the risk of war we would expect that the fitted probabilities follow a trend where higher temperatures correspond with higher fitted probabilities. To examine this I plot the fitted probabilities against the temperature deviations from the country mean, as shown in figure 5.2. I use deviations from the country mean in order to better compare across countries.[10] The figure illustrates that there is no clear trend with regard to higher temperatures being associated with higher probabilities of war. The figure does show that in general the model is accurate in correctly predicting the incidence of armed conflict, as most observations with war correspond with higher fitted probabilities.

[7] Beck and Katz (2011) shows that estimating a LPM is as good as logit as long as the explanatory variables are normally distributed. An additional concern, not addressed in this study, is that due to the inclusion of fixed effects there is the concern of Nickell bias (Nickell, 1981) with $N = 41$ and $T = 21$. I refer to Gaibulloev et al. (2014) for an extensive discussion on the inconsistencies arising from the use of fixed effects in dynamic panel data.

[8] The heteroskedasticity will be accounted for by the use robust standard errors clustered by country.

[9] Model 1 generates 15 values above 1 and 334 below 0. Because of the probability of biased and inconsistent estimates, the LPM should be used as a basis for comparison with more appropriate models such as logit. See the appendix for model estimations done using logit.

[10] This also parallels the model as it is estimated using country fixed effects which demeans the temperature variables using within-transformation (i.e. $T_{it} - \overline{T_i}$).

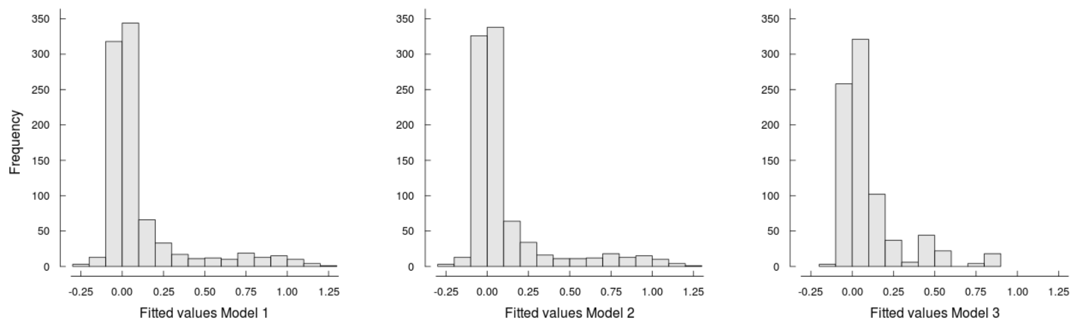

Figure 5.1: Histograms for fitted values of the linear probability model according to three different specifications.

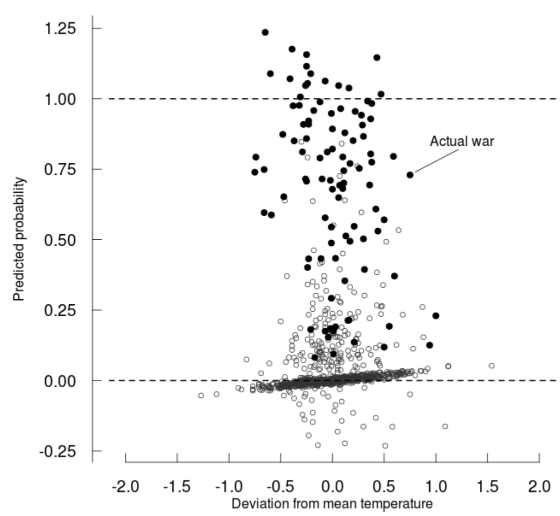

Figure 5.2: Fitted probabilities versus temperature deviations from the mean for preferred model (model 1).

To measure the model's in-sample predictive power I use a separation plot, shown in figure 5.3. In a separation plot the predicted outcomes of the model are ordered along the x-axis from low to high (also indicated by the line through the plot), and the dark (light) panels correspond with incidences of war (no war) (Greenhill et al., 2011). [11] If a model is capable of matching high-probability predictions with actual events, and low-probability predictions with no events, we should observe a plot separating the dark and light panels. Figure 5.3 shows that all three models perform well in separating the cases from the controls. Looking at the Area Under the Curve (AUC) statistic confirms the high in-sample predictive power with values of about 0.98 for model 1 and 2 and 0.94 for model 3. Similar to Buhaug (2010) I find that the high predictive power of the model seems to be predominantly driven by the inclusion of the fixed effects and that the temperature variable has little explanatory power (see appendix).

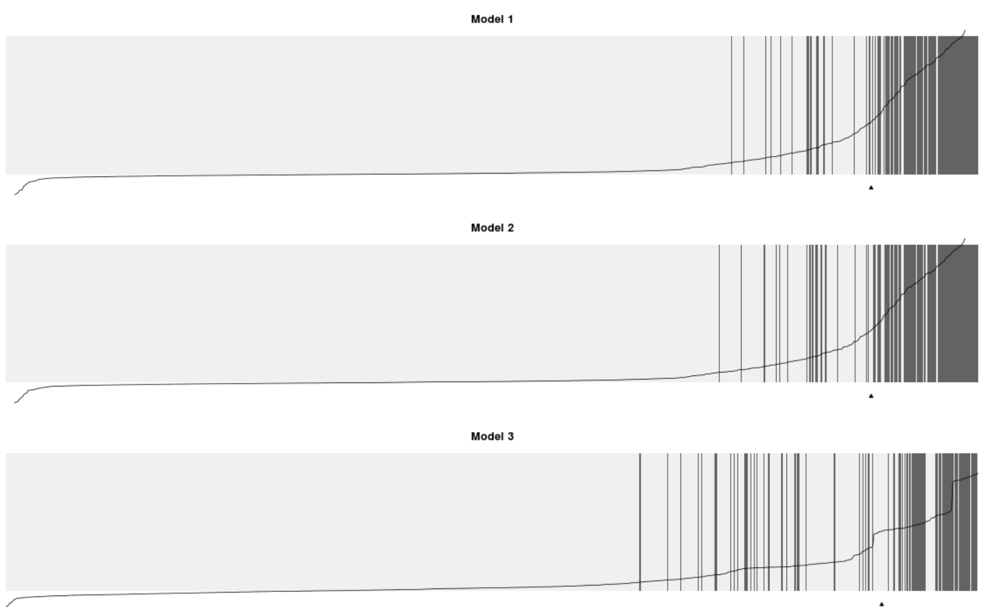

Figure 5.3: In-sample separation plots for the three model specifications.

[11] The triangular marker indicates the expected number of events (from right to left) based on the cumulative of predicted probabilities.

5.2.2 Out-of-sample predictions

For the out-of-sample predictions I update the dataset to cover the period between 2003-2013 using the most recent data on conflict, temperature, income, and regime type.[12] The outcome variable in the model is the incidence of major conflicts, i.e. conflicts resulting in > 1,000 battle-related deaths in a given year, identical to the original work. Figure 5.4 shows the average temperature for each country and the whole sample along with the proportion of countries that experience civil war. The figure illustrates that for all countries there has been increase in temperature over time. For 2003-2013 the average temperature is about $0.3°C$ higher than in 1980s. The upward trend in temperature is what we would expect given the results from the climate change research (IPCC, 2014).[13] At the same time the figure also illustrates that there has been a decreasing trend in the number of civil wars in line with the thesis of Pinker (2011). Although on average Sub-Sahara Africa has been getting warmer, there has been a decline in the number of civil wars. This challenges the idea that warming increases the risk of civil war.

The main model is cross validated by generating predictions for 2003-2013. Similar to the in-sample predictions, the LPM generates predicted probabilities outside the unit interval, ranging from -0.97 to 1.22 (upper panel figure 5.5) with about 37% of all values outside the interval.[14] With an AUC statistic of 0.80, the predictions seem reasonably accurate.[15] Inspection of the separation plot shows however that the model is not entirely accurate in its predictions (upper panel figure 5.5). At the higher end of the probability distribution the model correctly separates observations with war

[12] Conflict data is taken from UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002). Climate data comes from the Climatic Research Unit of the University of East Anglia (Harris et al., 2014). Income data is taken from the World Development Indicators (World Bank, 2012) and data on regime type from Polity IV Project (Marshall et al., 2013).

[13] See figure D.2 for a graph of only the temperature data.

[14] I don't report results for predictions using the other two models as the predicted probabilities fall well outside the unit interval. For example, when including rainfall the predicted probabilities range from -11 to 14. Analytically this does not make much sense.

[15] $N = 451$, 18 cases of war.

from those without but there are also clusters of false negatives. This is not entirely surprising as war is relative rare with just 4% of the observations coded as experiencing civil war.

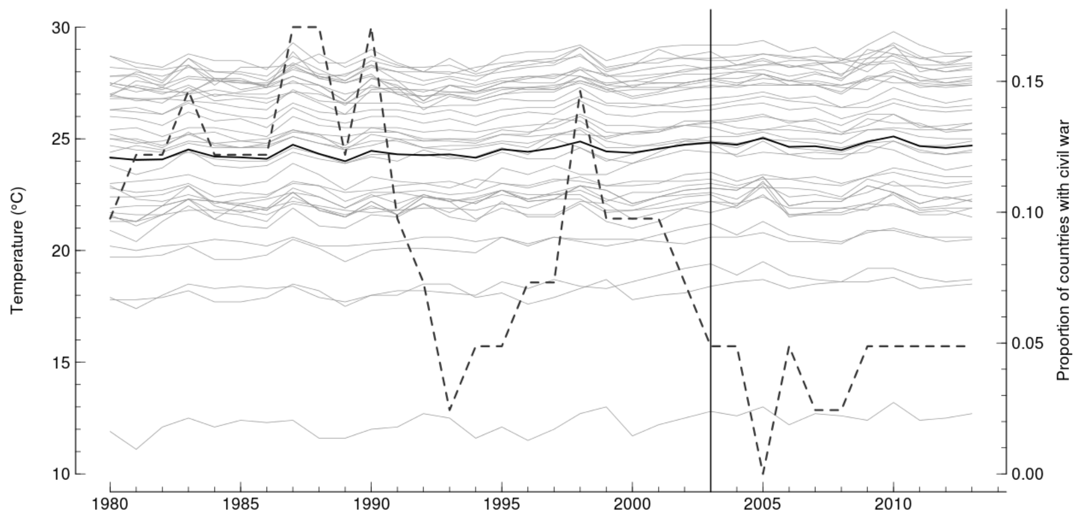

Figure 5.4: Temperature over time and proportion of countries with civil war, 1980-2013 The light shaded lines represent the temperature time series for each individual country while the darker shaded line represents the sample average. The dashed line shows the proportion of countries in civil war. *Source* Temperature data comes from Climatic Research Unit-Univeristy of East Anglia, conflict data comes from UCDP/PRIO.

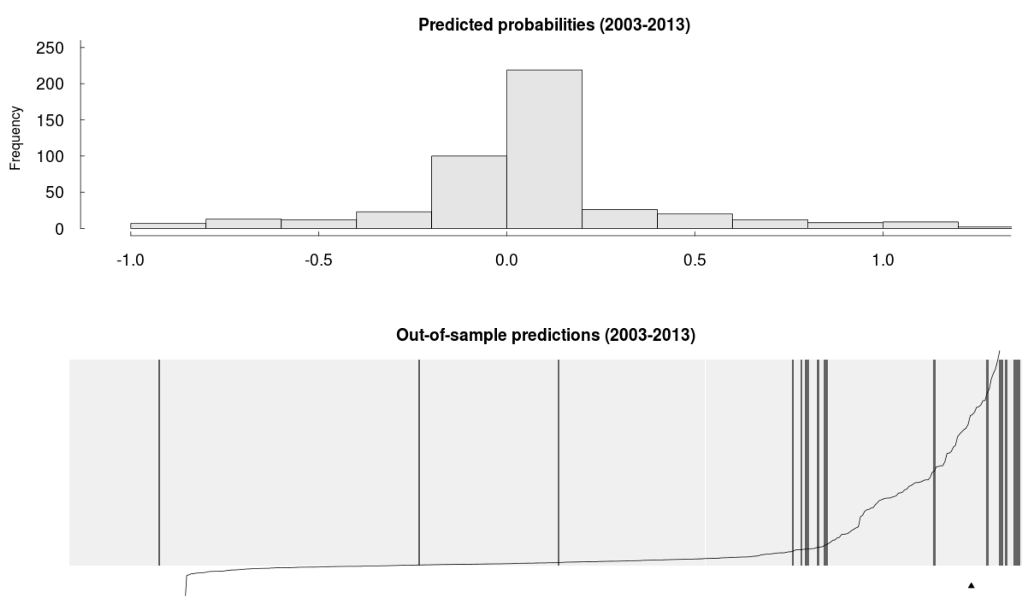

Figure 5.5: Out-of-sample predicted values and separation plot (2003-2013)

This is also illustrated by figure 5.6. In contrast with the in-sample predictions (figure 5.2), the model is less accurate in correctly predicting the outcome leading to more false positives. Similar to the in-sample predictions the results show that there no clear association between higher temperatures and higher predicted probabilities of war.[16]

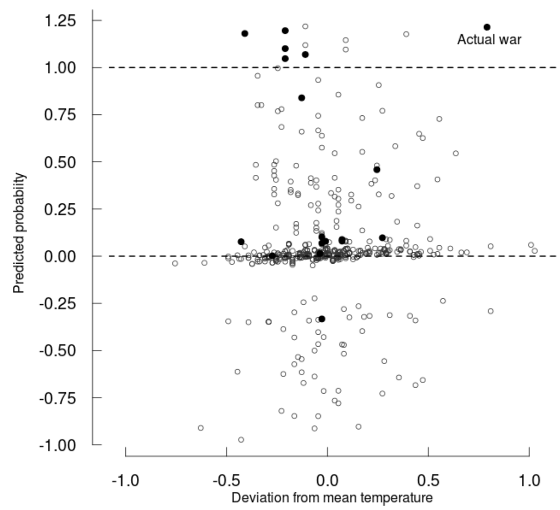

Figure 5.6: Predicted probabilities versus temperature deviations from the mean for preferred model.

In general the model seems to over-predict the incidence of violent armed conflict. Using $\hat{p} > 0.5$ as a threshold for forecasting war, the model predicts wars in 37 observations. Out of these 37 observations 7 actually experience war leaving 30 false positives as well as generating 11 false negatives (all summarised in table 5.1).[17] If we only consider the predicted wars than then out-of-sample prediction success rate drops considerably: only 18.9% of the predicted wars actually experienced a war compared with a 68.2% success rate for the in-sample data.

[16] As the graph shows there is one exception which is Sudan in 2010, but this was an ongoing war.
[17] The logit model performs similarly but includes more false positives.

Interestingly the model identifies a number of countries in the Great Lakes region such as Burundi, DRC, and Rwanda as high risk countries. The model also consistently generated high probabilities for Sudan which to some extent resonates with the results by Maystadt et al. (2014).

Table 5.1: Actual versus predicted wars out-of-sample for 2003-2013

	$\hat{p} \leq 0.5$	$\hat{p} > 0.5$
No war	403 obs.	Angola (2003-2005) Burundi (2003-2013) DRC (2003-2012) Rwanda (2013) Sudan (2005, 2007-2009, 2013)
War	Chad (2006) Liberia (2003) Nigeria (2013) Rwanda (2009) Somalia (2007-2012) Uganda (2004)	DRC (2013) Sudan (2003, 2004, 2006, 2010-2012)

A possible explanation for the over prediction could be that over the past decade African wars have become less sensitive to climate, an argument also brought forth by Burke et al. (2010).[18] For 15 of the 30 false positives there was a conflict in the predicted country-year, although at a lower intensity level (<1,000 battle-related deaths).[19] This could suggest that maybe the conflicts that are responsive to temperature have become less intense.[20] Accounting for this by including minor conflicts with between 25 and 999 battle-related deaths does triple the correct prediction rate for conflicts (from 7 to 22) and reduces the false positive rate by half (from 30 to 15). However, there is also a steep increase in the false negative rate which stands at 69 now.

[18]Burke et al. (2010) state that "African conflict appears less sensitive to climate over the past decade, a change likely related to the unprecedented growth and democratization that most of the continent has recently experienced".

[19]There were civil conflicts in the following country-years: Angola 2004; Burundi 2003-2006, 2008; DRC 2006-2008, 2012; Sudan 2005, 2007-2009.

[20]See figure D.3 for trends in conflict over time.

Rather than focussing on predicted conflict in specific country-years we can also consider the general forecast of civil wars. For each year I tally all the predicted probabilities and compare it with the actual number of wars, as shown in figure 5.7 which includes both the in-sample and out-of-sample forecasts. Save for some local reversals the actual number of civil wars in a given year has declined from around 5 per year between 1981-2002, to 2 per year for 2003-2013. This trend in the data is captured by the model through the inclusion of the country fixed effects and specific time trends. The forecast number of wars moves towards zero over time. In the training data (1981-2002) the temperature variables capture some of the local reversions which is also reflected in the out-of-sample data. In contrast with the previous exercise, based on predicted probabilities alone the model performs slightly better. The forecast number of wars is on average only 0.5 off the actual number of wars and 0.3 if I exclude 2005 which seems like an outlier.[21]

Figure 5.7: Forecast of number of wars versus the actual number of wars.

[21] For 2003-2013 the model forecast 24 wars. The actual number was 18. For the training data the sum of predicted probabilities equals the actual number of wars (98).

A worry with regard to the predicted outcomes is that these could be predominantly driven by the inclusion of country fixed effects and country-specific time trends, as the predicted probabilities with values >0.5 are all in countries with high levels of past conflict prevalence. Omitting country fixed effects from the model, estimating only with the temperature variable and country-specific year trend leads to exactly the same predictions as the full model.[22] It therefore seems that the effect of factors such as geographical characteristics and colonial history on conflict risk are comparable across countries.

To test the predictive power of the temperature variable I generate predictions based on a model estimated with fixed effects and time trends only, the results for which are very similar to the full model (including temperature variables). The main difference is that this model leads to a slightly larger number of false positives, 34 versus 30, but it correctly predicts the same wars.[23] The results are identical when generating predictions from a model with country-specific time trends only, indicating that the predicted probabilities are almost exclusively driven by the inclusion of these effects. Figure 5.8 illustrates these differences in predictive power for three different models: A model specified with the temperature variables and country-specific year trend, a model with only the temperature variables, and a model with only the country-specific year trend. The results show that including the country-specific time trend is beneficial for the predictive power of the model, and also that there is little difference between a LPM with or without temperature.

[22]Using a model omitting the country-specific time trend reduces the range of predicted values and leads to fewer predicted wars. The number of correctly predicted wars decreases by 1, false positives by 3 while false negatives increase by 1.

[23]See table D.3 for results

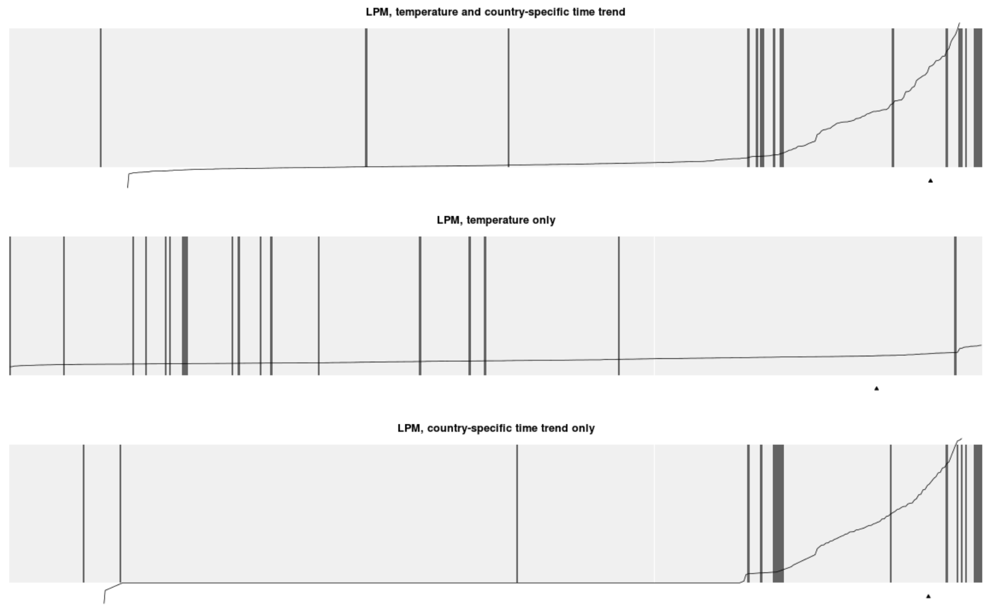

Figure 5.8: Predictive performance linear probability model based on alterations in model specification.

As an additional check I generate predictions using a benchmark civil war model including lagged time-varying covariates on GDP per capita, population, regime type, natural resource rents, and a fixed variable for ethnic polarisation.[24] The model is estimated using OLS as well as logit.

Accurately predicting war is difficult as illustrated by figure 5.9. In all estimations the predicted outcomes are below 0.5, which was used as threshold so far. The LPM model including the temperature variable is the only one producing predicted probabilities outside the 0-1 interval. In general the LPM and logit results are comparable and in both cases separation is not perfect. According to the AUC statistic, the LPM actually has a slight edge over logit (0.769 vs. 0.765) in correctly predicting the outcome (*note:* these are the models without the temperature variable). However, since there are a lot of zeroes in the data it is not too difficult to register high AUC statistics, and as shown both models have trouble correctly identifying the cases that experienced civil war.

[24]Data on GDP, population, and natural resource rents all taken from World Bank Development Indicators. Resource rents are measured as percentage of GDP. Regime type is taken from the Polity IV project and data on ethnic polarisation from Garcia-Montalvo and Reynal-Querol (2005)

Estimating the benchmark model including the temperature variables leads to a 8 percentage point reduction in the *AUC* statistic and reduces the predictive power of the model as illustrated in the lower panel of figure 5.9.

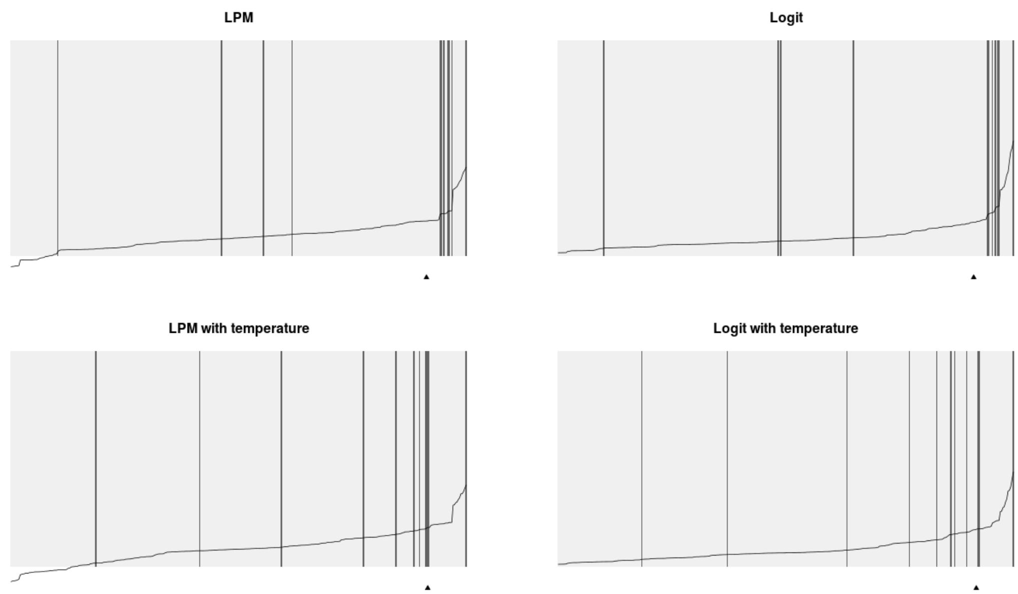

Figure 5.9: Predictive performance of a standard civil war model using linear probability model and logit with and without temperature variables.

5.3 Discussion

Predicting conflict accurately is a difficult task. There are many complex underlying dynamics that are overlooked by the statistical models and there is always the issue that certain social constructions don't behave uniformly which makes predicting conflict very difficult indeed. In the quantitative literature on violent armed conflict there seems to be very little appreciation for the predictive power of the models as most analyses focus on the statistical significance of the variables. This studies follows Ward et al. (2010) and argues that examining predicted probabilities and generating out-of-sample predictions can provide useful insights in the performance of the models.

To illustrate this I focus on the highly contested research area of climate-conflict. Using one of the standard models linking temperature to climate, I find that it produces inaccurate out-of-sample predictions which are mainly driven by the inclusion of country fixed effects and country-specific time trends rather than the variable of interest. Using a benchmark civil war model I find that out-of-sample prediction is difficult in general: the time-varying covariates have little predictive power and this model performs worse when including temperature.

As I attempt to gauge the predictive power of temperature variation on conflict, there are two issues that are not accounted for and that might be of interest for future research on conflict prediction and are also described in O'Loughlin et al. (2012) and O'Loughlin et al. (2014). First, the model estimates the link between weather variation and conflict using the country-year as unit of analysis. This means that it neglects within-country as well as within-year variability in both climate and conflict. Second, using a crude binary indicator means that a lot of information on conflict intensity is lost. Additionally, the assumption that the relationship observed between climate and conflict in the past will be the same in the future might be misleading. These are factors worth taking into account for further examination of the predictive power of climate variability on violence.

Bibliography

Aas Rustad, S. C., H. Buhaug, A. Falch, and S. Gates (2011). All Conflict is Local: Modeling Sub-National Variation in Civil Conflict Risk. *Conflict Management and Peace Science 28*(1), 15–40.

Abadie, A. and J. Gardeazabal (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review 93*(1), 113–132.

Addison, T. and S. M. Murshed (2001). The Fiscal Dimensions of Conflict and Reconstructions. WIDER Discussion Paper, 2001/49.

Adler, R. F., G. J. Huffman, A. Chang, R. Ferraro, P.-P. Xie, J. Janowiak, B. Rudolf, U. Schneider, S. Curtis, D. Bolvin, A. Gruber, J. Susskind, P. Arkin, and E. Nelkin (2003). The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–Present). *Journal of Hydrometeorology 4*(6), 1147–1167.

Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003). Fractionalization. *Journal of Economic Growth 8*, 155–194.

Alesina, A., W. Easterly, and J. Matuszeski (2011). Artificial states. *Journal of the European Economic Association 9*(2), 246–277.

Allison, P. D. and R. P. Waterman (2002). Fixed-Effects Negative Binomial Regression Models. *Sociological Methodology 32*(1), 247–265.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly Harmless Econometrics : An Empiricist ' s Companion*. Princeton University Press.

Anselin, L. and R. J. Florax (1995). *Small Sample Properties of Tests for Spatial Dependence in Regression Models: Some Further Results*. Springer Berlin Heidelberg.

Arcand, Jean-Louis, B. A. and J. Labonne (2011). Conflict, ideology and foreign aid. CERDI Working Papers No. 201021.

Arcand, J. and L. Chauvet (2001). Foreign Aid, Rent-Seeking Behavior, and Civil War. CSAE Conference Paper.

Arezki, R. and M. Brückner (2011). Food prices and political instability. IMF working paper.

Auffhammer, M., S. Hsiang, W. Schlenker, and A. Sobel (2013). Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Review of Environmental Economics and Policy 7*(2), 181–198.

Baquedano, F. G. and W. M. Liefert (2014). Market integration and price transmission in consumer markets of developing countries. *Food Policy 44*, 103–114.

Barrios, S., L. Bertinelli, and E. Strobl (2010). Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. *The Review of Economics and Statistics 92*(2), 350–366.

Bazzi, S. and C. Blattman (2014). Economic Shocks and Conflict: Evidence from Commodity Prices. *American Economic Journal: Macroeconomics 6*(4), 1–38.

Beck, N., K. Gleditsch, and K. Beardsly (2006). Space Is More than Geography: Using Spatial Econometrics in the Study of Political Economy. *International Studies Quarterly 50*, 27–44.

Beck, N. and J. N. Katz (2011). Modeling Dynamics in Time-Series-Cross-Section Political Economy Data. *Annual Review of Political Science 14*, 331–352.

Bellemare, M. (2015). Rising Food Prices, Food Price Volatility, and Social Unrest. *American Journal of Agricultural Economics 97*(1), 1–21.

Berazneva, J. and D. Lee (2013). Explaining the African food riots of 2007-2008: An empirical analysis. *Food Policy 39*, 28–39.

Berman, E., J. Felter, J. Shapiro, and E. Troland (2013). Modest, Secure and Informed: Successful Development in Conflict Zones. *American Economic Review: Papers & Proceedings 103*(3), 512–517.

Bernauer, T., T. Böhmelt, and V. Koubi (2012). Environmental changes and violent conflict. *Environmental Research Letters 7*(1), 015601.

Besley, T. and T. Persson (2008). The incidence of civil war: Theory and evidence. NBER Working Paper No. w14585.

Besley, T. and T. Persson (2011). The Logic of Political Violence. *The Quarterly Journal of Economics 126*(3), 1411–1445.

Besley, T. and M. Reynal-Querol (2014). The Legacy of Historical Conflict: Evidence from Africa. *American Political Science Review 108*(2), 1–31.

Blair, R. A., C. Blattman, and A. Hartman (2014). Predicting Local Violence. Available at SSRN: http://ssrn.com/abstract=2497153.

Blattman, C. and E. Miguel (2010). Civil War. *Journal of Economic Literature 48*(1), 3–57.

Blaydes, L. and M. A. Kayser (2011). Counting Calories: Democracy and Distribution in the Developing World. *International Studies Quarterly 55*(4), 887–908.

Blouin, M. and S. Pallage (2008). Humanitarian Relief and Civil Conflict. *Journal of Conflict Resolution 52*, 548–565.

Bohorquez, J. C., S. Gourley, A. R. Dixon, M. Spagat, and N. F. Johnson (2009). Common ecology quantifies human insurgency. *Nature 462*(7275), 911–4.

Bosker, M. and J. de Ree (2014). Ethnicity and the spread of civil war. *Journal of Development Economics 108*, 206–221.

Bound, J., D. Jaeger, and R. Baker (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association 90*(430), 443–450.

Brooks, S., A. Gelman, G. L. Jones, and X.-L. Meng (2011). *Handbook of Markov Chain Monte Carlo*. Chapman & Hall/CRC.

Brooks, S. P. and A. Gelman (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics 7*(4), 434–455.

Brückner, M. and A. Ciccone (2010). International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa. *The Economic Journal 120*, 519–534.

Buhaug, H. (2010). Climate not to blame for African civil wars. *Proceedings of the National Academy of Sciences of the United States of America 107*(38), 16477–82.

Buhaug, H. (2014). Concealing agreements over climate-conflict results. *Proceedings of the National Academy of Sciences of the United States of America 111*(6), E636.

Buhaug, H. and K. Gleditsch (2008). Contagion or Confusion? Why Conflicts Cluster in Space. *International Studies Quarterly 52*, 215–233.

Buhaug, H., J. Nordkvelle, T. Bernauer, T. Böhmelt, M. Brzoska, J. Busby, A. Ciccone, H. Fjelde, E. Gartzke, N. Gleditsch, J. Goldstone, H. Hegre, H. Holtermann, V. Koubi, J. Link, P. Link, P. Lujala, J. O'Loughlin, C. Raleigh, J. Scheffran, J. Schilling, T. Smith, O. Theisen, R. Tol, H. Urdal, and N. von Uexkull (2014). One effect to rule them all? a comment on climate and conflict. *Climatic Change 127*(3-4), 391–397.

Burke, M., J. Dykema, D. Lobell, E. Miguel, and S. Satyanath (2010). Climate and civil war: Is the relationship robust? NBER Working Paper No. 16440.

Burke, M., J. Dykema, D. B. Lobell, E. Miguel, and S. Satyanath (2014). Incorporating Climate Uncertainty into Estimates of Climate Change Impacts. *The Review of Economics and Statistics Forthcoming*(October), 1–33.

Burke, M., E. Miguel, S. Satyanath, J. A. Dykema, and D. B. Lobell (2009). Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences of the United States of America 106*(49), 20670–4.

Burke, M. B., E. Miguel, S. Satyanath, J. A. Dykema, and D. B. Lobell (2010). Reply to Sutton et al.: Relationship between temperature and conflict is robust. *Proceedings of the National Academy of Sciences 107*(25), E103–E103.

Böhnke, J. and C. Zurcher (2013). Aid, Minds and Hearts: The Impact of Aid in Conflict Zones. *Conflict Management and Peace Science 30*, 411–432.

Cederman, A. L.-e. and L. Girardin (2007). Beyond Fractionalization : Mapping Ethnicity onto Nationalist Insurgencies. *The American Political Science Review 101*(1), 173–185.

Chamarbagwala, R. and H. E. Morán (2011). The human capital consequences of civil war: Evidence from Guatemala. *Journal of Development Economics 94*(1), 41–61.

Chassang, S. and G. Padró i Miquel (2009). Economic Shocks and Civil War. *Quarterly Journal of Political Science 4*(3), 211–228.

Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics 3*(4), 215–227.

CIESIN (2004). Gridded population of the world (gpw) version 3.

Claeskens, G., T. Krivobokova, and J. Opsomer (2009). Asymptotic properties of penalized spline estimators. *Biometrika 96*(3), 529–544.

Clemens, M. (2015). The Meaning of Failed Replications : A Review and Proposal.

Cohen, M. J. and J. L. Garrett (2010). The food price crisis and urban food (in)security. *Environment and Urbanization 22*(2), 467–482.

Colin Cameron, A. and P. K. Trivedi (1986). Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests. *Journal of Applied Econometrics 1*(1), 29–53.

Collier, P. and A. Hoeffler (1998). On economic causes of civil war. *Oxford Economic Papers 50*, 563–573.

Collier, P. and A. Hoeffler (2002). Aid, Policy and Peace: Reducing the Risks of Civil Conflict. *Defence and Peace Economics 13*(6), 435–450.

Collier, P. and A. Hoeffler (2007). Unintended Consequences: Does Aid Promote Arms Races? *Oxford Bulletin of Economics and Statistics 69*(1), 1–27.

Costalli, S. and F. Moro (2012). Ethnicity and strategy in the Bosnian civil war: Explanations for the severity of violence in Bosnian municipalities. *Journal of Peace Research 49*(6), 801–815.

Couttenier, M. and R. Soubeyran (2014). Drought and Civil War In Sub-Saharan Africa. *The Economic Journal 124*(575), 201–244.

Crost, B., J. Felter, and P. Johnston (2014). Aid under fire: Development projects and civil conflict. *American Economic Review 104*(6), 1833–1856.

Cuesta, J., A. Htenas, and S. Tiwari (2014). Monitoring global and national food price crises. *Food Policy 49*, 84–94.

Dal Bó, E. and P. Dal Bó (2011). Workers, warriors, and criminals: social conflict in general equilibrium. *Journal of the European Economic Association 9*(4), 646–677.

Danneman, N. and E. Ritter (2013). Contagious Rebellion and Preemptive Repression. *Journal of Conflict Resolution 58*(2), 254–279.

Dawe, D. and I. Maltsoglou (2014). Marketing margins and the welfare analysis of food price shocks. *Food Policy 46*, 50–55.

de Ree, J. and E. Nillesen (2009). Aiding Violence or Peace? The Impact of Foreign Aid on the Risk of Civil Conflict in Sub-Saharan Africa. *Journal of Development Economics 88*(2), 301–313.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature 52*(3), 1–70.

Demeke, M., G. Pangrazio, and M. Maetz (2008). Country responses to the food security crisis: Nature and preliminary implications of the policies pursued.

Department for International Development (2013). Annual reports and accounts 2012-13.

Devajaran, S. and V. Swaroop (1998). The implications of foreign aid fungibility for development assistance. World Bank Policy Research Working Paper 2022.

Dixon, J. (2009). What Causes Civil Wars? Integrating Quantitative Research Findings. *International Studies Review 11*(4), 707–735.

Djankov, S., J. Garcia-Montalvo, and M. Reynal-Querol (2008). The Curse of Aid. *Journal of Economic Growth 13*(3), 1835–1865.

Djankov, S. and M. Reynal-Querol (2010). Poverty and civil war: Revisiting the evidence. *The Review of Economics and Statistics 92*(4), 1035–1041.

Doucouliagos, H. and M. Paldam (2008). Aid Effectiveness on Growth: A Meta Study. *European Journal of Political Economy 24*(1), 1–24.

Doucouliagos, H. and M. Paldam (2011). The Ineffectiveness of Development Aid on Growth: An Update. *European Journal of Political Economy 27*(2), 399–404.

Dube, O. and J. Vargas (2013). Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *The Review of Economic Studies 80*(4), 1384–1421.

Dunning, T. (2008). Model Specification in Instrumental-Variables Regression. *Political Analysis 16*(3), 290–302.

Easterly, W. and T. Pfutze (2008). Where does the money go? best and worst practices in foreign aid. *Journal of Economic Perspectives 22*(2), 29–52.

Eck, K. (2012). In Data We Trust? A Comparison of UCDP GED and ACLED Conflict Events Datasets. *Cooperation and Conflict 47*(1), 124–141.

FAO Statistical Division (2013). http://faostat3.fao.org/faostat-gateway/go/to/home/E. (Accessed 22 April 2013).

Fearon, J. and D. Laitin (2003). Ethnicity, insurgency, and civil war. *American political science review 97*(1), 75–90.

Feridun, M. (2014). Foreign aid fungibility and military spending: the case of north cyprus. *Defence and Peace Economics 25*(5), 499–508.

Feyzioglu, T., V. Swaroop, and M. Zhu (1998). A panel data analysis of the fungibility of foreign aid. *The World Bank Economic Review 12*(1), 29–58.

Findley, M. G., J. Powell, D. Strandow, and J. Tanner (2011). The Localized Geography of Foreign Aid: A New Dataset and Application to Violent Armed Conflict. *World Development 39*(11), 1995–2009.

Fjelde, H. and N. von Uexkull (2012). Climate triggers: Rainfall anomalies, vulnerability and communal conflict in Sub-Saharan Africa. *Political Geography 31*(7), 444–453.

Fotheringham, A. and D. Wong (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A 23*(7), 1025 – 1044.

Franzese, R. and J. Hays (2007). Spatial Econometric Models of Cross-Sectional Interdependence in Political Science Panel and Time-Series-Cross-Section Data. *Political Analysis 15*(2), 140–164.

GADM (2012). Database of global administrative areas version 2.0.

Gaibulloev, K., T. Sandler, and D. Sul (2014). Dynamic Panel Analysis under Cross-Sectional Dependence. *Political Analysis 22*, 258–273.

Garcia-Montalvo, J. and M. Reynal-Querol (2005). Ethnic polarization, potential conflict, and civil wars. *The American Economic Review 95*(3), 796–816.

Gehlke, C. and K. Biehl (1934). Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association 29*(185), 169–170.

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine 27*, 2865–2873.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin (1995). *Bayesian Data Analysis*. Chapman & Hall/CRC.

Gelman, A. and J. Hill (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press.

Gelman, A. and J. Hill (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

German Advisory Council on Global Change (2008). *World in Transition: Climate Change as a Security Risk*. Earthscan.

Gil-Alana Alberiko, L. and P. Singh (2013). Violence and the Market for Food : Evidence from Kenya. Available at SSRN: http://ssrn.com/abstract=2276250.

Gilbert, C. and C. Morgan (2010). Food price volatility. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences 365*(1554), 3023–34.

Gilmore, E., N. P. Gleditsch, P. Lujala, and J. K. Rød (2005). Conflict diamonds: A new dataset. *Conflict Management and Peace Science 22*(3), 257–292.

Gleditsch, K. and M. Ward (2013). Forecasting is difficult, especially about the future: Using contentious issues to forecast interstate disputes. *Journal of Peace Research 50*(1), 17–31.

Gleditsch, N. (2012). Whither the weather? Climate change and conflict. *Journal of Peace Research 49*(1), 3–9.

Gleditsch, N., P. Wallensteen, M. Eriksson, M. Sollenberg, and H. Strand (2002). Armed Conflict 1946-2001: A New Dataset. *Journal of Peace Research 39*(5), 615–637.

Goldstone, J., R. Bates, D. Epstein, T. R. Gurr, M. B. Lustik, M. G. Marshall, J. Ulfelder, and M. Woodward (2010). A global model for forecasting political instability. *American Journal of Political Science 54*(1), 190–208.

Greenhill, B., M. D. Ward, and A. Sacks (2011). The Separation Plot: A New Visual Method for Evaluating the Fit of Binary Models. *American Journal of Political Science 55*(4), 991–1002.

Grossman, H. (1992). Foreign aid and insurrection. *Defence Economics 3*(4), 275–288.

Harris, I., P. Jones, T. Osborn, and D. Lister (2014). Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology 34*(3), 623–642.

Hausman, J. A., B. Hall, and Z. Griliches (1984). Econometric Models for Count Data with an Application to the Patents-R&D Relationship. *Econometrica 52*(4), 909–938.

Hegre, H., G. Ostby, and C. Raleigh (2009). Poverty and Civil War Events: A Disaggregated Study of Liberia. *Journal of Conflict Resolution 53*(4), 598–623.

Hegre, H. and N. Sambanis (2006). Sensitivity Analysis of Empirical Results on Civil War Onset. *Journal of Conflict Resolution 50*(4), 508–535.

Henderson, J., A. Storeygard, and D. Weil (2012). Measuring economic growth from outer space. *American Economic Review 102*(2), 994–1028.

Hendrix, C. S. and S. M. Glaser (2007). Trends and triggers: Climate, climate change and civil conflict in Sub-Saharan Africa. *Political Geography 26*(6), 695–715.

Hendrix, C. S., S. Haggard, and B. Magaloni (2009). Grievance and opportunity: Food prices, political regime, and protest. presentation at the International Studies Association Convention, New York (August, 2009).

Hendrix, C. S. and I. Salehyan (2012). Climate change, rainfall, and social conflict in Africa. *Journal of Peace Research 49*(1), 35–50.

Hendrix, C. S. and I. Salehyan (2013). Social Conflict in Africa Database (SCAD). (Accessed 18 May 2013).

Heston, A. (1994). A brief review of some problems in using national accounts data in level of output comparisons and growth studies. *Journal of Development Economics 44*(1), 29–52.

Hodler, R. and D. S. Knight (2012). Ethnic fractionalisation and aid effectiveness. *Journal of African Economies 21*(1), 65–93.

Hodler, R. and P. A. Raschky (2014a). Economic shocks and civil conflict at the regional level. *Economics Letters 124*(3), 530–533.

Hodler, R. and P. A. Raschky (2014b). Regional Favoritism. *Quarterly Journal of Economics 129*, 995–1033.

Horrace, W. C. and R. L. Oaxaca (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters 90*, 321–327.

Hsiang, S., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151).

Hsiang, S., M. Burke, and E. Miguel (2014). Reconciling climate-conflict meta-analyses: reply to buhaug et al. *Climatic Change 127*(3-4), 399–405.

Hsiang, S. and K. Meng (2014). Reconciling disagreement over climate-conflict results in Africa. *Proceedings of the National Academy of Sciences 111*(6), 2100–2103.

Hsiang, S. M. and M. Burke (2013). Climate, conflict, and social stability: what does the evidence say? *Climatic Change 123*(1), 39–55.

Ianchovichina, E., J. Loening, and C. Wood (2014). How vulnerable are Arab countries to global food price shocks? *Journal of Development Studies 50*(9), 1302–1319.

IPCC (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC.

Ivanic, M. and W. Martin (2008). Implications of higher global food prices for poverty in low-income countries. *Agricultural Economics 39*, 405–416.

Jensen, P. and K. Gleditsch (2009). Rain, growth, and civil war: the importance of location. *Defence and Peace Economics 20*(5), 359–372.

Johnson, S., W. Larson, C. Papageorgiou, and A. Subramanian (2013). Is newer better? Penn World Table revisions and their impact on growth estimates. *Journal of Monetary Economics 60*(2), 255–274.

Kalkuhl, M. (2014). How Strong Do Global Commodity Prices Influence Domestic Food Prices in Developing Countries ? A Global Price Transmission and Vulnerability Mapping Analysis. ZEF - Discussion Papers on Development Policy No. 191.

King, G. and L. Zeng (2001). Explaining Rare Events in International Relations. *International Organization 55*(3), 693–715.

Klomp, J. and E. Bulte (2013). Climate change, weather shocks, and violent conflict: A critical look at the evidence. *Agricultural Economics 44*(s1), 63–78.

Koubi, V., T. Bernauer, A. Kalbhenn, and G. Spilker (2012). Climate variability, economic growth, and civil conflict. *Journal of Peace Research 49*(1), 113–127.

Kreutz, J. (2010). How and when armed conflicts end: Introducing the UCDP Conflict Termination dataset. *Journal of Peace Research 47*(2), 243–250.

Kuhn, P. M. and N. B. Weidmann (2013). Unequal We Fight : The Impact of Economic Inequality Within Ethnic Groups on Conflict Initiation. Unpublished manuscript, Princeton University and University of Konstanz.

Lagi, M., K. Z. Bertrand, and Y. Bar-Yam (2011). The Food Crises and Political Instability in North Africa and the Middle East. Available at SSRN: http://ssrn.com/abstract=1910031.

LeSage, J. P. (2000). Bayesian estimation of limited dependent variable spatial autoregressive models. *Geographical Analysis 32*(1), 19–35.

LeSage, J. P. and R. K. Pace (2010). The Biggest Myth in Spatial Econometrics. Available at SSRN: http://ssrn.com/abstract=1725503.

Lloyd-Smith, J. O. (2007). Maximum likelihood estimation of the negative binomial dispersion parameter for highly overdispersed data, with applications to infectious diseases. *PLOS One 2*(2), e180.

Lujala, P. (2010). The spoils of nature: Armed civil conflict and rebel access to natural resources. *Journal of Peace Research 47*(1), 15–28.

Lujala, P., N. P. Gleditsch, and E. Gilmore (2005). A diamond curse? civil war and a lootable resource. *Journal of Conflict Resolution 49*(4), 538–562.

Lujala, P., J. K. Rød, and N. Thieme (2007). Fighting over oil: Introducing a new dataset. *Conflict Management and Peace Science 24*(3), 239–256.

Marshall, M. G., K. Jaggers, and T. R. Gurr (2013). Polity IV Project: Political Regime Characteristics and Transitions, 1800-2012.

Maystadt, J.-F., M. Calderone, and L. You (2014). Local Warming and Violent Conflict in North and South Sudan. *Journal of Economic Geography 15*(3), 649–671.

Maystadt, J. F., G. De Luca, P. G. Sekeris, and J. Ulimwengu (2014). Mineral resources and conflicts in DRC: A case of ecological fallacy? *Oxford Economic Papers 66*, 721–749.

Maystadt, J.-F., J.-F. Trinh Tan, and C. Breisinger (2014). Does Food Security Matter for Transition in Arab Countries? *Food Policy 46*, 106–115.

McCauley, J. F. and D. N. Posner (2014). African Borders as Sources of Natural Experiments Promise and Pitfalls. *Political Science Research and Methods (Forthcoming)*, 1–10.

Meierding, E. (2013). Climate change and conflict: Avoiding small talk about the weather. *International Studies Review 15*, 185–203.

Michalopoulos, S. and E. Papaioannou (2015). The Long-Run Effects of the Scramble for Africa.

Miguel, E. and S. Satyanath (2011). Re-examining Economic Shocks and Civil Conflict. *American Economic Journal: Applied Economics 3*(4), 228–232.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy 112*(4), 725–753.

Minot, N. (2011). Transmission of World Food Price Changes to Markets in Sub-Saharan Africa. International Food Policy Research Institute Discussion Paper No. 01059.

Minot, N. (2014). Food price volatility in sub-Saharan Africa: Has it really increased? *Food Policy 45*, 45–56.

Nelson, G. C., M. W. Rosegrant, A. Palazzo, I. Gray, C. Ingersoll, R. Robertson, S. Tokgoz, T. Zhu, T. B. Sulser, C. Ringler, S. Msangi, and Y. Liangzhi (2010). *Food security, farming, and climate change to 2050 : scenarios, results, policy option.* International Food Policy Research Institute.

Nicholson, S. (2001). Climatic and environmental change in Africa during the last two centuries. *Climate Research 17*, 123–144.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica 49*(6), 1417–1426.

Nielsen, R. A., M. G. Findley, Z. S. Davis, T. Candland, and D. L. Nielson (2011). Foreign Aid Shocks as a Cause of Violent Armed Conflict. *American Journal of Political Science 55*(2), 219–232.

Nunn, N. and N. Qian (2014). U.S. Food Aid and Civil Conflict. *American Economic Review 104*(6), 1630–66.

Nuzzo, R. (2014). Scientific method: Statistical errors. *Nature 506*, 150–152.

O'Loughlin, J., A. M. Linke, and F. D. Witmer (2014). Modeling and data choices sway conclusions about climate-conflict links. *Proceedings of the National Academy of Sciences of the United States of America 111*(6), 2054–5.

O'Loughlin, J., F. D. Witmer, A. M. Linke, A. Laing, A. Gettelman, and J. Dudhia (2012). Climate variability and conflict risk in East Africa, 1990-2009. *Proceedings of the National Academy of Sciences of the United States of America 109*(45), 18344–9.

Openshaw, S. (1983). *The Modifiable Areal Unit Problem.* Geo Books.

Papaioannou, E. and G. Siourounis (2008). Economic and social factors driving the third wave of democratization. *Journal of Comparative Economics 36*(3), 365–387.

Petřík, J. (2008). Does Foreign Aid Alleviate Violent Tensions? *Global Change, Peace & Security 20*(August 2014), 305–322.

Pinker, S. (2011). *The better angels of our nature: The decline of violence in history and its causes.* Viking.

Pinstrup-Andersen, P. and S. Shimokawa (2008). Do poverty and poor health and nutrition increase the risk of armed conflict onset? *Food Policy 33*(6), 513–520.

Plummer, M. (2014). Jags: A program for analysis of bayesian graphical models using gibbs sampling. (Version 3.4.0).

Plümper, T. and E. Neumayer (2010). Model Specification in the Analysis of Spatial Dependence. *European Journal of Political Research 49*(3), 418–442.

Posner, D. N. (2004). Measuring Ethnic Fractionalization in Africa. *American Journal of Political Science 48*(4), 849–863.

Raleigh, C. and D. Kniveton (2012). Come rain or shine: An analysis of conflict and climate variability in East Africa. *Journal of Peace Research 49*(1), 51–64.

Raleigh, C., A. Linke, H. Hegre, and J. Karlsen (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature. *Journal of Peace Research 47*(5), 651–660.

Raleigh, C., A. Linke, and J. O'Loughlin (2014). Extreme temperatures and violence. *Nature Climate Change 4*, 76–77.

Reuters (2008). Food riots to worsen without global action: U.N.

Roodman, D. (2007). The Anarchy of Numbers: Aid, Development, and Cross-Country Empirics. *The World Bank Economic Review 21*(2), 255–277.

Rosales, L. and T. Krivobokova (2012). Instant Trend-Seasonal Decomposition of Time Series with Splines. No. 131. Courant Research Centre: Poverty, Equity and Growth-Discussion Papers.

Ross, M. (2006). A closer look at oil, diamonds, and civil war. *Annual Review of Political Science 9*, 265–300.

Ross, M. L. (2004). What Do We Know about Natural Resources and Civil War? *Journal of Peace Research 41*(3), 337–356.

Savun, B. and D. C. Tirone (2011). Foreign Aid, Democratization, and Civil Conflict: How Does Democracy Aid Affect Civil Conflict? *American Journal of Political Science 55*(2), 233–246.

Scheffran, J., M. Brzoska, J. Kominek, P. M. Link, and J. Schilling (2012a). Climate Change and Violent Conflict. *Science 336*(6083), 869–871.

Scheffran, J., M. Brzoska, J. Kominek, P. M. Link, and J. Schilling (2012b). Disentangling the climate-conflict nexus: Empirical and theoretical assessment of vulnerabilities and pathways. *Review of European Studies 4*(5), 1–13.

Schrodt, P. (2013). Seven deadly sins of contemporary quantitative political analysis. *Journal of Peace Research 51*(2), 287–300.

Serneels, P. and M. Verpoorten (2013). The impact of armed conflict on economic performance: Evidence from rwanda. *Journal of Conflict Resolution (Forthcoming)*.

Shor, B., J. Bafumi, L. Keele, and D. Park (2007). A bayesian multilevel modeling approach to time-series cross-sectional data. *Political Analysis 15*(2), 165–181.

Smith, T. (2014). Feeding unrest: Disentangling the causal relationship between food price shocks and sociopolitical conflict in Urban Africa. *Journal of Peace Research 51*(6), 679–695.

Stern, N. (2006). *Stern Review: The economics of climate change.*, Volume 30. London: HM Treasury.

Strandow, D., M. Findley, D. Nielson, and J. Powell (2011). *The UCDP-AidData codebook on Geo-referencing Foreign Aid. Version 1.1.* Uppsala Conflict Data Program, Uppsala University.

Strandow, D., J. Powell, J. Tanner, and M. Findley (2014). The Geography of Foreign Aid and Violent Armed Conflict. Unpublished working paper.

Sundberg, R., M. Lindgren, and A. Padskocimaite (2010). *UCDP GED Codebook version 1.0-2011.* Department of Peace and Conflict Research, Uppsala University.

Sundberg, R. and E. Melander (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research 50*(4), 523–532.

Sutton, A. E., J. Dohn, K. Loyd, A. Tredennick, G. Bucini, A. Solórzano, L. Prihodko, and N. P. Hanan (2010). Does warming increase the risk of civil war in Africa? *Proceedings of the National Academy of Sciences of the United States of America 107*(25), E102; author reply E103.

Tadesse, G., B. Algieri, M. Kalkuhl, and J. von Braun (2013). Drivers and triggers of international food price spikes and volatility. *Food Policy 47*, 117–128.

Tahir, N. (2015). Does aid cause conflict in pakistan. *Defence and Peace Economics.*

Taylor, L. (1996). Food Riots Revisited. *Journal of Social History 30*(2), 483–496.

TEDxBerkeley (2014). Climate, conflict, and African development: Edward Miguel at TEDxBerkeley.

The Economist (2012a). Food and the Arab spring: Let them eat baklava. http://www.economist.com/node/21550328. (Accessed 30 June 2012).

The Economist (2012b). Protests in Nigeria: Let them have fuel. http://www.economist.com/node/21543199. (Accessed 30 June 2012).

Themnér, L. and P. Wallensteen (2011). Armed conflict, 1946-2010. *Journal of Peace Research 48*(4), 525–536.

Tierney, M. J., D. L. Nielson, D. G. Hawkins, J. T. Roberts, M. G. Findley, R. M. Powers, B. Parks, S. E. Wilson, and R. L. Hicks (2011). More Dollars than Sense: Refining Our Knowledge of Development Finance Using AidData. *World Development 39*(11), 1891–1906.

Verpoorten, M., A. Arora, N. Stoop, and J. Swinnen (2013). Self-reported food insecurity in Africa during the food price crisis. *Food Policy 39*, 51–63.

Ward, M., B. Greenhill, and K. Bakke (2010). The perils of policy by p-value: Predicting civil conflicts. *Journal of Peace Research 47*(4), 363–375.

Weidmann, N. (2009). Geography as Motivation and Opportunity: Group Concentration and Ethnic Conflict. *Journal of Conflict Resolution 53*(4), 526–543.

Weidmann, N. and M. Ward (2010). Predicting Conflict in Space and Time. *Journal of Conflict Resolution 54*(6), 883–901.

Weidmann, N. B., J. K. Rød, and L.-E. Cederman (2010). Representing ethnic groups in space: A new dataset. *Journal of Peace Research 47*(4), 491–499.

World Bank (2012). World development indicators.

World Bank (2013a). Global Economic Monitor (GEM) Commodities. http://data.worldbank.org/data-catalog/commodity-price-data. (Accessed 23 April 2013).

World Bank (2013b). Manufactures Unit Value Index. http://data.worldbank.org/data-catalog/MUV-index. (Accessed 23 April 2013).

Østby, G., R. Nordas, and J. K. Rød (2009). Regional Inequalities and Civil Conflict in 21 Sub-Saharan African Countries , 1986 – 2004. *International Studies Quarterly 53*(2), 301–324.

Appendix A

Economic shocks and civil conflict onset in Sub-Saharan Africa, 1981-2010

A.1 Descriptive statistics

Table A.1: Descriptive Statistics (1981-2010)

	Mean	Std. Dev.	Obs.
	A. Civil Conflict		
Civil conflict ($\geq$ 25 deaths)	0.21	0.41	1389
Onset	0.06	0.23	1101
Offset	0.24	0.43	289
Onset (5-year intermittency period)	0.04	0.19	954
	B. Precipitation		
Rainfall (mm)	1023.44	552.55	1389
Rainfall growth$_t$	0.02	0.23	1389
Rainfall growth$_{t-1}$	0.02	0.23	1389
Rainfall anomaly$_t$	-0.01	0.99	1389
Rainfall anomaly$_{t-1}$	-0.01	0.99	1389
	C. Economic Growth		
GDP growth rate$_t$	0.01	0.07	1299
GDP growth rate$_{t-1}$	0.01	0.07	1288
Agricultural sector growth rate$_t$	0.00	0.10	1088
Industrial sector growth rate$_t$	0.02	0.11	1058
	D. Country Controls		
Peace years	14.40	13.50	1389
Ln Population$_{t-1}$	15.46	1.47	1389
Regime type$_{t-1}$	37.33	26.61	1356
Ln GDP per capita 1979	7.05	0.74	1389
Ethnolinguistic fractionalization (PREG index)	0.40	0.24	1221
Rough terrain (% land area covered by mountains)	12.08	21.07	1389
Oil exports$_{t-1}$	0.07	0.26	1387

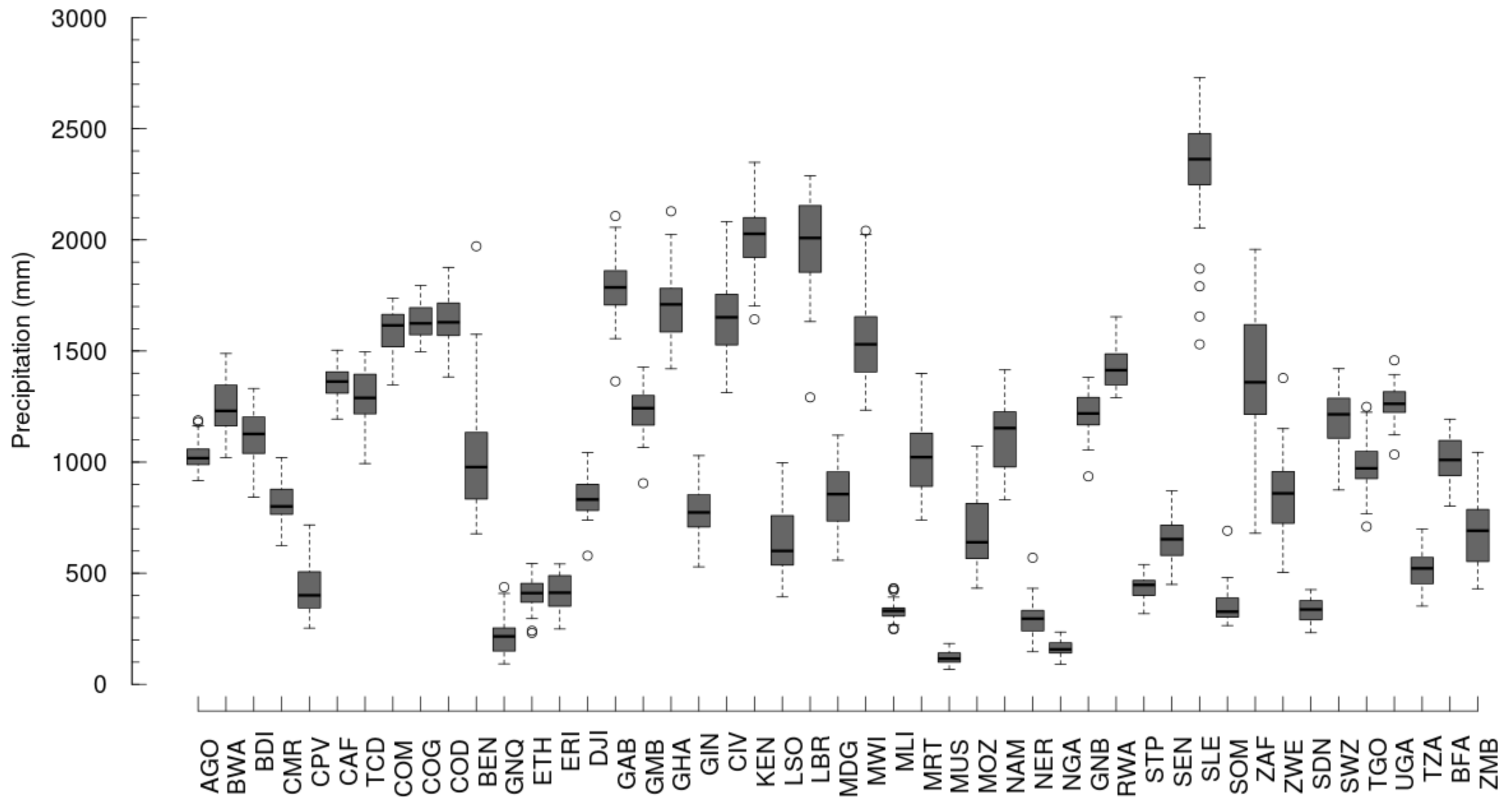

Figure A.1: Rainfall distribution for countries in sample, 1981-2010. *Source* GPCP.

A.2 Additional regression results

Table A.2: Effect of rainfall on economic growth, 1981−1999 (IV−2SLS, first stage)

	MSS rainfall data		New rainfall data			
Rainfall measure	Growth		Growth		Anomaly	
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall$_t$	0.06***	0.05***	0.06***	0.06***	0.01***	0.01***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)
Rainfall$_{t-1}$	0.03**	0.03**	0.04***	0.04***	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Country FE	–	Yes	–	Yes	–	Yes
Country-specific year trend	–	Yes	–	Yes	–	Yes
Root MSE	0.07	0.07	0.07	0.07	0.07	0.07
N	743	743	743	743	743	743

Notes. Data from Miguel et al. (2004)). Columns 3 to 6 use new rainfall data. Estimates rounded to two decimals. FE, Fixed effects; MSE, Mean squared error. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table A.3: Effect of rainfall on economic growth for different periods (IV−SLS, first stage)

Period	1981-2010		1981-1999		2000-2010	
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall$_t$	0.02**	0.01***	0.02*	0.01***	0.01	0.00*
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Rainfall$_{t-1}$	0.02**	0.00	0.02**	0.00	0.00	0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes
Root MSE	0.07	0.07	0.07	0.07	0.05	0.05
N	1299	1299	796	796	503	503

Notes. Results in odd columns are for growth, anomalies in even columns. Estimates rounded to two decimals. FE, Fixed effects; MSE, Mean squared error. Robust standard errors, clustered at country-level, in parentheses. *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Appendix B

Food prices and the incidence of violence in Africa, 1990-2011

B.1 Descriptive statistics

Table B.1: Descriptive statistics food price index (FPI) per country.

Country	Mean FPI	SD FPI	Minimum FPI	Maximum FPI	N
Algeria	2.098	0.3227	1.4388	3.0123	264
Angola	0.3925	0.0856	0.2503	0.6181	264
Benin	0.7576	0.1731	0.4947	1.334	264
Botswana	0.5181	0.0941	0.342	0.77	264
Burkina Faso	0.8782	0.2418	0.4772	1.7337	264
Burundi	0.3468	0.0812	0.148	0.5806	264
Cameroon	0.3003	0.0495	0.2053	0.4535	264
Central African Republic	0.8774	0.1817	0.4994	1.3763	264
Chad	0.3176	0.0588	0.2175	0.477	264
Congo, Republic Of	0.3273	0.0646	0.2066	0.5786	264
Congo, The Democratic Republic Of	0.7757	0.1403	0.555	1.2639	264
Côte D'Ivoire	0.6956	0.1706	0.4164	1.3268	264
Egypt	1.9979	0.3198	1.3985	3.0462	264
Eritrea	2.4914	0.4164	1.7181	3.8799	228
Ethiopia	0.8165	0.1413	0.5822	1.3421	264
Gabon	0.1388	0.0264	0.096	0.2364	264
Gambia	3.4681	0.8263	2.0223	5.6178	264
Ghana	0.5736	0.1124	0.3772	0.8544	264
Guinea	1.7418	0.4093	1.1673	2.9135	264
Guinea-Bissau	3.1163	0.7763	1.9169	5.717	264
Kenya	0.5623	0.1588	0.3277	0.9958	264
Lesotho	2.3232	0.3729	1.5566	3.3365	264
Liberia	8.7718	2.3693	5.0858	16.7674	264
Libya	1.1448	0.1736	0.8402	1.6254	264
Madagascar	0.133	0.1389	-0.1598	0.6801	264
Malawi	1.2074	0.3427	0.3151	2.1994	264
Mali	1.1642	0.2858	0.6525	1.9147	264
Mauritania	5.3745	1.1267	3.2312	8.3928	264
Mauritius	-4.6571	1.6668	-8.9297	-1.2986	264
Morocco	0.7574	0.1316	0.4931	1.1452	264
Mozambique	2.5048	0.4356	1.865	3.7611	264
Namibia	0.5117	0.1207	0.2648	0.8436	264
Niger	1.6399	0.3591	1.0577	2.6294	264
Nigeria	0.1815	0.0411	0.1155	0.2837	264
Rwanda	0.5863	0.1465	0.3703	0.9925	264
Senegal	1.9777	0.4597	1.2253	3.6105	264
Sierra Leone	3.4262	0.8413	2.1188	6.2787	264
Somalia	5.4937	1.1084	3.6927	9.3888	264
South Africa	-0.3345	0.0498	-0.4717	-0.2254	264
Sudan	0.326	0.092	0.1743	0.6278	264
Swaziland	-6.2454	2.1404	-11.8534	-1.9659	264
Tanzania	0.2254	0.0632	0.1206	0.4128	264
Togo	1.6226	0.3316	1.0559	2.4632	264
Tunisia	1.5192	0.237	1.0697	2.2687	264
Uganda	0.1614	0.036	0.0971	0.2645	264
Zambia	0.3815	0.0602	0.2699	0.5717	264
Zimbabwe	-1.0203	0.2251	-1.6383	-0.5624	264

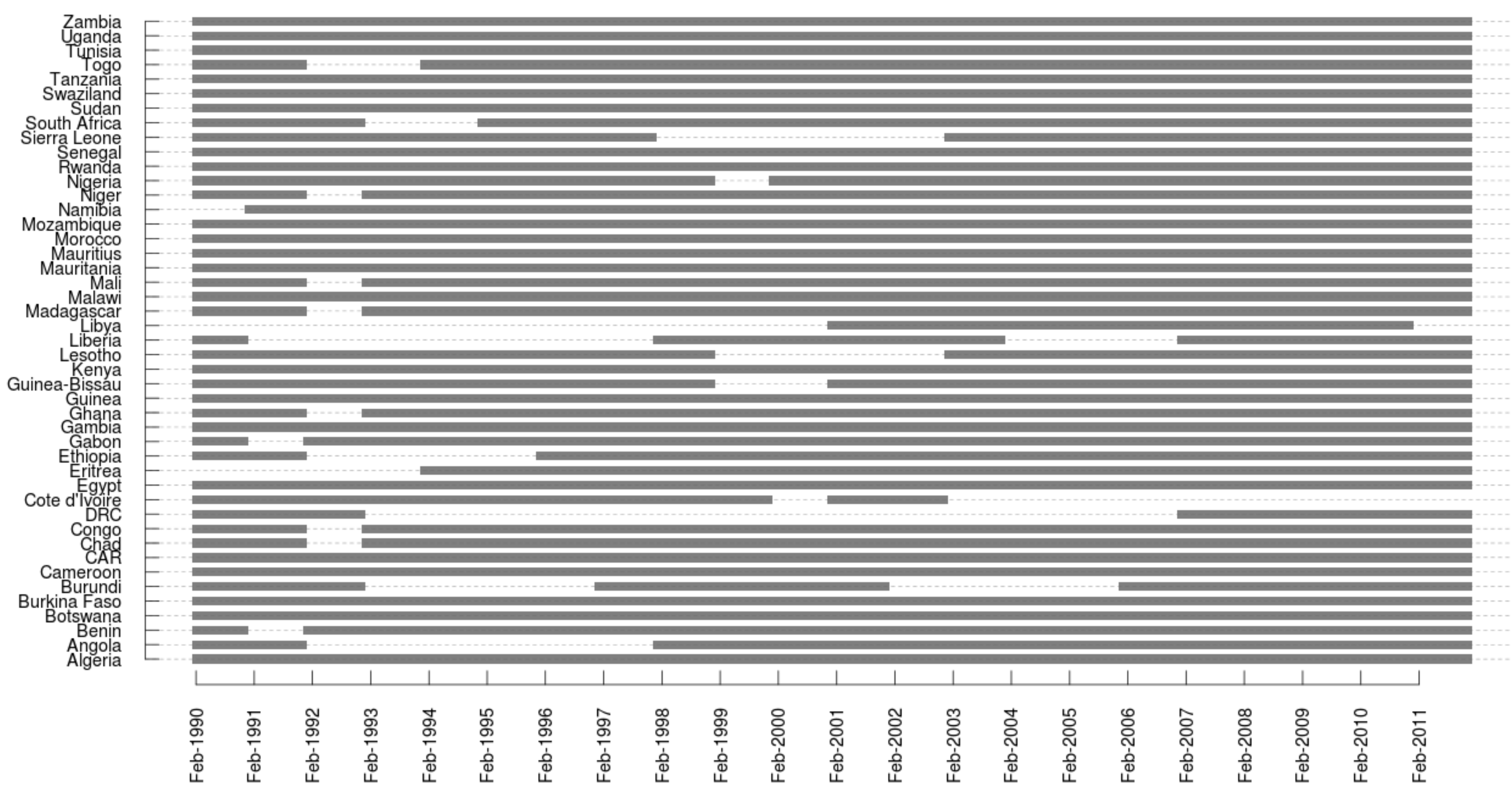

Figure B.1: Data coverage of country-months for the main model estimations.

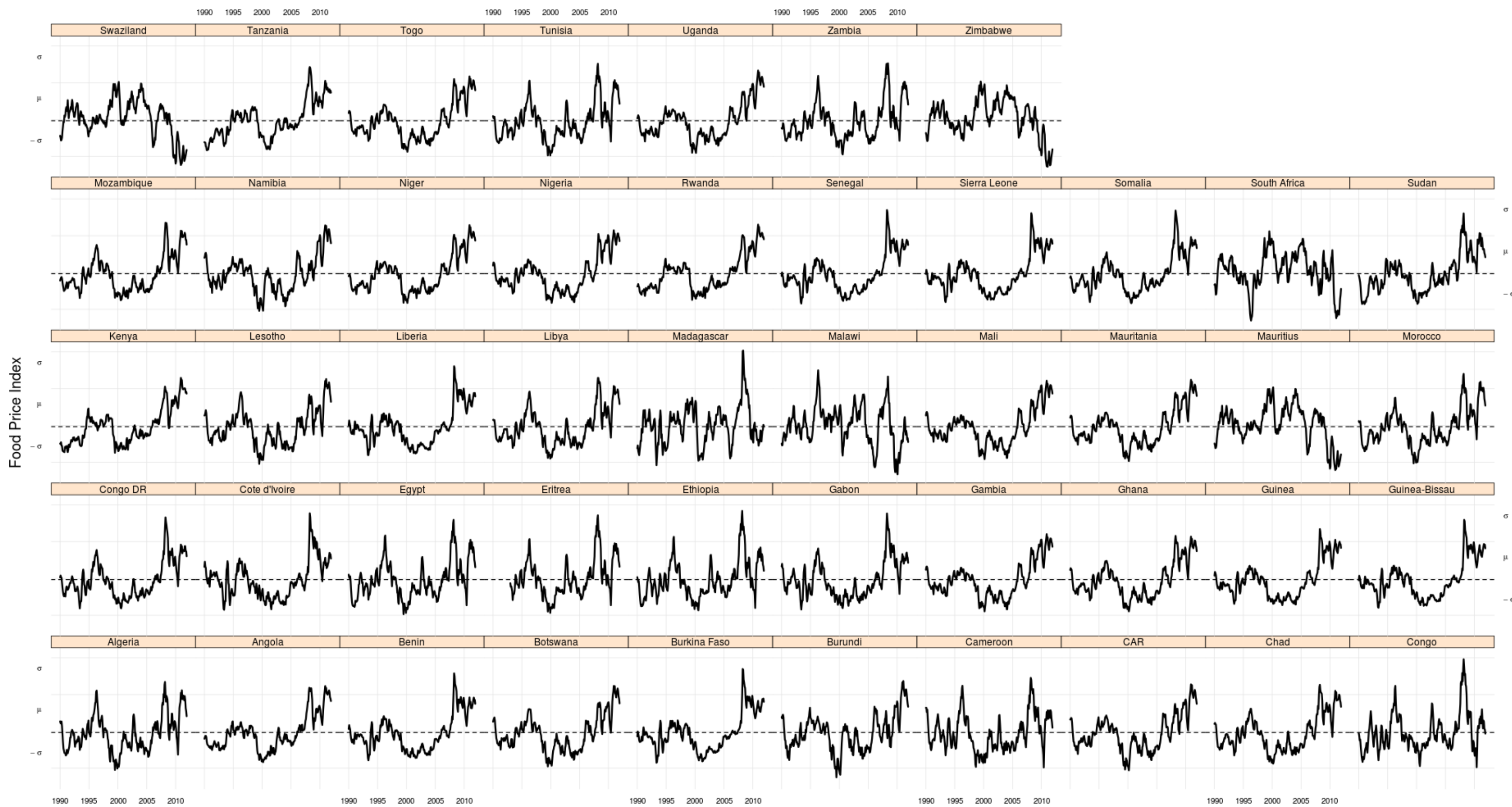

Figure B.2: Food price index values over time per country, 1990-2011.

Table B.2: Overview political heterogeneity across countries, oil exporters, and landlocked countries.

Autocracy	Anocracy	Democracy	Democratisation process	Oil exporters	Landlocked
Algeria	Central African Republic	Benin	Benin	Algeria	Botswana
Angola	Ethiopia	Botswana	Central African Republic	Angola	Burkina Faso
Burkina Faso	Lesotho	Ghana	Ethiopia	Cameroon	Burundi
Burundi	Madagascar	Mali	Gambia	Chad	Central African Republic
Cameroon	Malawi	Mauritius	Ghana	Congo	Chad
Chad	Mozambique	Namibia	Lesotho	Egypt	Ethiopia
Congo	Niger	Senegal	Madagascar	Gabon	Lesotho
Congo, DR	Nigeria	South Africa	Malawi	Ghana	Malawi
Ivory Coast	Tanzania		Mali	Libya	Mali
Egypt	Zambia		Mozambique	Nigeria	Niger
Eritrea			Niger	Sudan	Rwanda
Gabon			Nigeria	Tunisia	Uganda
Gambia			Senegal		Zambia
Guinea			South Africa		Zimbabwe
Guinea-Bissau			Tanzania		
Kenya			Zambia		
Liberia					
Libya					
Mauritania					
Morocco					
Rwanda					
Sierra Leone					
Sudan					
Swaziland					
Togo					
Tunisia					
Uganda					

B.2 Complementary results

B.2.1 Comparison of delayed prices effects and price spikes

Table B.3: Comparison of the effects of lagged food prices, growth, and anomalies on violence.

Specifications	(1)	(2)	(3)	(4)
FPI	0.6	-0.7		
	(0.4)	(0.8)		
$\text{FPI}_{(t-1)}$		2		
		(2)		
$\text{FPI}_{(t-2)}$		-2		
		(2)		
$\text{FPI}_{(t-3)}$		2.5		
		(0.9)***		
$\text{FPI}_{(t-4)}$		-1.1		
		(0.8)		
$\text{FPI}_{(t-5)}$		-0.5		
		(0.5)		
Δ FPI			-0.027	
			(0.005)***	
Δ $\text{FPI}_{(t-1)}$			0.11	
			(0.01)	
FPI_{σ}				0.1
				(0.1)
$\text{FPI}_{\sigma,(t-1)}$				0.2
				(0.1)
Residual deviance	6009.8	6008.2	6055.8	5998.0
AIC	12146	12150	11966	12134
AUC	0.7901	0.7902	0.802	0.791

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country controls (not reported), country and year fixed effects. FPI is the country-specific food price index. AIC, Akaike information criterion; AUC, Area Under the Curve. $N = 10722$

The main model focuses on the effect of anomalies in food price levels on violence. Recent research has shown that over the past years volatility of prices has not increased Minot (2014) and also that the link between food prices and unrest is mainly associated with a level effect Bellemare (2015). I therefore estimate the model using current levels, the results show a positive correlation between fluctuations from the long term trend in food prices and violence (see table B.3 col.1). The coefficient is not statistically significant within the orthodox boundaries with a p-value of 0.13 (Z-value=1.5).

Since we are dealing with international food prices, it could be that there is a delay in the responsiveness of domestic prices (Baquedano and Liefert, 2014). The model is specified to include additional time lags to control for past 5 months of food price levels (col.2) The estimation produces relatively large coefficients with equally large standard errors. Only for $t-3$ I find that there is a positive link with violence. Moving from low to high values corresponds with an increase in the log count of the outcome variable of 2.5 which is very large. It could be that both the government and consumers are more sensitive to sudden increases in prices, rather than levels, as this puts certain immediate constraints on their budget. I estimate the model using inter-monthly growth rates and find that current growth rates are negatively linked to violence. Although the effect is statistically significant, the magnitude is very low: moving from low to high growth rates corresponds with a decrease in the log count of just 0.027. The main results focused on current shocks which were positively associated with violence levels. Including an additional lag in the model reduces the magnitude of the estimated effect and it ceases to be statistically significant (col.4).

I also estimate the model including an interaction term between the FPI and a dummy indicating whether there was a food crises in that particular month, based on the characteristics described in Cuesta et al. (2014). For both 5 months of positive growth or an increase in prices of at least 15% in 5 months time I found that there was no clear effect with regard to violence levels.[1]

[1] Results available on request.

B.2.2 Other outcome variables

One of the advantages of the SCAD dataset, compared to other available datasets on violence and conflict, is that it codes the events for various types of social conflict. This means that it covers a large spectrum of violence intensity ranging from protests to civil conflict as well as including information on the location of the event (i.e. urban and rural areas). This information is used to examine whether food prices might be linked to particular types of unrest or unrest in particular places. I re-estimate the main model changing the outcome variable to correspond with a particular type of unrest, the results for which are summarised in figure B.3 where the estimated effect from the main model is included as a reference point.[2]

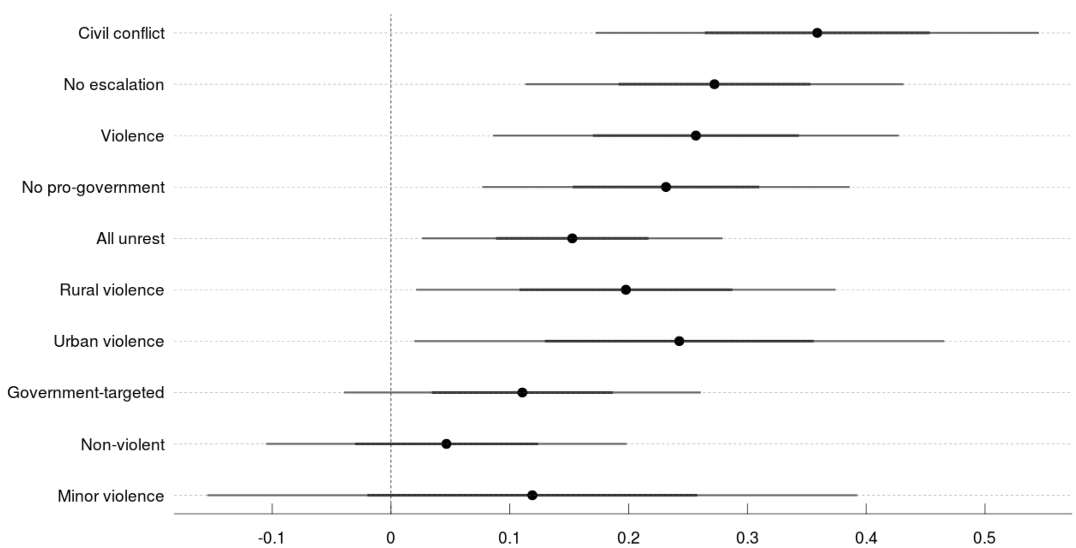

Figure B.3: Point estimates, 68% and 95% interval for the effect of food prices on different event types (see table B.4).

[2]See table B.4 and B.5 for full results.

The main outcome variable (*violence*) includes events which initially start out as non-violent, such as peaceful demonstrations, but then escalate into violence. Excluding these escalations from the outcome variable does not affect the results much as the effect's magnitude and level of statistical significance remain similar. I do find that when excluding cases of pro-government violence from the outcome variable the standard error increases while there is a small reduction in coefficient size reducing the level of the statistical significance of the results.

I now move on to estimating the link between food prices and different types of events: The main outcome variable includes violent evens within a large range of intensity. The results seem to suggest that there is a particular strong association between food prices and civil conflict compared to the other event types.[3] However, this result should be interpreted with caution though as civil conflicts are also most likely to be picked up by the media. The results provide no evidence for a clear pattern between food price shocks and a particular event type such as strikes and protests (non-violent events) or government-targeted events (directed at the local or central government.). For most event types the uncertainty interval includes the value of the coefficient in the main model though. These results could simply be due to a bias in measurement. The only exception to this is are non-violent events, but this coefficient still has an overlapping uncertainty interval although it doesn't include the main coefficient.

To account for possible within-country differences I test whether the effect of food prices is different in urban compared to rural areas. Although urban dwellers tend to be relatively wealthier and have higher purchasing power than their rural counterparts, they also tend to be food net-consumers whereas rural inhabitants often dependent on subsistence agriculture which makes them slightly less dependent on food imports and international price changes (Cohen and Garrett, 2010). The results show that the estimated effect is not much different in urban areas ($\beta = 0.24$, $s.e = 0.11$) compared to

[3] Civil conflict is in this case defined as a violent event waged by militant factions.

rural areas ($\beta = 0.20$, $s.e = 0.09$).[4]

[4]The reported number of violent incidents is almost equal: urban, 1483; rural, 1598.

Table B.4: Effect of food prices on different types of civil unrest.

Outcome variable	All unrest	Civil conflict	Minor violence	Government-targeted events	Non-violent event	Excluding escalation	Excluding pro-government violence
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FPI	0.15	0.36	0.1	0.11	0.05	0.27	0.23
	(0.06)**	(0.10)***	(0.1)	(0.08)	(0.08)	(0.08)***	(0.08)
Violence$_{(t-1)}$	0.36	0.45	0.28	0.35	0.26	0.39	0.40
	(0.06)***	(0.07)***	(0.05)***	(0.08)***	(0.06)***	(0.06)***	(0.06)***
Residual deviance	7988.2	3346.3	4329.7	6382.5	6266.5	5549.4	5818.9
AIC	17825	6413.4	8036.2	13258	12586	10985	11567
AUC	0.7735	0.8446	0.7858	0.758	0.7634	0.7996	0.7919

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country controls (not reported), country and year fixed effects. FPI is the country-specific food price index. AIC, Akaike information criterion; AUC, Area Under the Curve $N = 10722$

Table B.5: The effect of food prices on violence in rural and urban areas.

	Negative binomial		Logit	
Outcome variable	Urban violence	Rural violence	Urban violence	Rural violence
Specifications	(1)	(2)	(3)	(4)
FPI	0.2	0.20	0.3	0.25
	(0.1)**	(0.09)**	(0.1)**	(0.10)**
Violence$_{t-1}$	0.29	0.41	0.54	0.6
	(0.06)***	(0.07)***	(0.08)***	(0.1)***
Violence$_{C-i}$	0.07	−0.09	0.09	−0.05
	(0.07)	(0.07)	(0.09)	(0.09)
Δ GDP pc.	−0.3	0	−0.3	0.1
	(0.2)	(0.08)	(0.2)*	(0.1)
IMR	−1.7	−1	−1.3	−0.7
	(0.4)***	(1)	(0.5)**	(1.0)
Population	−3	−4	−2	−2
	(3)	(7)	(3)	(6)
Regime type	−0.1	0.1	−0.1	0
	(0.2)	(0.2)	(0.2)	(0.3)
Residual deviance	4169.5	3880.7	5766.6	5360.0
AIC	7391.2	7300	5909.6	5506
AUC	0.7888	0.8315	0.7929	0.8346

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country and year fixed effects. FPI is the country-specific food price index. IMR, Infant mortality rate; AIC, Akaike information criterion; AUC, Area Under the Curve. $N = 10722$

B.2.3 Political heterogeneity and country characteristics

Although the estimation results shown that the variable for regime type had little explanatory power, the study by Hendrix et al. (2009) found that the food-unrest nexus was largely contingent on regime type. I examine whether there is a potential link between political heterogeneity, food prices, and violence using data from Papaioannou and Siourounis (2008) to categorise countries into three main groups: autocracies, anocracies, and democracies. Additionally, I also create categories for countries that have undergone a democratisation process, as these states might suffer more instability, and oil exporters who could use oil revenues for social spending to counter higher food prices.[5] I re-estimate the model including an interaction effect between the country type and the FPI to estimate if the effect might be stronger in particular countries. The estimation results, shown in table B.6, indicate that for some regime types the effect of food prices on unrest can be more profound, i.e. in autocracies. Surprisingly the estimated coefficients for both anocracies and countries that have experienced change are negative, indicating a negative link between food prices and violence intensity. The estimated effect is much stronger than in democracies and oil exporting countries and comes with greater certainty.

[5]Country types are given in table B.2

Table B.6: Effect of food prices on violence across different regime types and oil exporting countries.

	Autocracies	Democracies	Anocracies	Democratisation process	Oil exporters
Specifications	(1)	(2)	(3)	(4)	(5)
FPI	0.1	0.30	0.3	0.43	0.3
	(0.1)	(0.08)***	(0.1)***	(0.08)***	(0.1)***
FPI × country type	0.3	−0.1	−0.3	−0.3	−0.1
	(0.1)**	(0.2)	(0.1)**	(0.1)**	(0.1)
Residual deviance	6011.5	5998.0	6006.0	6011.1	6003.5
AIC	12122	12134	12126	12121	12117
AUC	0.7917	0.791	0.7916	0.7916	0.7925

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country control (not reported), country and year fixed effects. FPI is the country-specific food price index. AIC, Akaike information criterion; AUC, Area Under the Curve. $N = 10722$

B.3 Robustness checks and additional tables

Table B.7: Comparison of the effect of food prices on violence per period.

	(1)	(2)	(3)	(4)
Specifications	*1990-1994*	*1995-1999*	*2000-2004*	*2005-2011*
FPI	0.2	0	0.1	0.2
	(0.2)	(0.2)	(0.1)	(0.1)*
Violence$_{(t-1)}$	0.26	0.07	0.11	0.26
	(0.08)***	(0.04)*	(0.06)**	(0.09)***
Violence$_{(C-i)}$	0.3	0	0.04	-0.05
	(0.1)**	(0.1)	(0.10)	(0.07)
Δ GDP pc.	-0.1	-0.2	0.1	0.05
	(0.2)	(0.1)	(0.2)	(0.08)
IMR	6	1	0	-1
	(3)**	(2)	(2)	(2)
Population	0	-29	10	-13
	(8)	(19)	(14)	(10)
Regime type	0	0.4	-0.7	-0.1
	(0.4)	(0.3)	(0.2)***	(0.3)
Residual deviance	951.07	1228.4	1462.1	2245.5
AIC	1955.1	2452.9	2787.9	4626.8
AUC	0.8186	0.8199	0.7943	0.8242
N	2226	2412	2460	3624

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country and year fixed effects. FPI is the country-specific food price index. IMR, Infant mortality rate; AIC, Akaike information criterion; AUC, Area Under the Curve.

Table B.8: Effect of food prices on violence controlling for increased time lags for violence.

	3 months	6 months	12 months
Specifications	(1)	(2)	(3)
FPI	0.25	0.23	0.22
	(0.08)***	(0.09)***	(0.10)***
Violence$_{(lag)}$	0.53	0.6	0.6
	(0.09)***	(0.1)***	(0.1)***
Residual deviance	6006.2	5940.4	5880.6
AIC	11994	11887	11741
AUC	0.7943	0.7942	0.7942
N	10638	10512	10260

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country controls (not reported), country and year fixed effects. FPI is the country-specific food price index. AIC, Akaike information criterion; AUC, Area Under the Curve.

Table B.9: Regression results different model estimation methods.

	Poisson	Logit	Quasi-Poisson	OLS	OLS
Outcome variable	*Count*	*Binary*	*Log-count*	*Log-count*	*Binary*
Specifications	(1)	(2)	(3)	(4)	(5)
ΔFPI	0.20	0.36	0.20	0.038	0.044
	(0.09)**	(0.08)***	(0.07)***	(0.010)***	(0.010)***
Residual deviance	6056.5	8026.8	4278.8	–	–
Residual standard error	–	–	–	0.3153	0.3414
AIC	11966	8172.8	–	–	–
AUC	0.787	0.7973	0.7378	0.731	0.7941

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include the standard explanatory variables (not reported), country and year fixed effects. FPI is the country-specific food price index. AIC, Akaike information criterion;AUC, Area Under the Curve. $N = 10722$

Table B.10: Robustness checks for the effect of food prices on violence.

	(1)	(2)	(3)	(4)	(5)
Specifications	*Excluding lagged outcome variable*	*Oil price index*	*Interaction with landlocked countries*	*Including food aid*	*Excluding Nigeria and South Africa*
FPI	0.28	0.25	0.26	0.24	0.26
	(0.10)***	(0.09)***	(0.09)***	(0.09)***	(0.09)***
Oil price index		0.1			
		(0.1)			
Food aid$_{(ln)}$				0.4	
				(0.1)***	
FPI × Landlocked			0.1		
			(0.1)		
Violence$_{(t-1)}$		0.41	0.39	0.41	0.41
		(0.07)***	(0.07)***	(0.07)***	(0.07)***
Residual deviance	6011.8	5997.2	6013.5	5998.5	5998.3
AIC	12323	12135	12113	12135	12133
AUC	0.781	0.791	0.792	0.791	0.791

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include the standard explanatory variables (not reported), country and year fixed effects. FPI is the country-specific food price index; AIC, Akaike information criterion; AUC, Area Under the Curve. $N = 10722$

Table B.11: Different specifications of the food price index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specifications	*Nominal prices*	*Real prices*	*Average GDP weight*	*Terms of trade weight*	*Trade balance*	*No weights*	*Generic food price index*	*Main traded grains only*	*Wheat only*
FPI	0.4	0.3	0.22	0.26	0.26	0.1	0.1	0.12	0.15
	(0.1)***	(0.08)***	(0.09)**	(0.09)**	(0.09)**	(0.1)	(0.1)	(0.08)	(0.05)**
Residual deviance	6000.9	6002.3	6004.1	5998.4	5998.4	6011.9	6008.8	6005.6	6013.7
AIC	12127	12125	12143	12133	12133	12151	12151	12148	12145
AUC	0.791	0.7911	0.7903	0.791	0.791	0.7897	0.7897	0.7899	0.7899

Notes. Robust standard errors, clustered at country-level, in parentheses where ***, **, and * respectively indicate statistical significance at the 1%, 5%, and 10% levels. All specifications include country controls (not reported), country and year fixed effects. FPI is the country-specific food price index; AIC, Akaike information criterion;AUC, Area Under the Curve. $N = 10722$

Appendix C

A spatial analysis of the effect of foreign aid in conflict areas

C.1 Descriptive statistics

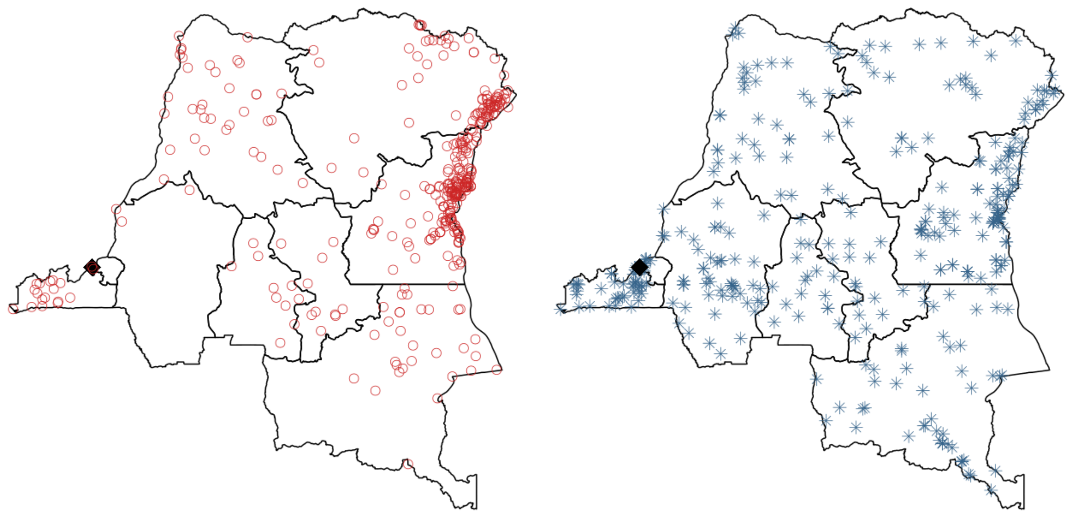

Figure C.1: Conflict incidence *(left)* and aid locations *(right)* for the Democratic Republic of the Congo, 1999-2008. Capital indicated with black diamond.

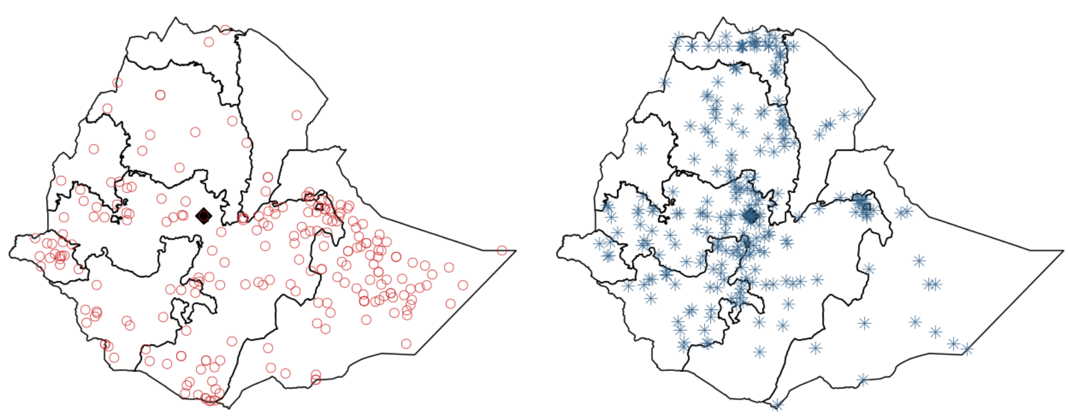

Figure C.2: Conflict incidence *(left)* and aid locations *(right)* for Ethiopia, 1999-2008. Capital indicated with black diamond.

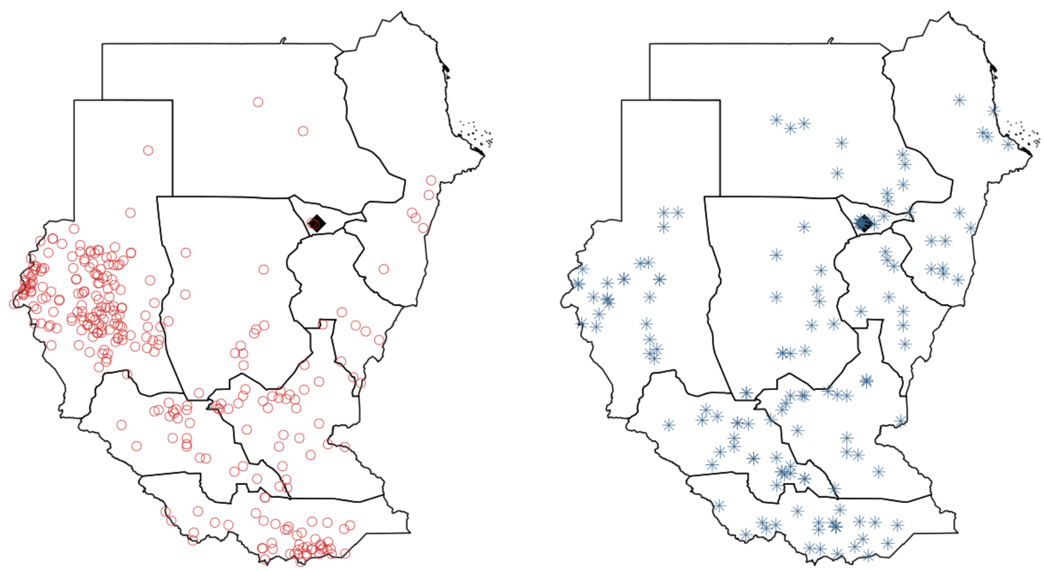

Figure C.3: Conflict incidence *(left)* and aid locations *(right)* for Sudan, 1999-2008. Capital indicated with black diamond.

Table C.1: Summary statistics

Variable	Province level			District level		
	All data (N=203)	No conflict at t (N=92)	Conflict at t (N=111)	All data (N=952)	No conflict (N=719)	Conflict (N=233)
Conflict Onset	0.11	0	0.21	0.09	0	0.36
Log Conflict intensity	5.36	0	5.97	3.67	0	5.08
Log Conflict intensity$_{t-1}$	5.49	1.91	6.08	3.79	2.03	4.35
Log Conflict intensity$_k$	6.27	6.34	6.20	4.14	4.06	5.06
Log Foreign aid$_{t-1}$	16.63	16.27	16.86	14.44	14.19	14.96
Log Fungible aid$_{t-1}$	14.60	14.72	14.49	12.63	12.43	13.06
Log Non-fungible aid$_{t-1}$	16.23	15.90	16.44	14.16	13.90	14.69

C.2 Local Moran's I test

To correct for spatial autocorrelation in the outcome variable the spatial lag is included in the model structuring the model as a spatial autoregressive model (SAR).[1] This section reports the tests results of the Moran's I test for spatial autocorrelation. Moran's I statistic is a global measure of spatial autocorrelation, which means that it assumes that the spatial process is homogeneous across the different regions.

Two different measures for conflict are tested: conflict intensity which is measured by the natural log of the number of battle-related fatalities, and conflict incidence level which is the sum of all conflict years between 1999-2008. Additionally I also test foreign aid for spatial autocorrelation which is in this case measure by the natural log of the total amount of foreign aid committed to the region.

Results for the Moran's I test, done at the provincial (ADM1) and district (ADM2) level, are shown in table C.2 where the odd columns report the results using the binary spatial weights matrix and even columns for the row-standardised matrix as a robustness check.[2] Although the Moran's I test performs well in small samples (Anselin

Table C.2: Moran's I

	Province level *(ADM1)*		District level *(ADM2)*	
	(1)	(2)	(3)	(4)
Conflict intensity	0.07	0.03	0.47***	0.48***
Conflict incidence	0.18**	0.14*	0.41***	0.46***
Foreign aid	− 0.04	− 0.08	0.04	0.03
Row standardised	–	Yes	–	Yes

Notes. Test statistics obtained under randomisation. Number of Monte Carlo simulations under randomisation: 10,000. $N = 29$ for ADM1, and $N = 136$ for ADM2. *** p≤ 0.01, ** p≤ 0.05, * p≤ 0.1.

[1] The SAR model is chosen based on the assumption that the interdependence in the outcome variable is more than just a nuisance which can be corrected using a spatial error model, and thus needs an autoregressive term to correctly model the spatial pattern.

[2] Note that in this case the spatial weights matrix only includes regions in the selected countries and thus omits data attributes in regions in neighbouring countries.

and Florax, 1995) it could be that the results are sensitive to the skewed distribution on the spatial data attributes. Since there are a relatively few number of observations as the test is done at the cross-sectional level, the Moran's I is estimated using Monte Carlo simulations.[3] Moran's I is measured on a -1 to 1 scale where 0 indicates no spatial autocorrelations, small values (approaching -1) indicate spatial diffusion and large values (approaching 1) indicate spatial clustering.

The results show that there is some variability in the extent of spatial autocorrelation with respect to conflict comparing across the levels of aggregation and the two different measures. For conflict intensity the results indicate that there is almost no spatial autocorrelation at the provincial level as the test shows no statistically significant results and are accompanied by values with very low magnitude.

For the district level on the other hand we see that there is spatial autocorrelation between the regions were districts with similar levels of fatalities, and thus conflict intensity, tend to cluster. This result is statistically significant at the 1% level and also robust to using a different spatial weights matrix and using a cruder measure for conflict. These results are also illustrated by the local Moran's I plot shown in figure C.4 for both the provincial and district level, where regions tend to cluster at the lower left for low intensity and upper right for high intensity.

Focussing on the simple incidence measure the results do show some autocorrelation at the provincial level in this case but the magnitude is much lower compared to the district level. It is likely that the difference in results is driven by the level of aggregation and thus by the size of the administrative level, indicating that the clusters of violence in general tend to be relatively small and highly localised. As far as foreign aid is concerned the test results rule out any strong spatial dependence between regions as all test statistics are close to zero, fail to reach statistical significance, and this result is not sensitive to the level of aggregation.

[3] N=29 for the ADM1 level and N=136 for ADM2 level.

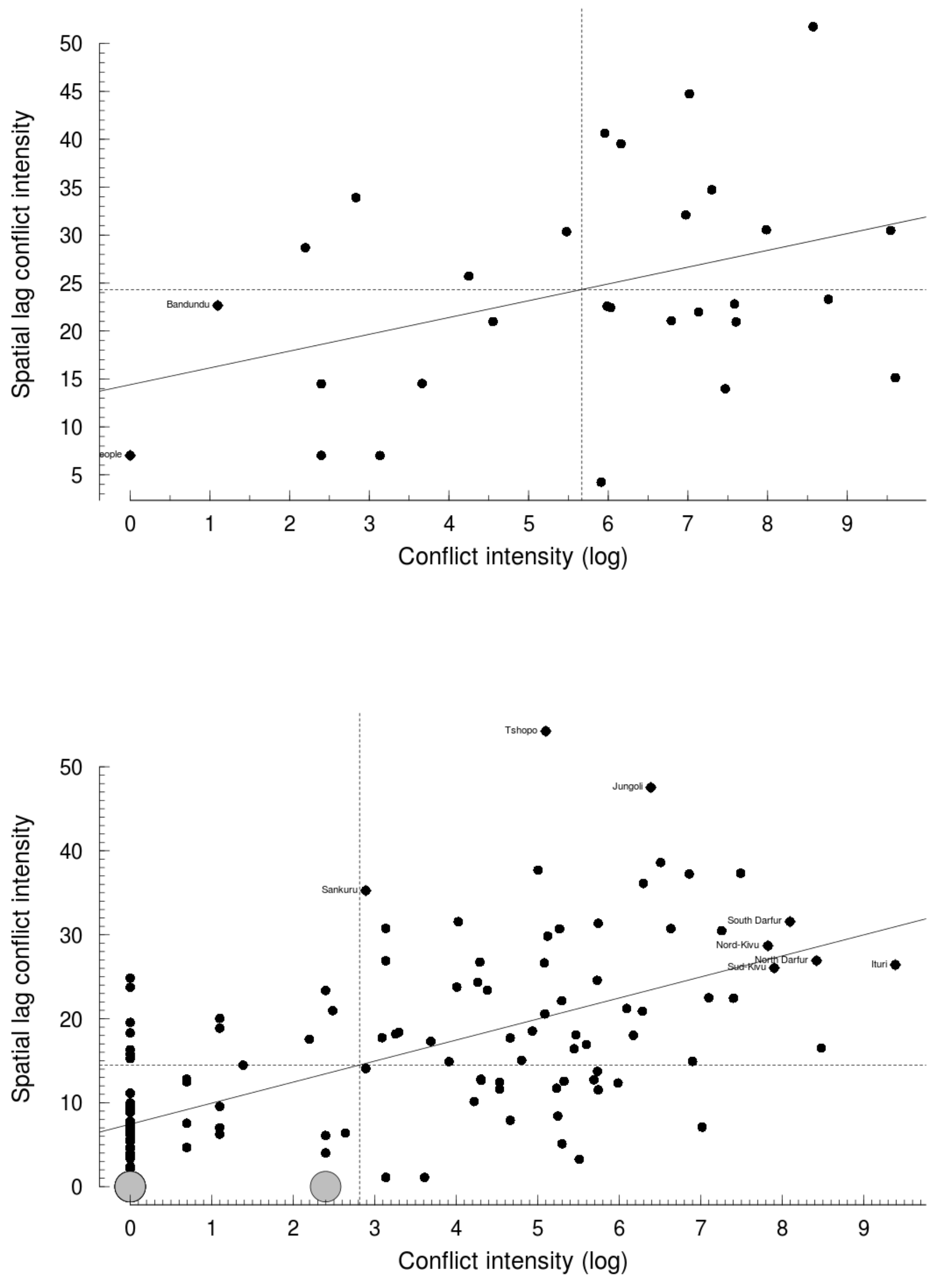

Figure C.4: Local Moran's *I* measures at the provincial level *(top)* and district level *(bottom)*.

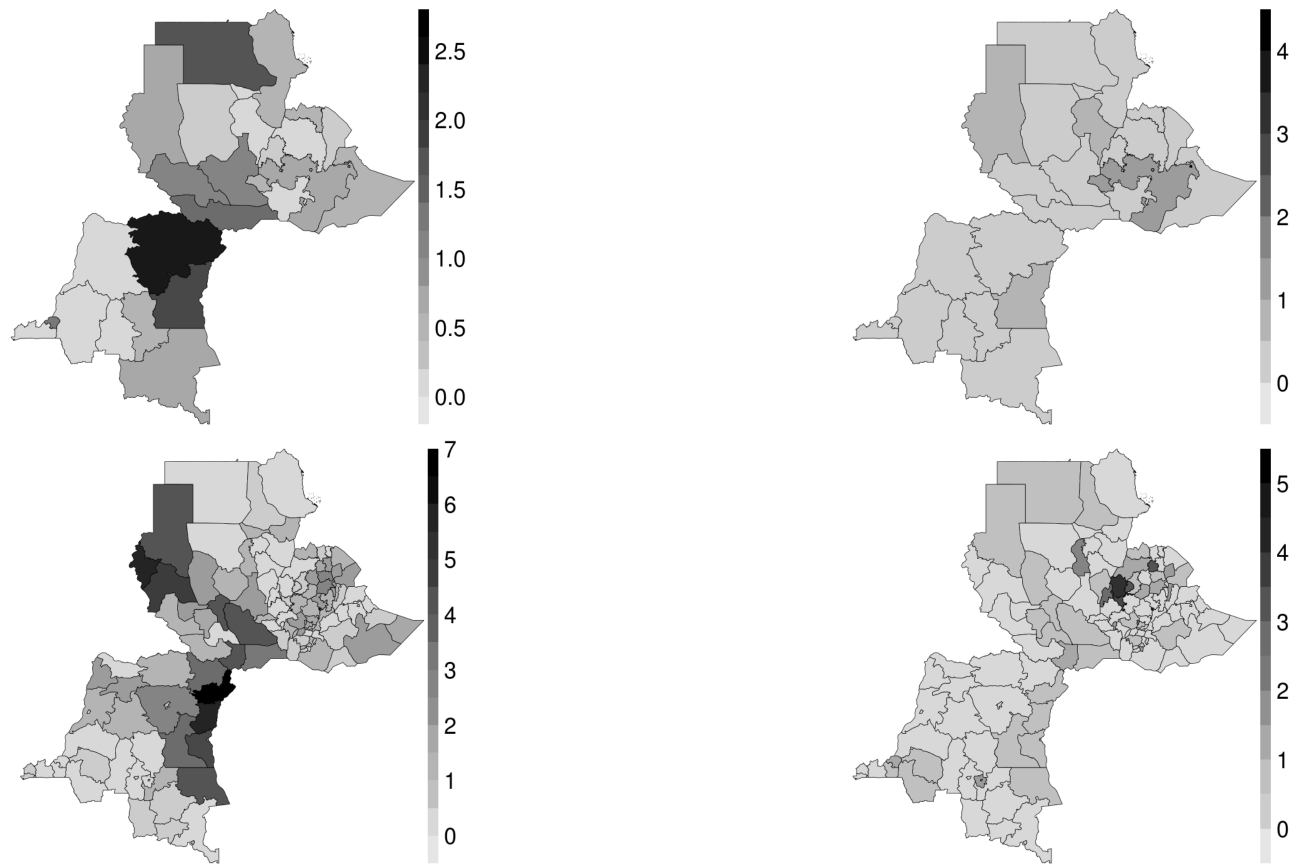

Figure C.5: Local Moran's I at the provincial level *(top)* and district level *(bottom)* for conflict intensity *(left)* and aid locations *(right)*.

C.3 Preliminaries

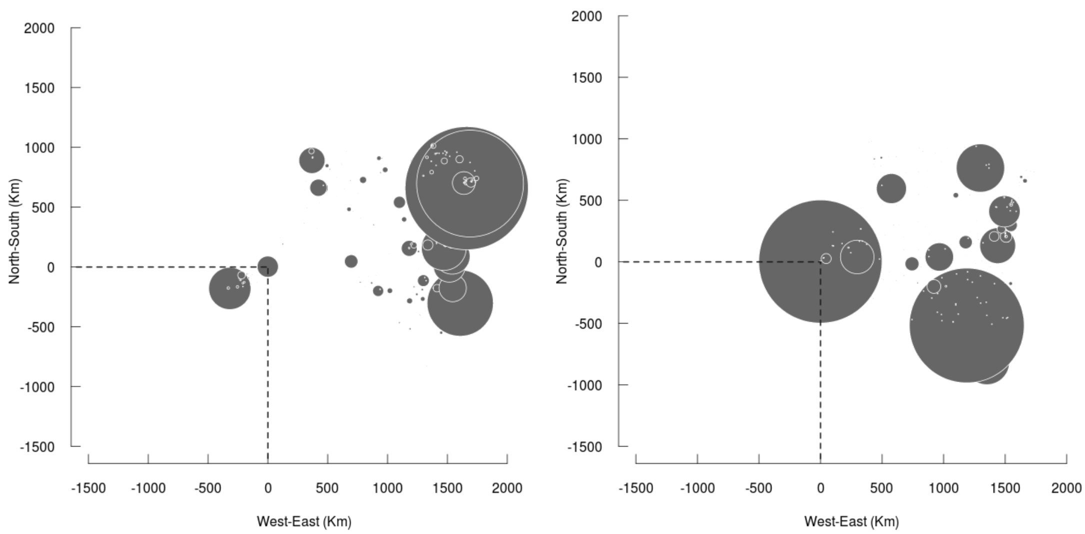

Figure C.6: Spatial distribution for the Democratic Republic of the Congo of conflict *(left)* and aid *(right)* relative to the capital. The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

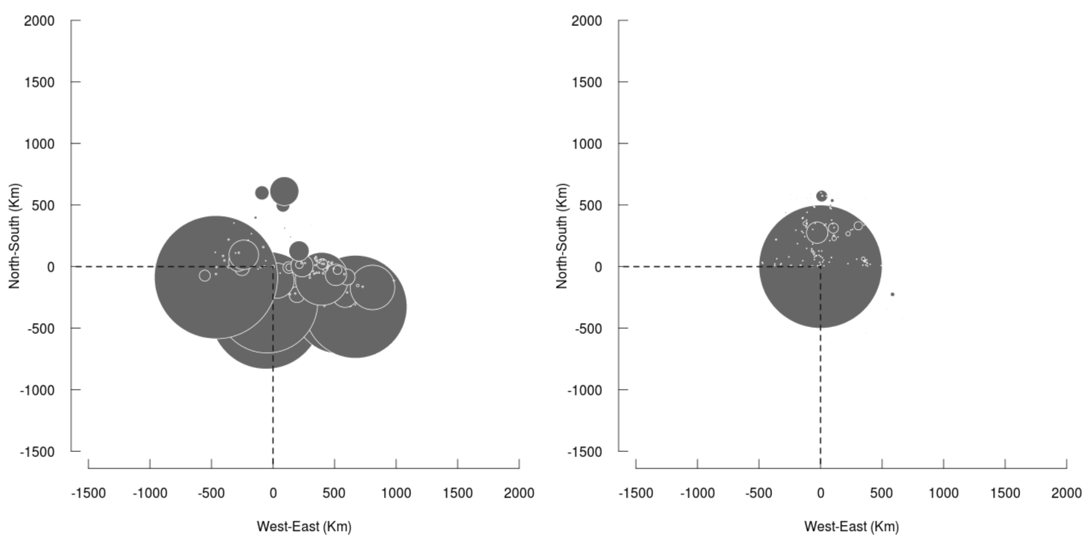

Figure C.7: Spatial distribution for Ethiopia of conflict *(left)* and aid *(right)* relative to the capital. The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

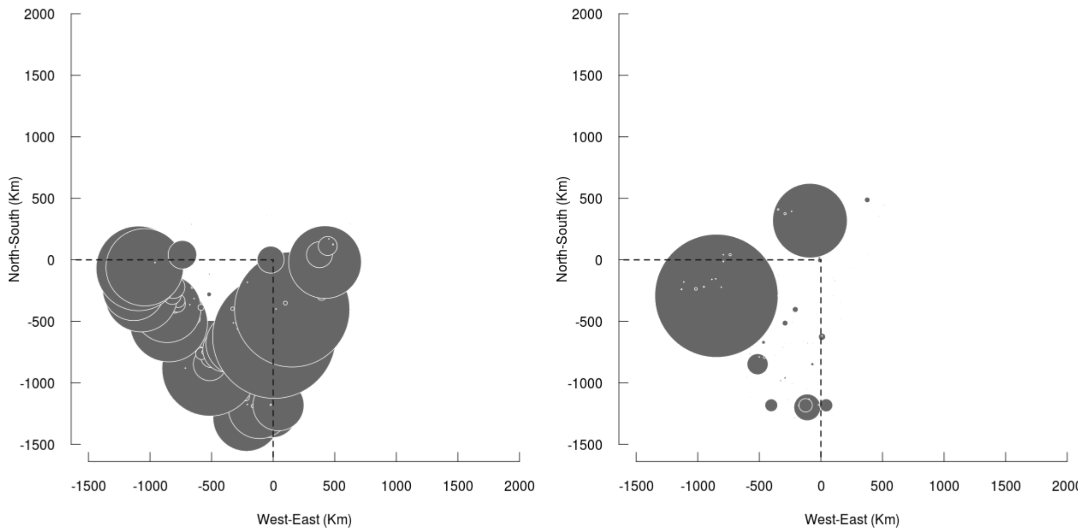

Figure C.8: Spatial distribution for Sudan of conflict *(left)* and aid *(right)* relative to the capital. The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

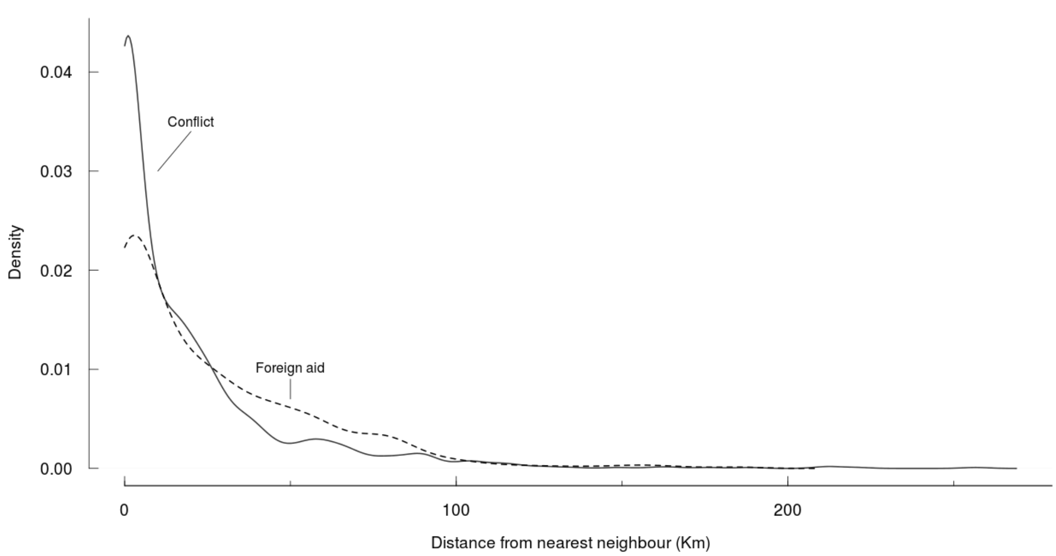

Figure C.9: Density of nearest neighbour distance for conflict and aid.

C.3.1 Kernel density estimation

Figure C.10 shows the kernel density estimation results, using the cross-sectional data of aid and conflict, where darker shaded areas indicate higher density values.[4] There is some clustering of aid and conflict in the region west of the DRC capital, the Eastern part of DRC, the Southern part of Sudan[5], and the Somali region in Ethiopia. However, these values are predominantly driven by conflict incidence and since the estimation is based on cross-sectional data it is not possible to establish the causal direction as conflict ridden areas might see an influx of aid.[6]

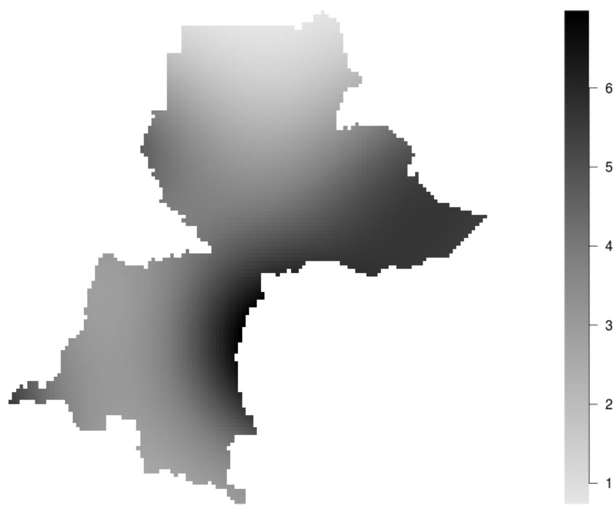

Figure C.10: Kernel density estimation cross-section foreign aid projects and conflict incidence.

[4]Figure C.11 shows kernel density estimations for aid and conflict separately.

[5]What is now the independent nation of South Sudan. On an unrelated note, this is also where the Nubian giraffe *(Giraffa camelopardalis camelopardalis)*, one of the nine subspecies of giraffe, can be found.

[6]Besides a visual inspection I also used a spatial Kolmgorov-Smirnov test to estimate the goodness-of-fit of a Complete Spatial Randomness (CRS) pattern, generated by a Poisson process, with the observed values based on the distribution of the longitude coordinates of each point. For both conflict incidence and foreign aid locations I find that the null hypothesis of a random spatial pattern is rejected at the 99% level with D-statistics of 0.13 and 0.18 respectively ($N_{conflict} = 885$, $N_{aid} = 754$).

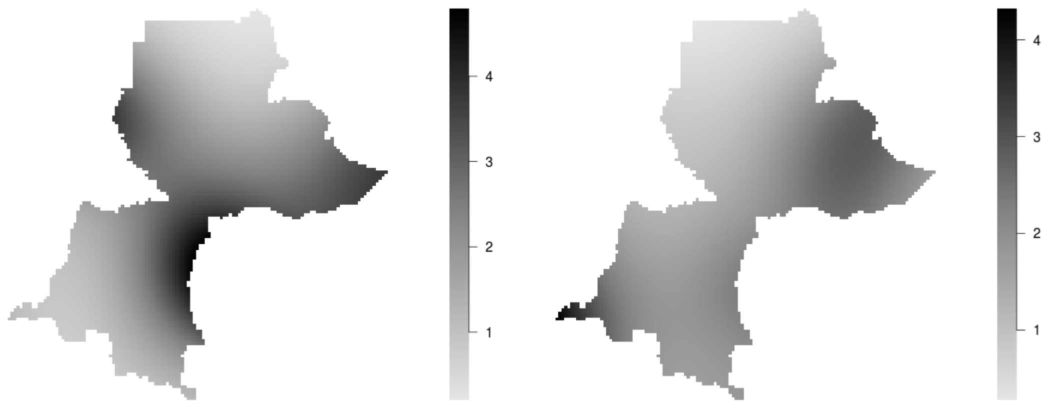

Figure C.11: Kernel density estimations conflict incidence *(left)* and aid locations *(right)*.

C.4 Regression results

Table C.3: Predicting changes in conflict intensity (province level)

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.3	−0.2	−0.2	−0.2	
	(−0.8; 0.3)	(−0.7; 0.3)	(−0.7; 0.3)	(−0.7; 0.3)	
Foreign aid to government			0.2	0.2	
			(−0.4; 0.8)	(−0.4; 0.8)	
Fungible aid					0
					(−0.5; 0.5)
Non-fungible aid					−0.5
					(−1.0; 0)
Spatial lag		−0.2	−0.2	−0.2	−0.1
		(−0.7; 0.3)	(−0.7; 0.3)	(−0.8; 0.3)	(−0.7; 0.4)
Temporal lag		−1.4	−1.4	−1.4	−1.4
		(−1.9, −0.9)	(−1.9, −0.9)	(−1.9, −0.9)	(−1.9; −0.9)
Population				−0.2	
				(−0.7; 0.4)	
Night lights				−0.1	
				(−0.6; 0.5)	

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$. $N = 203$.

Table C.4: Predicting changes in conflict intensity (district level)

Specifications	Parsimonuous (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.1	0.01	0.01	0.01	
	(−0.3; 0.1)	(−0.17; 0.19)	(−0.17; 0.19)	(−0.17; 0.19)	
Foreign aid to government			−0.1	−0.1	
			(−0.3; 0.1)	(−0.3; 0.1)	
Fungible aid					0.02
					(−0.15; 0.20)
Non-fungible aid					−0.06
					(−0.24; 0.12)
Spatial lag		0.12	0.13	0.12	0.11
		(−0.06; 0.30)	(−0.05; 0.30)	(−0.05; 0.30)	(−0.07; 0.29)
Temporal lag		−1.32	−1.32	−1.33	−1.31
		(−1.50, −1.14)	(−1.50, −1.14)	(−1.51, −1.14)	(−1.49; −1.14)
Population				−0.12	
				(−0.31; 0.07)	
Night lights				0	
				(−0.19; 0.19)	

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$. $N = 952$

Table C.5: OLS estimation province level

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.3	−0.2	−0.2	−0.2	
	(0.3)	(0.2)	(0.2)	(0.2)	
Foreign aid to government			0.2	0.2	
			(0.3)	(0.3)	
Fungible aid					0
					(0.3)
Non-fungible aid					−0.5
					(0.2)**
Spatial lag		−0.2	−0.2	−0.2	−0.2
		(0.3)	(0.3)	(0.3)	(0.3)
Temporal lag		−1.4	−1.4	−1.4	−1.4
		(0.3)***	(0.3)***	(0.3)***	(0.3)***
Population				−0.2	
				(0.2)	
Night lights				−0.1	
				(0.2)	
adjusted R^2	0.01	0.13	0.13	0.13	0.14
AIC	841.5	815.3	816.8	820.4	814.3

Notes. $N = 203$. AIC, Akaike information criterion. Robust standard errors clustered at unit level (given in parentheses).
*** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table C.6: OLS estimation district level

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.1	0	0	0	
	(0.1)	(0.1)	(0.1)	(0.1)	
Foreign aid to government			−0.1	−0.1	
			(0.1)	(0.1)	
Fungible aid					0
					(0.1)
Non-fungible aid					−0.06
					(0.10)
Spatial lag		0.12	0.13	0.12	0.11
		(0.10)	(0.10)	(0.10)	(0.1)
Temporal lag		−1.3	−1.3	−1.3	−1.3
		(0.1)***	(0.1)***	(0.1)***	(0.1)***
Population				−0.12	
				(0.07)*	
Night lights				0	
				(0.05)	
adjusted R^2	0.01	0.19	0.19	0.19	0.19
AIC	3529.9	3340.5	3340.7	3343.2	3342.0

Notes. $N = 952$. AIC, Akaike information criterion. Robust standard errors clustered at unit level (given in parentheses).
*** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table C.7: Interaction effects province level

Specifications	Time lag	Space lag	Distance	Ethnicity
Foreign aid	−0.2 (−0.7; 0.3)	−0.2 (−0.8; 0.3)	−0.1 (−0.7; 0.4)	−0.2 (−0.7; 0.4)
Foreign aid x time lag	−0.4 (−1.5; 0.8)			
Foreign aid x spatial lag		0.1 (−0.6; 0.8)		
Foreign aid x distance to capital			−1 (−3; 1)	
Foreign aid x ethnic polarisation				−0.3 (−1.1; 0.6)
Spatial lag	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)
Temporal lag	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9; −0.9)

Notes. Table presents point estimates with their 95% intervals between parentheses. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table C.8: Interaction effects district level

Specifications	Time lag	Space lag	Distance	Ethnicity
Foreign aid	0.02 (−0.16; 0.20)	0.01 (−0.17; 0.19)	0.02 (−0.16; 0.21)	0.01 (−0.17; 0.19)
Foreign aid x time lag	−0.4 (−0.7; −0.1)			
Foreign aid x spatial lag		−0.1 (−0.4; 0.2)		
Foreign aid x distance to capital			−0.1 (−0.7;0.4)	
Foreign aid x ethnic polarisation				−0.2 (−0.5; 0.2)
Spatial lag	0.11 (−0.07; 0.29)	0.12 (−0.06; 0.30)	0.12 (−0.06; 0.30)	0.12 (−0.06; 0.30)
Temporal lag	−1.30 (−1.48, −1.13)	−1.32 (−1.50, −1.14)	−1.32 (−1.49, −1.14)	−1.31 (−1.49, −1.14)

Notes. Table presents point estimates with their 95% intervals between parentheses. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table C.9: Predicting changes in conflict intensity: Aid shocks

Specifications	Provinces ($N = 203$) (1)	Districts ($N = 952$) (2)
σ Foreign aid	-0.2	-0.06
	$(-0.7; 0.4)$	$(-0.24; 0.12)$
Spatial lag	-0.3	0.12
	$(-0.8; 0.3)$	$(-0.06; 0.30)$
Temporal lag	-1.4	-1.31
	$(-1.9, -0.9)$	$(-1.49; -1.13)$

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table C.10: Predicting conflict onset (logit)

Specifications	Provinces ($N = 203$) (1)	Districts ($N = 952$) (2)
Δ Foreign aid	0.4	0.4
	$(-0.8; 1.7)$	$(-0.1;0.9)$
Spatial lag	-0.6	0
	$(-1.9; 0.6)$	$(-0.5; 0.5)$
Population	-1.0	-0.4
	$(-4; 1)$	$(-1.2; 0.3)$
Night lights	0.4	0.1
	$(-0.7; 1.6)$	$(-0.6; 0.7)$
Ethnic polarisation	0.2	1.2
	$(-1.6; 2.0)$	$(0.5; 2.0)$
Natural resources	1	0.3
	$(-2; 4)$	$(-0.4;1.0)$
Mean intercept	-3	-3
	$(-9; 3)$	$(-10; 4)$

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

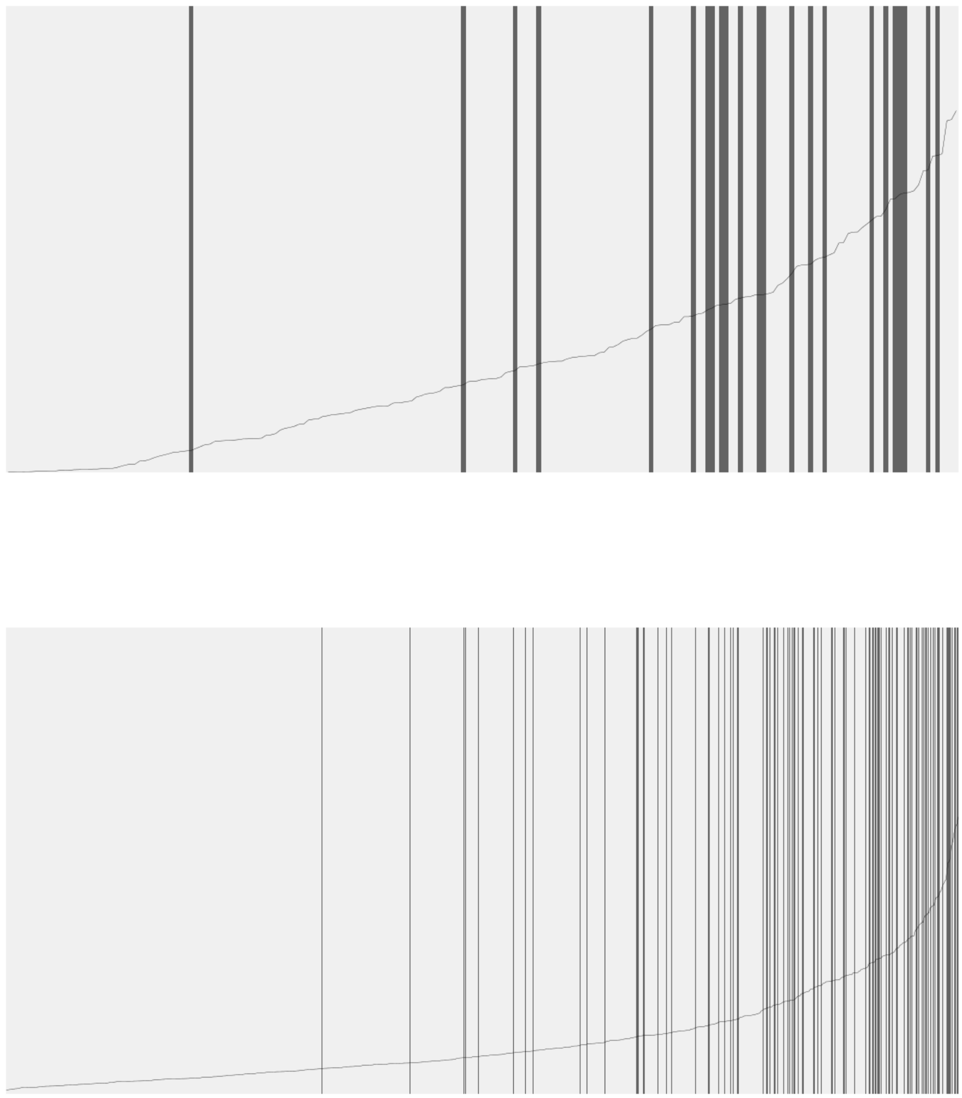

Figure C.12: Separation plot for province (*top*) and district (*bottom*) level. The separation plot (Greenhill et al., 2011) orders the cases from left to right according to their predicted probability. The dark grey lines indicate positive cases (conflict onset) and light grey lines negative cases. The figure illustrates that the model is marginally better at predicting the outcome at the district than at the province level.

Appendix D

Using climate variability to predict war in Sub-Saharan Africa

D.1 Complementary results

D.1.1 Logit estimation

Re-estimating the model using logit (results in table D.1) shows that for model 1 and 2 the effect of temperature ceases to be statistically significant within the traditional boundaries.[1] Model 3 does report a statistically significant coefficient for temperature but the magnitude of the effect is lower than that of GDP: at the upper bound, a unit increase in temperature corresponds with a 29.5% positive difference in the probability of observing war, while a unit increase in GDP per capita decreases the likelihood of war by 79.5%.

Table D.1: Results model estimation using logit

	Model 1	Model 2	Model 3
Temperature	1.3	1.4	1.2
	(0.9)	(0.9)	(0.6)**
Temperature$_{(t-1)}$	0.4	0.6	0.6
	(0.9)	(1.1)	(0.7)
Precipitation		−0.9	−0.8
		(2.3)	(1.6)
Precipitation$_{(t-1)}$		2.0	0
		(2.1)	(1.6)
GPD per capita$_{(t-1)}$			−3.2
			(1.6)***
Regime type$_{(t-1)}$			0
			(0.1)
Deviance	165.52	164.45	255.96
AIC	333.52	336.45	345.96
AUC	0.9805	0.9805	0.936
N	889	889	815
Number of wars	98	98	81
Country FE	Yes	Yes	Yes
Country-specific time trend	Yes	Yes	–
Time FE	–	–	Yes

Notes. Intercept not reported. FE, fixed effects; AIC, Akaike information criterion. Robust standard errors clustered at country level (given in parentheses). *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

[1] Note that due to the inclusion of the country and year indicators perfect prediction occurs in countries with little variation in the outcome variable.

D.1.2 Explanatory power variables

As stated in the main text, p-values are not meant as a definitive test (Nuzzo, 2014) but serve as an indicator for results that are worth closer examination. As Ward et al. (2010) argue we should not rely too much on these p-values to determine the strength of a particular model and be cautious about the implied effects.

A useful measure for the explanatory power of variables of interest is the change in the AUC statistics. To gauge the in-sample predictive power of temperature I re-estimate model 3 omitting one variable at a time to measure the change in the AUC statistic. The results shown in figure D.1 illustrate that in general most variables have very little explanatory power, and in some cases the model is even better off not including them in the model specification. Although temperature seems to be the best predictor of armed conflict, its explanatory power is marginal. Omitting temperature from the model leads to a reduction of 0.002 in predictive power.

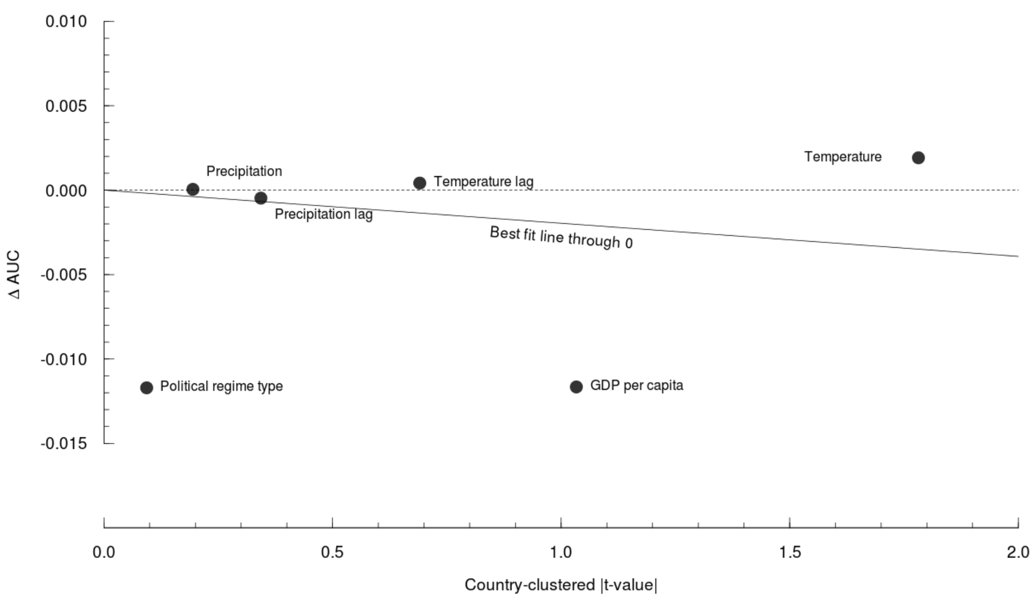

Figure D.1: Statistical significance versus predictive power of variables (model also includes country and time fixed effects).

D.1.3 In-sample predictions

Using $\hat{p} > 0.5$ as the threshold for predicted war, the main model (model 1) correctly predicts 73 conflicts while generating 11 false positives and 25 false negatives. The specific cases are shown in table D.2.

Most of the false positives are generated for countries that have high levels of conflict prevalence such as Sudan which experienced conflict in 18 out of the 22 years in the sample and Angola (17 out of 19). The model has more trouble with correctly predicting conflict in countries with relatively lower levels of war prevalence such as Sierra Leone, Rwanda, and Chad. These results seem to suggest that the fitted probabilities of this model are driven largely by country-specific trends rather than the temperature variable. Estimating the model omitting the temperature variable and only including fixed effects and country-specific time trends leads to almost exactly the same predictions. The only difference is that South Africa-1987 has a lower predicted probability leading to an additional false negative.

Table D.2: Actual versus predicted wars in-sample for 1981-2002

	$\hat{p} \leq 0.5$	$\hat{p} > 0.5$
No war	780 obs.	Angola (1996-1997) DRC (2002) Ethiopia (1986) South Africa (1984-1985) Sudan (1981-1982, 1993-1994) Uganda (1990)
War	Burundi (1998) Chad (1987, 1990) DRC (1997-2000) Congo (1997-1998) Ethiopia (1991) Guinea-Bissau (1998) Liberia (1990-1992) Rwanda (1991-1992, 1998, 2001) Sierra Leone (1998-1999) Somalia (1988, 1990-1992) South Africa (1988) Uganda (1991)	Angola (1981-1995, 1998-1999) Burundi (2000-2002) Ethiopia (1981-1985, 1987-1990) Mozambique (1981-1992) South Africa (1981-1983, 1986-1987) Sudan (1983-1992, 1995-2002) Uganda (1981-1989)

D.1.4 Additional figures

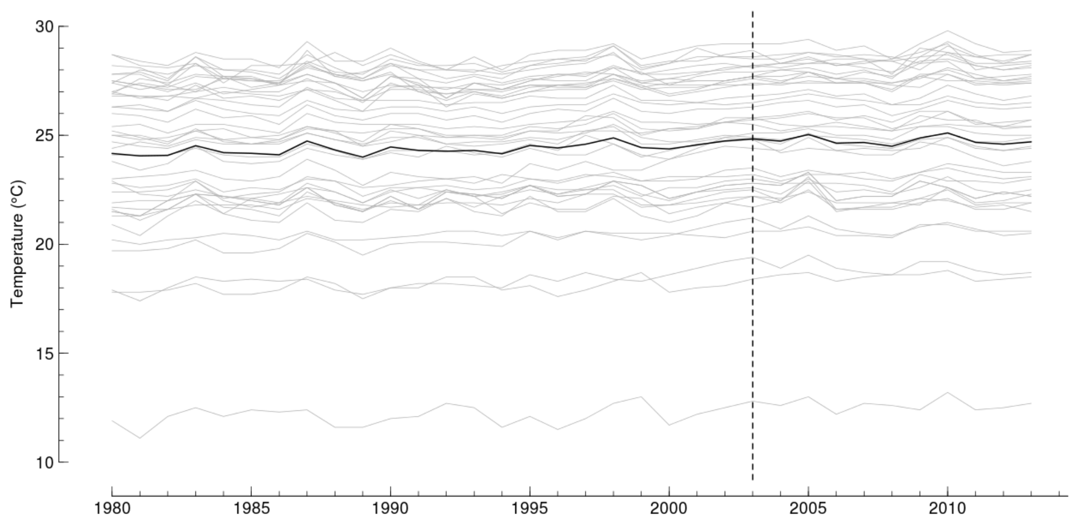

Figure D.2: Average temperature over time for 1980-2013. The light shaded lines represent the country average, the dark shaded line the continent average. The vertical line indicates 2003. Data: Climatic Research Unit, University of East Anglia.

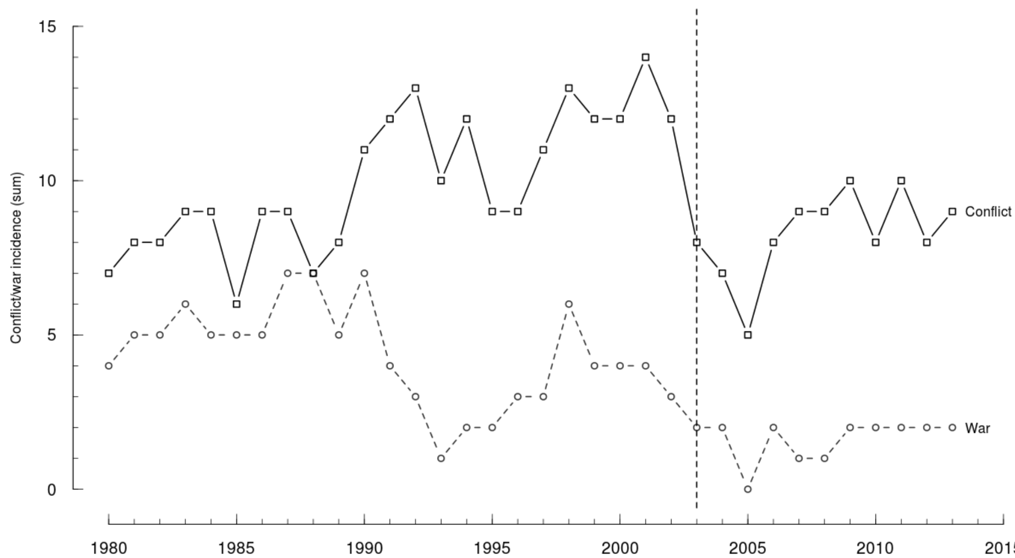

Figure D.3: Number of civil conflicts and war over time for 1980-2013. *"Conflict"* includes all conflicts with the number of battle-related deaths between 25-999, while *"War"* includes all conflicts with the number of battle-related deaths above 1,000. Data: UCDP/PRIO.

Figure D.4: Forecast model only including country fixed effects and country-specific time trends

D.1.5 Out of sample predictions

Table D.3: Actual versus predicted wars out-of-sample for 2003-2013 (Model with country fixed effects and country-specific time trends only)

	$\hat{p} \leq 0.5$	$\hat{p} > 0.5$
No war	403 obs.	Angola (2003-2007) Burundi (2003-2013) DRC (2003-2012) Rwanda (2010-2013) Sudan (2005, 2007-2009)
War	Chad (2006) Liberia (2003) Nigeria (2013) Rwanda (2009) Somalia (2007-2012) Uganda (2004)	DRC (2013) Sudan (2003, 2004, 2006, 2010-2013)