The University of Adelaide
Faculty of Professions
School of Economics

# Agriculture, Income and Conflicts

a thesis

by

Weidong Liang

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# Abstract

Since the 1950s, armed conflicts have become more and more recurrent. Most conflicts occur in countries where incomes are heavily dependent on the agricultural sector. This dissertation aims to systematically investigate the interconnection between agriculture, income and conflicts.

The first chapter is the introduction of this dissertation. Background information about conflicts is provided in this chapter. In particular, we offer statistical evidence about the quantity of conflicts, distribution of conflicts in terms of time and location and the number of deaths as the result of these conflicts. This background information is important for understanding the severity of conflicts and the significance of reducing them.

The second chapter is the overview chapter. The purpose of the overview chapter is to provide a literature review about the interrelationship between agriculture, income and conflicts. In this overview chapter, we start our discussion about how conflicts can hinder economic development emphasizing the importance of studying conflicts. We also discuss the development of conflict-related studies in the literature, estimation methods and potential issues when researchers attempt to investigate the effect of income variations on conflicts. We then end this chapter by analyzing the role of agriculture, especially the impact of agricultural productivity on conflicts.

The third chapter is the main study in this dissertation and is about estimating the effect of rainfall shocks on conflicts. We thoroughly examine the results on the negative relationship between rainfall shocks and conflicts in African countries from Miguel, Satyanath and Sergenti (2004). We consider the role of data revision and cross-sectional dependence in their estimation. We find that the negative relationship between rainfall shocks and conflicts in Miguel, Satyanath and Sergenti (2004) is not valid when the revised rainfall and conflicts datasets are used in their estimation. However, we propose a new estimator that is able to take cross-sectional dependence arising from spatially-dependent weather patterns and cross-border conflict spillovers into account to examine the link between rainfall shocks and conflicts.

Using this new estimator, we find that rainfall variations are indeed a determinant of conflicts.

The fourth chapter is another main study and examines the effects of productivity-enhancing technology in agriculture on conflicts. We consider the commercial legalization of Genetically-Modified (GM) soybean cultivation in Brazil in 2003 and investigate the effects of GM soybean cultivation on land conflicts in Brazil. In this chapter, we provide a theoretical model to show that the enhancement of agricultural productivity induced by GM soybean cultivation can reduce land value and then mitigate land conflicts. To assess the validity of this theoretical prediction, we employ the Difference-in-Differences estimation and find that states that have more land that is suitable for cultivating GM soybeans after the legalization in 2003 are negatively associated with land conflicts. The empirical results on the mitigating effect of GM soybean cultivation on land conflicts are reinforced by a series of robustness checks. The fifth chapter is the conclusion of this dissertation. Specifically, we summarize the contents and achievement of this dissertation.

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# Declaration

I, Weidong Liang, certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

I give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

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# Chapter 1

# Introduction

In the last 50 years, armed conflicts have become increasingly prevalent. According to the Armed Conflict Dataset version 2015 (ACD 2015) from the Uppsala Conflict Data Program (UCDP) and International Peace Research Institute Oslo (PRIO) which covers 171 countries from 1946 to 2014, conflicts can be grouped into three categories: 1) civil conflict incidence, 2) war incidence and 3) conflict onset.[1] According to statistics from UCDP/PRIO and their conflict definitions, 102 out of 171 countries experienced at least one civil conflict incidence from 1946 to 2014. This accounts for 60% of observational countries in the ACD 2015. UCDP/PRIO also reveals that war incidence occurs most among these three conflict types. A summary of frequencies of conflicts are provided in Table 1.1:

Table 1.1: Frequency of conflicts (1946-2014)

| Conflict type | Frequency |
|---|---|
| War incidence | 1855 |
| Civil conflict incidence | 1408 |
| Conflict onset | 169 |
| Total | 3432 |

The frequencies of war incidence, civil conflict incidence and conflict onset from

[1] Civil conflict incidence is a contested incompatibility which 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. War incidence is the same as civil conflict incidence except the battle-related deaths is at least 1000. Conflict onset is new outbreak of civil conflict or war incidence.

1946 to 2014 are 1855, 1408 and 169 respectively for 171 countries in the world. According to statistics from the ACD 2015 provided by UCDP/PRIO, in terms of the total number of conflicts (civil conflict and war incidence and onset) from 1946 to 2014, Burma (177), India (134), Israel(134), Philippines (132), Ethiopia (124), Sudan (123), Iraq (114), Colombia (111), Afghanistan (109), and Angola (87) are the top 10 countries with the most number of conflicts encountered.

Figure 1.1: Civil conflict incidence (1946-2014)

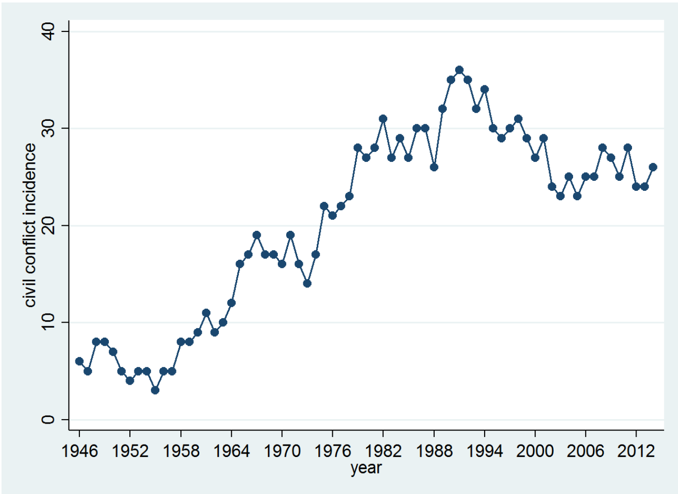
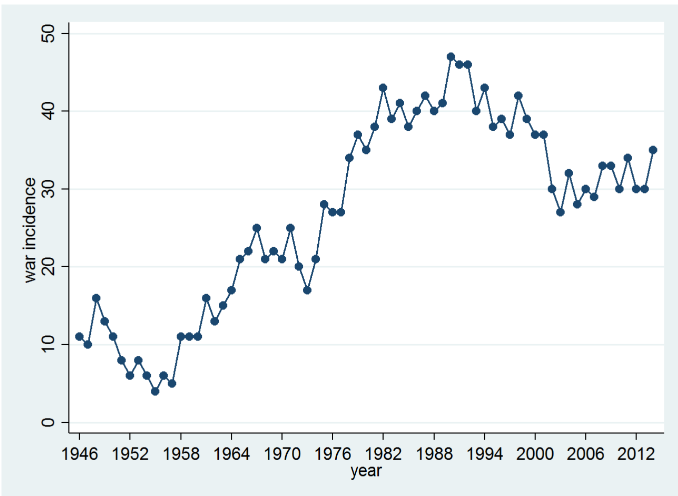



Figure 1.2: War incidence (1946-2014)




Figures 1.1, 1.2 and 1.3 show the changes in civil conflict incidence, war incidence and onset from 1946 to 2014. It shows that the number of conflicts begins to increase in the 1950s and reaches its peak in the mid-1990s. Additionally, conflicts are highly concentrated in some regions. From Table 1.2, we can see most of conflicts occurred

in Africa and Asia. For instance, there are 916 civil conflict incidences in Africa and Asia. This accounts for about 65% of total civil conflicts. A similar pattern is observed in war incidence and onset. There are 1255 war incidences and 113 onsets in Africa and Asia. They account for more than 67% of total war incidences and onsets.

Figure 1.3: Onset (1946-2014)

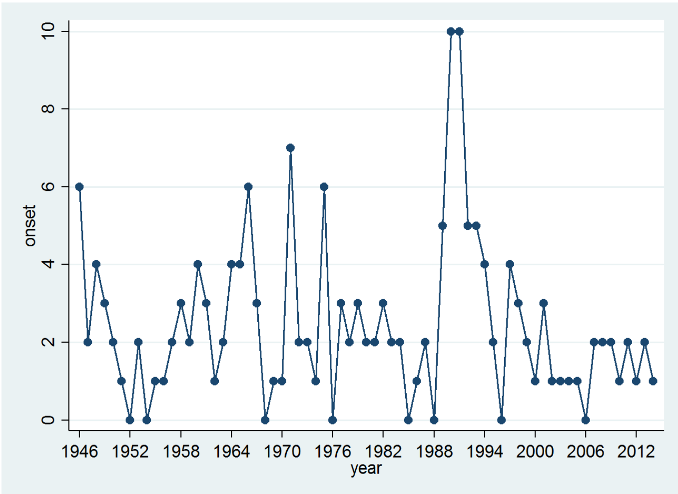
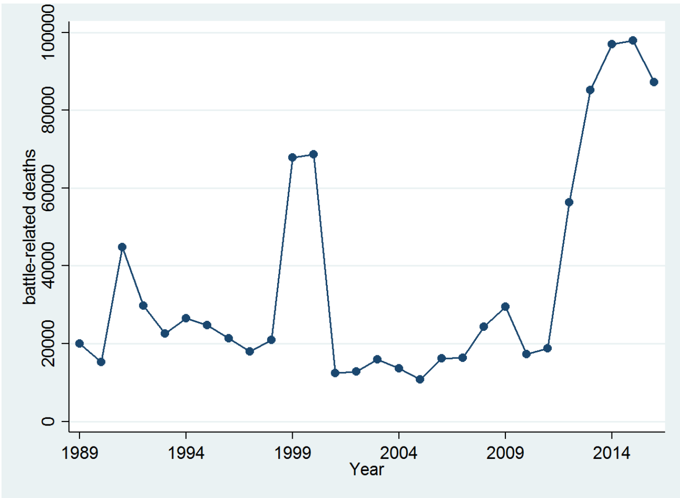



Table 1.2: Distribution of conflicts (1946-2014)

| Region | Civil conflict incidence | War incidence | Onset |
|---|---|---|---|
| Africa | 473 | 636 | 60 |
| Asia | 443 | 619 | 53 |
| Central America | 72 | 91 | 9 |
| Europe | 78 | 100 | 19 |
| Middle East | 228 | 277 | 16 |
| North America | 16 | 17 | 2 |
| Ocenia | 6 | 6 | 1 |
| South America | 92 | 109 | 9 |
| Total | 1408 | 1855 | 169 |

A rise in the number of conflicts is followed by an increase in casualties. According to UCDP/PRIO, 992,219 people have been killed from conflicts between 1989 to 2016 (see Figure 1.4 for the battle-related deaths).

Figure 1.4: Battle-related deaths (1989-2016)




The rest of this thesis is structured as follows. Chapter 2 provides a literature review on the relationship between agriculture, income and conflicts. In general, developing countries tend to be dependent on the agricultural sector. Given that income shocks can cause conflict, there is a large literature that looks at how conflicts may arise due to negative rainfall shocks. In Chapter 3, I discuss issues concerning the existing literature and provide a new study on estimating the impact of rainfall shocks on conflicts in light of these concerns.

Because negative shocks to the agricultural sector could lead to conflicts, it is plausible that productivity-enhancing technology in agriculture can help reduce conflicts in agriculturally dependent regions. In Chapter 4, I investigate the effect of an improvement in agricultural productivity induced by the adoption of Genetically-modified (GM) soybeans on conflicts. Specifically, I exploit the policy experiment about the commercial legalization of GM soybean cultivation in 2003 in Brazil and examine its impact on land conflicts. In Chapter 5, I conclude this thesis with a summary on what this thesis achieves.

# Chapter 2

# Overview: Agriculture, Income and Conflicts

## 2.1 Introduction

This chapter provides an overview of existing studies on the relationship between agriculture, income and conflicts.[1] We first discuss the implications of armed conflicts on economic development. We then review the development of conflict-related studies in the literature and the econometric methods used to estimate the effect of income variations on conflicts. Specifically, we provide thorough discussion about the use of instrument variable estimation strategy to examine the effect of income on conflicts. Next, we extend our investigation to the role of agriculture on conflicts and more importantly, we argue that the enhancement of agricultural productivity can mitigate conflicts.

[1] Conflicts are defined as any type of conflicts explained above in chapter 1.

## 2.2 The Importance of Studying Conflicts from an Economic Development Perspective

To understand the reasons for studying conflicts, we begin by comprehending how conflicts can hinder economic development. In this section, we argue that armed conflicts can precipitate sex ratio imbalance, child mortality and the spread of HIV virus in victim countries. Moreover, people who are exposed to conflicts will undergo disadvantages in the labour market in the future. Therefore, it is highly important to study and understand the determinants of conflicts from an economic development perspective.

Firstly, conflicts can distort the marriage market and precipitate sex ratio imbalance and child mortality. Conflicts are usually accompanied by high casualty. For instance, Brainerd (2017) shows that World War II caused about 13.5% of the prewar population (or about 26 to 27 million) in Soviet Union to be killed. Bethmann and Kvasnicka (2013) also provides evidence that about half a million military personnels were missing only in the state of Bavaria in Germany during World War II. Men accounted for the majority of casualties. In return, the supply of men in the marriage market was in shortage and the sex ratio between men and women was imbalanced. This can lead to a marriage squeeze and an increase of out-of-wedlock childbearing (Brainerd 2017). Additionally, an increase of out-of-wedlock childbearing because of a man shortage induced by conflicts is positively associated with infant mortality. To take the state of Bavaria in Germany as an example, about one in six children was born by out-of wedlock mothers died after World War II (Bethmann and Kvasnicka 2013). Therefore, conflicts can cause marriage market distortion, sex ratio imbalance and high child mortality.

Secondly, HIV infection during and after conflicts can be escalated rapidly. Iqbal and Zorn (2010) argue that the high prevalence of HIV in Africa attributes to armed conflicts. There are two reasons to explain the link between conflict incidence and HIV prevalence. The first reason is that conflicts can increase the chances of uninfected people interacting with infected ones. Movement of people is particularly high during and after armed conflicts as many refugees and migrants are displaced. This can result in spreading of HIV (Decosas et al. 1995; Decosas and Adrien 1996). The second reason is that conflicts can cause an increase in abnormality of sexual behavior and then in the likelihood of contracting HIV. Elbe (2002) reveals that soldiers during conflicts are of sexually active age and are prone to perform high-risk sexual behavior. Consequently, armed conflicts would lead to higher HIV prevalence.

Thirdly, young victims in conflicts will experience adversity in the future labour market. For example, Galdo (2013) argues that victims in conflicts have more difficulty in obtaining jobs and earn less even if they are employed in the future. The obvious reason is that many facilities that are used for education and training are destroyed in conflicts. Therefore, young victims in conflicts cannot acquire the skills and qualifications that they need for their future jobs. As a result, they will earn less and some will be unemployed.

## 2.3 The Development of Conflict-related Studies in the Literature

Initially, economic researchers disregard topics of conflicts in the international economic development (Blattman and Miguel 2010). For instance, Blattman and Miguel (2010) find that conflict-related topics are not covered in two highly used development economics textbooks in undergraduate courses.[2] Moreover, they surveyed 36 development economics syllabus in major U.S. universities and discovered that only 13% of undergraduate and 24% of graduate courses discussed conflict-related topics. Therefore, topics of conflicts are neglected in the early stages of economic development studies.

The seminal studies in conflict literature may be Collier and Hoeffler (1998), Fearon and Laitin (2003) and Collier and Hoeffler (2004). These studies system-

[2] These two development economics textbooks are Ray (1998) and Todaro (1999).

atically provide cross-country evidence to understand the impact of economic and ethnic factors on conflicts. Specifically, Collier and Hoeffler (1998) and Collier and Hoeffler (2004) apply logit and probit models to examine the roles of initial income, initial share of primary commodity exports to GDP, ethno-linguistic fractionalisation and population level on occurrence of armed conflicts. Their studies find that income, rather than ethnic fractionalization and social grievance, can affect conflict likelihood. However, Fearon and Laitin (2003) argue that conflicts are positively influenced by ethnic and language fractionalization.

These three papers provide early discussion and understanding on the determinants of conflicts. However, there are two major drawbacks in these three studies. Firstly, their studies are cross-sectional studies on developing countries. Therefore, it is impossible to control the country fixed effect in their estimation. This leads to a problem of omitted variable bias in their estimation. Moreover, the problem of omitted variable bias is further presented in their papers as factors that are correlated with conflicts and income cannot be fully controlled in their empirical models. For example, income levels are positively correlated with institutional qualities and these institutional qualities are potential determinants of conflict incidence.[3] Lastly, identifying the true effect of income on conflicts is undermined by reverse causality as occurrence of conflicts can affect income (Blattman and Miguel 2010). Therefore, the effect of income on conflicts cannot identify correctly in light of reverse causality.

## 2.4 The Estimation of the Effect of Income Variations on Conflicts

Given the drawbacks that exist in Collier and Hoeffler (1998), Collier and Hoeffler (2004) and Fearon and Laitin (2003), researchers seek better estimation strategies to investigate the effect of income on conflicts properly. We will survey these estimation strategies and summarize them in this section. In particular, we discuss the uses of

[3]Institutional qualities are democracy and corruption level.

instrument variable estimation for identifying the impact of income on conflicts.

### 2.4.1 Instrument Variable Strategy: Weather Conditions

As the problems of omitted variable bias and reverse causality prevail, the literature explores the panel data structure and seeks valid instruments to identify the effect of income on conflicts. The pioneering study that applies instrument variable strategy to estimate the effect of income on conflict is Miguel, Satyanath and Sergenti (2004). Their study explores the variations of rainfall as a source of income shocks and finds that a decrease in rainfall growth is associated with an economic contraction, whilst an increase in rainfall growth is linked to economic expansion. Economic contractions can decrease the opportunity cost of participating in conflicts, which leads to a greater probability of conflict incidence. Conversely, economic expansions increase the opportunity cost of participating in conflicts, leading to fewer conflict incidences. Their paper is a seminal study on investigating the link between income shocks arising from weather variations (or climate change) and conflicts in African countries.

#### Mechanisms of Weather Conditions on Conflicts

In this section, we present the existing evidence on how weather variations (i.e. volatility of rainfall and temperature level) affects conflicts from three channels. The first channel is the income channel. Agricultural income plays a significant role in African and other developing economies. For instance, the World Bank data reveals that agricultural income accounts for more than 30% of GDP in Sub-Saharan Africa (SSA) from 1960 to 1997.[4] A report from the Food and Agriculture Organization of the United Nations (FAO) shows that over 60% of the workforce from developing countries is involved in the agricultural sector.[5] Given that many poor and rural people work in the agricultural sector, the growth of this sector can effectively alleviate the problem of poverty in SSA. All in all, performance of the

[4] please refer to Table 1 in Barrios, Bertinelli and Strobl (2010).

[5] please see $http://www.fao.org/docrep/015/i2490e/i2490e01b.pdf$

agricultural sector is crucial to income growth in developing countries.

Economic performance in the agricultural sector and aggregate income in developing countries are affected by weather conditions (i.e. variation of rainfall and temperature level). For example, if the precipitation supply is stable and sufficient (or the temperature is favorable for cultivating crops), crop yields are high. In contrast, if the precipitation supply is insufficient (or the temperature is too high or too low), arable land is destroyed and irrigation is negatively affected. In turn, the degradation of environment inevitably leads to a reduction in crop yields and then in household income. Dell, Jones and Olken (2012) demonstrate that a decrease in temperature can reduce agricultural output and economic growth in poor countries. Barrios, Bertinelli and Strobl (2010) also conclude that there is a positive relationship between favorable weather conditions and income in Sub-Saharan Africa. Hsiang (2010) examines the destructive effect of abnormal temperatures and cyclones on economic production in Central America and reinforces the relationship between weather and income.

Therefore, variations of rainfall and temperature level can affect economies that are highly dependent on agricultural income, which consequently affect the likelihood of conflict incidence. In the gun-or-butter model in Powell (1993) or the appropriate-or-production model in Grossman (1994) assume that people can participate in illegal activities like armed conflicts and that the likelihood of conflict incidence is governed by the opportunity cost of participating in these conflicts. Collier and Hoeffler (1998) argue that income variations can determine the opportunity cost of participating in conflicts. In the context of weather conditions, when there is favorable weather in terms of appropriate precipitation and temperature level, agricultural incomes are enhanced. In return, people are less willing to participate in conflicts as the opportunity cost of participating is increased. Therefore, there is a negative association between favourable weather conditions and conflict incidence.

The second channel is the environmental insecurity (Benjaminsen 2008). This literature argues that desertification and environmental degradation arising from extreme weather conditions can cause food supply scarcity and intensify sentiments of grievance toward a government. This results in social unrest and political instability. For example, Caruso, Petrarca and Ricciuti (2016) explain that rice crops are a staple food for the majority of Indonesians and that the supply of this staple food would be diminished if temperature rises or precipitation reduces. Consequently, the price of rice soars. The rising prices arouse dissatisfaction toward the government and then lead to social unrest. Hendrix and Haggard (2015) is another example argued that extreme weather can destroy crop cultivation environment and drive up the global food prices, which results in destabilizing political institutes in Africa.

The third channel is the impact of mass migration arising from abnormal weather on conflicts. Extreme weather leads to internal and external migration.[6] Marchiori, Maystadt and Schumacher (2012) develop a theoretical model to demonstrate that weather anomalies prompt mass migrations and conflicts. The key insight is that extreme weather can reduce income for people living in rural areas. This leads to urbanisation where rural families migrate to cities looking for employments. Subsequently, this generates a downward pressure on urban residents' wage and intensifies resource depletion and tension between different ethnic groups (Ghimire, Ferreira and Dorfman 2015). Empirically, Marchiori, Maystadt and Schumacher (2012) show that weather abnormality led to at least 128,000 people displaced in SSA between 1960 to 2000 and the displacements due to extreme weather resulted in an increasing violence incidence in migrant recipient regions.

### 2.4.2 Instrument Variable Strategy: Commodity Price Volatility and Foreign Interest Rate Movements

The literature also explores other identification strategies to estimate the effect of income on conflicts. For instance, Brückner and Ciccone (2010) and Bazzi and Blattman (2014) use international commodity prices as instrument variables to cap-

[6] Internal migration refers to migrant movement within a country whereas external migration means migrant movement between different countries.

ture the impact of income variations on conflicts in Africa. Their identification strategy is based on evidence showing income in these African countries is heavily dependent on commodity-exporting revenue. Fluctuation of international commodity prices can affect exporting revenue and then income in African countries. In other words, there is a positive income shock when international commodity prices increase. Hence, it is plausible to employ variation of international commodity prices to be the instrument variable for identifying the effect of income on conflicts.[7]

Additionally, other studies follow the spirit of Brückner and Ciccone (2010) and Bazzi and Blattman (2014) to use different types of price indexes for identifying income variations. The related studies are Maystadt and Ecker (2014) using variations of livestock prices and Fjelde (2015) exploring the volatility of agricultural price indexes. To summarize, many studies so far employ income variations from some specific industries (i.e. agriculture and exporting sectors) to develop the identification strategy.

Lastly, the literature also uses foreign interest rate movements to identify the effect of income shocks on conflicts. Hull and Imai (2013) argue that many developing countries commit to fixed exchange rate regimes and free capital mobility. This means that interest rate setting in many developing economies are fully sensitive to foreign interest rate fluctuations in developed countries like the U.S. and UK. This is because many developing economies must abandon their monetary dependency in order to implicitly or even explicitly peg their currencies against these developed economies (Calvo and Reinhart 2002; Aizenman, Chinn and Ito 2008). Since interest rate fluctuations can significantly influence short-run economic growth, developed countries' foreign interest rate movements are correlated with income variations in developing economies.[8] Therefore, interest rate movements in developed economies can serve as a good instrument variable to identify the impact of income on conflict incidence in developing countries.

[7]However, we must assume that African countries do not have market power to set international commodity prices in this identification strategy.

[8]However, interest rate settings in developed economies cannot be reversely affected by variations of interest rate in any developing economy.

### 2.4.3 The Effect of Income Shocks on Conflicts: Has a Consensus Been Reached?

Even though many studies employ different identification strategies to estimate the effect of income shocks on conflicts, a consensus about the relationship between income variations and conflict incidence still cannot be reached. For example, there are still many disputes among studies that examine the link between weather conditions and conflicts (Salehyan 2008). On one hand, Burke et al. (2009), Hsiang, Meng and Cane (2011), O'Loughlin et al. (2012) and Couttenier and Soubeyran (2014) assert that temperature and precipitation levels are determinants of conflict incidence. These papers focus on African countries with different time periods. Hodler and Raschky (2014) use sub-national administrative regions in Africa and find a negative relationship between rainfall and conflicts. Moreover, many other studies expand their investigations to other countries (i.e. Brazil, China and Indonesia) and draw the same conclusion about the association between weather abnormality and conflicts (see Hidalgo et al. 2010; Bai and Kung 2011; Caruso, Petrarca and Ricciuti 2016).

On the other hand, some studies challenge the validity of the association between weather conditions and conflicts. For instance, Ciccone (2011) finds that the result about the negative relationship between rainfall growth and conflict incidence is not robust after revising the conflict and rainfall datasets. Moreover, Buhaug (2010) challenges the results in Burke et al. (2009) and argues that the results in Burke et al. (2009) are sensitive to model specification and different measures of conflict variables. Some studies even find a positive, instead of negative, relationship between rainfall and conflicts as the literature suggests. For instance, Slettebak (2012) and Gartzke (2012) provide estimation results and argue that the link between rainfall and conflicts is positive.[9] So far, results about the effect of weather conditions on conflicts are mixed in the literature.

[9] Slettebak (2012) explains that people become more united and anti-social sentiment is less intensified during extreme weather events.

### 2.4.4 The Potential Issues in the Estimation of Income Variations on Conflicts

In this section, we discuss potential issues that could hinder the estimation of the impact of income on conflicts. In particular, we consider how problems arising from measurement errors in the conflict and rainfall datasets, the functional form of weather variables and cross-sectional dependence affect the estimation, which could lead to mixed results on the relationship between income variations and conflicts.

Firstly, data issues exist in the rainfall and conflict datasets. For instance, measurement errors due to coding errors in the previous conflict datasets can hinder the accuracy and inference of estimates in the estimation of the effect of weather conditions on conflicts. The Armed Conflict Dataset (ACD) for country-level studies is widely used by many studies.[10] The ACD is provided by UCDP/PRIO and is revised periodically to eliminate measurement errors. Therefore, there are multiple ACD versions available. The early versions of ACD contains specific coding errors that are recorded by the data provider.[11] These errors in the early ACD version can result in overcount or undercount in conflict variables. If studies use early conflict data versions to estimate the effect of rainfall on conflicts, estimates and their inference in the estimation are not robust. For example, Miguel and Satyanath (2010) reveal that the results in Ciccone (2011) are not robust because Ciccone (2011) was using the outdated conflict data. Additionally, the definition of conflict variables is unclear. Consequently, the number of conflicts in the conflict dataset may be different even if the observational time period and country are the same. For example, Buhaug (2010) finds that the results regarding the effects of temperature and precipitation on conflicts in Burke et al. (2009) are not valid after different definitions of conflicts are considered. Specifically, when Buhaug (2010) considers another conflict definition–civil conflict incidence that captures conflicts leading to at least 25 battle deaths, the results in Burke et al. (2009) are no longer robust.

[10] See Miguel, Satyanath and Sergenti (2004); Ciccone (2011) and Miguel and Satyanath (2011).
[11] To see the historical errata for each ACD version, please visit http://www.pcr.uu.se/research/ucdp/ucdp-data/replication-datasets/

Secondly, the functional form of weather variables can affect the estimation of the impact of weather on conflicts. Some studies select rainfall shocks to capture the effect of rainfall changes on conflicts in the estimation (see Miguel, Satyanath and Sergenti 2004; Miguel and Satyanath 2011).[12] However, Ciccone (2011) and Sarsons (2015) argue that using the functional form of rainfall shocks is not appropriate because of mean reversion in rainfall data. The property of mean reversion indicates that there is a long-run equilibrium or trend in the rainfall data and that a deviation from the long-run trend is temporary. In other words, mean reversion in the rainfall data implies that the negative rainfall shock at period $t$ is always followed by a positive rainfall shock in the next period(s). Therefore, Ciccone (2011) argues that the negative association between rainfall shocks and conflicts claimed by Miguel, Satyanath and Sergenti (2004) is because of the existence of mean reversion and the negative relationship is not valid when rainfall variable is in the log form.

Thirdly, the traditional two-way fixed effect estimator is highly used in the conflict literature. For example, Miguel, Satyanath and Sergenti (2004) and Ciccone (2011) employ this estimator to investigate the effect of rainfall on conflicts. Brückner and Ciccone (2010) and Blattman and Miguel (2010) also use this traditional estimator to examine the impact of commodity price on conflicts. This estimator assume that the observational units (i.e. countries) are cross-sectionally independent in the panel data structure. However, the assumption of cross-sectional independence in these studies mentioned above is problematic due to two reasons. The first reason is that weather patterns (i.e. rainfall and temperature levels) are spatially correlated across observational units (Auffhammer et al. 2013; Dell, Jones and Olken 2014). The second reason is that conflicts in one country may spill over onto neighboring countries (Aydin 2008). The conflict spillovers occur because of economic integration and mass migration flow among different countries when conflicts break out (see Murdoch and Sandler 2002; Murdoch and Sandler 2004). All in all, the

[12] Rainfall shocks are rainfall growth for country $i$ and period $t$, which is computed as: $(Rainfall_{it} - Rainfall_{it-1})/Rainfall_{it-1}$. $Rainfall_{it}$ and $Rainfall_{it-1}$ are rainfall levels at period $t$ and $t-1$ in country $i$.

observational units in the panel data structure in these conflict-related studies may be cross-sectionally dependent. If so, the traditional two-way fixed effect estimator is not suitable for estimating the effect of income variations on conflicts. Pesaran (2006) argue that estimates are not consistent and their statistical inferences are no longer robust when the problem of cross-sectional dependence prevails in the traditional two-way fixed effect model.

## 2.5 The Role of Agriculture in Economic Development

In may developing countries, the agricultural sector contributes significantly to their economies. According to Gollin (2010), 65% of the labor force in developing countries is directly employed in the agricultural sector and the agricultural sector in these countries accounts for 25-30% of its GDP.[13] In this section, a summary is provided to understand how agriculture can enhance economic development on the basis of the discussion in Johnston and Mellor (1961), Johnston (1970) and Timmer (2002).

Firstly, agricultural development can contribute to stabilization of food supply and prices (Johnson 1997). When the world population rises remarkably from the last centenary, meeting food demand becomes more and more challenging. If food demand cannot be met with a stable supply, food prices would soar. This would adversely affect many households. However, better agricultural development can expand food production to feed an increasing population and achieve the basic needs of an economy. More importantly, steady food production in the agriculture section can stabilize food prices, which will be beneficial to many households. Hence, agriculture is essential for economic development.

Secondly, Johnston and Mellor (1961) argue that an expansion in agriculture can increase national income by boosting agricultural exports. After agricultural

[13] Employment in the agricultural sector exceeds 70% of the working population in the East African region and the agricultural sector in Africa and Southern Asia contributes to over 40% of its GDP.

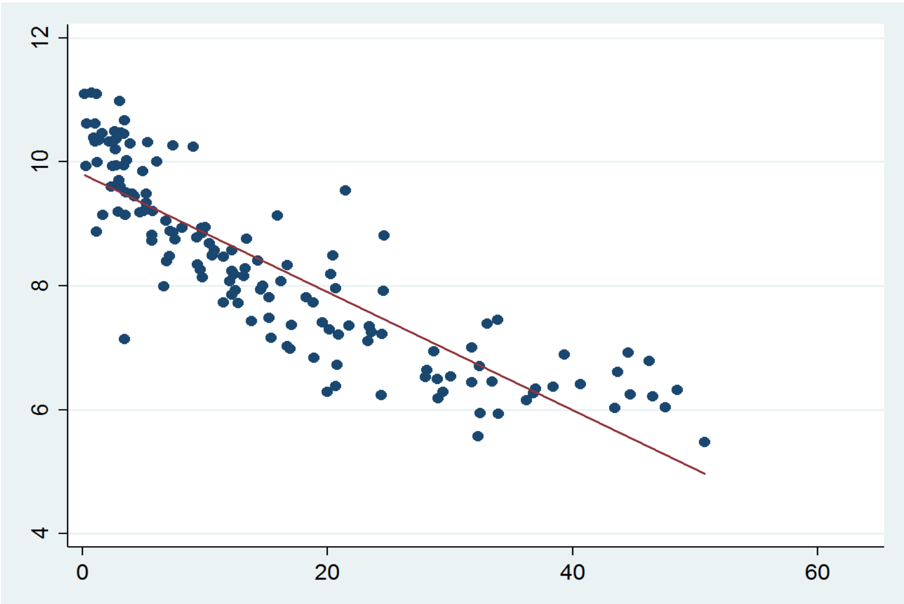
production can satisfy food demand in the domestic market, the production surplus can become cash crops and be exported to overseas markets. Dawson (2005) studies the role of agricultural exports in 62 developing countries and find a positive association between agricultural exports and economic growth. Therefore, agricultural development is an effective approach to accumulate foreign earning and improve national income.

Thirdly, agricultural development is interrelated with other non-agriculture sectors (i.e. service and manufacturing sectors) and the progress of agricultural development can accelerate industrialization and sustain long-run economic growth. Johnston (1970) argues that development in the agriculture sector can initiate a structural transformation and provide two important inputs for industrialization. The first input is labour. The agricultural development is accompanied by an increase of labour productivity in the agricultural sector. This results in a labour surplus in the agricultural sector and this surplus can be absorbed in the non-agricultural sectors that are in need of labour force. The second input is capital. Johnston and Mellor (1961) assert that agricultural development can contribute to capital formation and allocate this capital to other sectors. With the supply of labour and capital and their reallocation from the agricultural sector or low productivity sector to non-agricultural sectors or high productivity sectors, development in the agricultural sector is a prerequisite for industrialization and long-run economic growth in early stages of economic development in some industrialized countries. For example, Johnston (1951) analyzes the economic development in the early stages of Japan and UK and find that industrialization in these countries started with better development in the agricultural sector.

### 2.5.1 The Relationship Between Agricultural Income, GDP Per Capita and Civil Conflict Incidence

The discussion above argues that the role of agriculture is essential to economic development. However, this does not mean that developing agriculture sector absolutely leads to a high income level. As early as Fisher (1939), many studies assert that there is a negative association between the share of agriculture value and income level.[14] In other words, countries that are heavily dependent on their agriculture sector to generate income are low-income countries. To further justify this negative relationship, we extract data of GDP per capita and share of agriculture added value in GDP (unit being percentage) from 1960 to 2014 for 150 countries from the World Development Indicators.

Figure 2.1: Income and agriculture




*Note*: Data is extracted from World Development Indicators

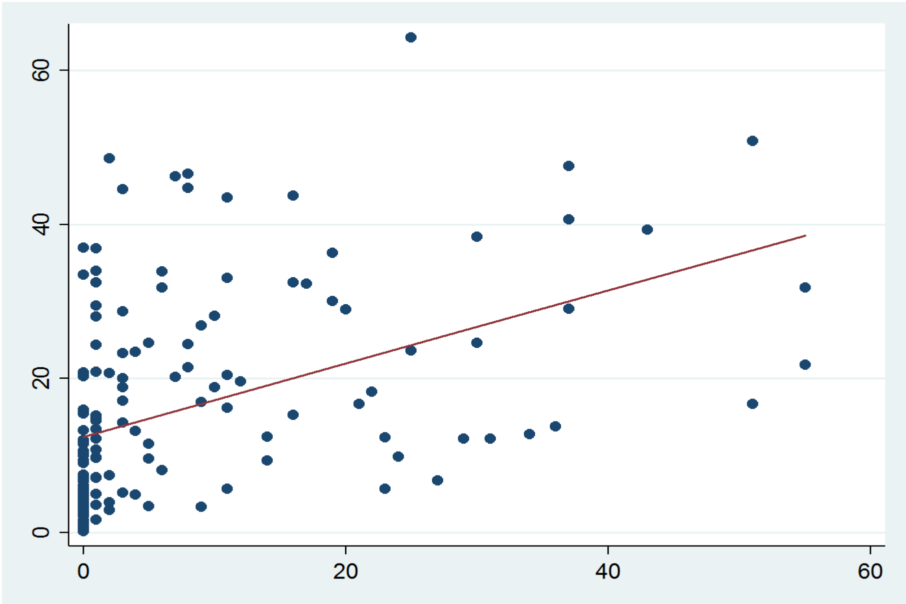
As we can see in Figure 2.1, the dots represent the log GDP per capita and the vertical axis is the percentage of agriculture added value in GDP. The claim about the negative relationship between income level and relative value of the agriculture sector in GDP is reinforced in Figure 2.1.

Given low income engenders more conflicts, the negative association between income and relative value of the agriculture sector in GDP implies that the relationship between relative value of the agriculture sector in GDP and conflicts is positive. Collier and Hoeffler (1998) and Collier and Hoeffler (2002) argue that an expansion of income can result in reduction of conflicts. Additionally, Miguel, Satyanath and

[14] Share of agriculture value can be measured as the size of employment and output in the agriculture sector. Please also see Kuznets (1963).

Sergenti (2004) reveal that a decrease in agricultural income arising from negative rainfall shocks leads to an increase in conflict incidence in the agriculture-led countries. This may suggest that the association between agriculture (especially its share in GDP) and conflicts is nontrivial.

Figure 2.2: Agriculture and conflicts




*Note*: Data is from World Development Indicators and UCDP/PRIO

We obtain the total number of civil conflict incidences for 150 countries between 1946 and 2014 from UCDP/PRIO.[15] In Figure 2.2, we plot the relationship between the value of the agricultural sector in GDP and a summation of civil conflict incidence for each country and find that their correlation is positive. This may suggest that countries that rely more on agricultural income are more prone to experience civil conflicts.

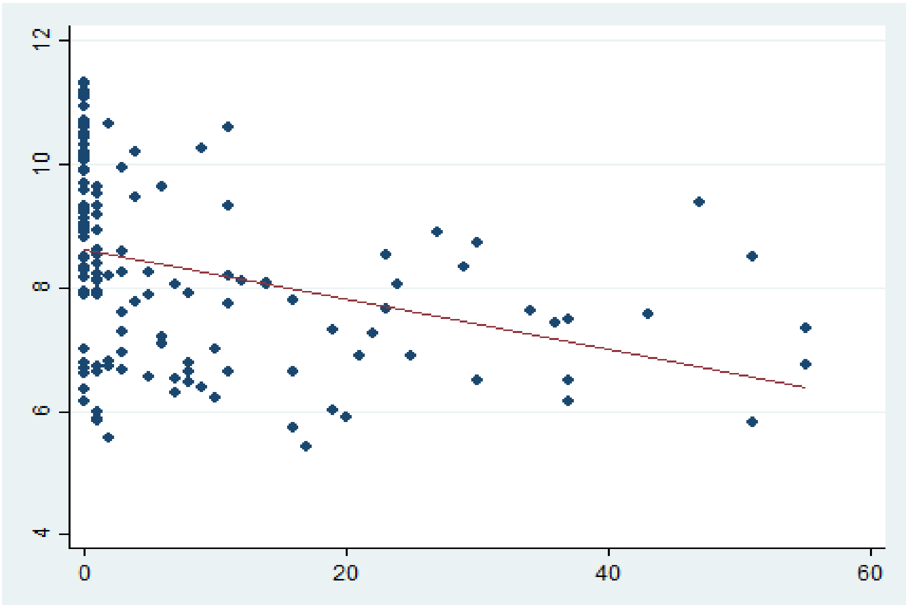
### 2.5.2 Can Agricultural Productivity Improvement Reduce Conflicts?

When income in a country relies more on the agricultural sector or the share of the agricultural sector in GDP is large, agricultural productivity level is particularly low (Johnston and Mellor 1961). Given the relationship between the value of the

[15]The definition of civil conflict incidence remains the same as the introduction chapter above.

agricultural sector in GDP and conflicts is positive, and the association between the value of agricultural sector in GDP and agricultural productivity is negative, we may argue that countries with low agricultural productivity are more likely to experience conflicts. To examine this claim, we plot labour productivity in the agricultural sector against the total number of civil conflicts for the same 150 countries from 1946 to 2014 in Figure 2.3. A negative relationship between agricultural productivity and conflicts is presented in Figure 2.3.

Figure 2.3: Agriculture productivity and conflicts




*Note*: Data is from World Development Indicators and UCDP/PRIO

The improvement of agricultural productivity can increase income level and subsequently reduce conflicts. The key mechanism is that improving agricultural productivity results in structural transformation and industrialization (Johnston 1951; Johnston 1970). This is because agricultural productivity enhancement can release manpower to non-agricultural sectors and accumulate capital (Johnston and Mellor 1961). Labour resource reallocation and capital accumulation are essential paths to industrialization. Therefore, an increase in agricultural productivity can results in an expansion of income and long-run economic growth (Gollin, Parente and Rogerson 2002; Self and Grabowski 2007). Thereby, conflicts are reduced because of an income increase induced by improvement of agricultural productivity.

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# Chapter 3

# Economic Shocks, Rainfall and Conflict: The Implications of Data Revisions and Cross-Sectional Dependence

Weidong Liang
School of Economics, University of Adelaide

**Abstract:** It is well-documented that rainfall shocks have an opposite effect on conflicts. However, much of this literature uses past versions of the rainfall and conflict datasets and does not account for cross-sectional dependence between countries that may arise from spatially dependent weather patterns and cross-border conflict spillovers. We find that estimates in the conflict and rainfall data are substantially varied across different versions and the statistical significance of the effect of rainfall shocks on conflicts disappears when the estimation is carried out with the most recently revised rainfall and conflict datasets. However, with the most recent rainfall and conflict data and taking cross-sectional dependence into account by using interactive fixed effect model, we find that the effect of rainfall on conflicts is statistically significant.

# Statement of Authorship

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| | | | |
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| Name of Principal Author (Candidate) | Weidong Liang | | |
| Contribution to the Paper | Planning the paper, data collection, estimation and writing the paper | | |
| Overall percentage (%) | 80% | | |
| Certification: | This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper. | | |
| Signature | Weidong Liang | Date | 12/01/2018 |

## Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

| | | | |
|---|---|---|---|
| Name of Co-Author | Nicholas Sim | | |
| Contribution to the Paper | Minor role in writing and in the development of the structure of the paper | | |
| Signature | | Date | 12/01/2018 |

## 3.1 Introduction

Over the last 50 years, civil conflict has occurred in nearly half of the countries in sub-Saharan Africa (SSAs in short). Because it severely impairs economic development, there has been great interest in understanding why it is so frequent in the SSAs. In an influential paper, Miguel, Satyanath and Sergenti (2004), henceforth MMS, show that civil conflict in the SSAs is strongly associated with the occurrence of negative rainfall shocks.[1] This conforms to the idea that since the SSAs are economically dependent on the agricultural sector, negative rainfall shocks are income reducing as they reduce agricultural output (Barrios, Bertinelli and Strobl 2010). Consequently, individuals would be more willing to participate in conflict as their income, and thus their opportunity cost of fighting, is reduced (Collier and Hoeffler 1998; Grossman 1991)

In this study, we investigate if the statistical significance of the negative association between rainfall and civil conflicts in the SSAs reported by MMS is robust to two departures from the way they estimated this effect, namely 1) the use of newer versions of rainfall and conflict datasets (from the ones used by MMS), and 2) the use of interactive fixed effects in panel regressions. The rainfall and conflict datasets employed by MMS are GPCP 2.0 (Global Precipitation Climatology Project, version 2.0) and ACD 2004 (Armed Conflict Database, version 2004) respectively. Since then, two revised rainfall (GPCP 2.1 and 2.2) and conflict (ACD 2010 and 2015) datasets have become available. The updates in these revised datasets are made primarily to eliminate measurement errors.[2] However, as it turns out, the measurement of rainfall and conflict contained in the later datasets vary substantively from what was reported by the earlier rainfall (GPCP 2.0) and conflict (ACD 2004) datasets used by MMS. At this point, it is not known how these revisions might affect the impact of rainfall on conflicts.

Besides the concern about data revisions, we also consider if the negative asso-

[1] The definition of rainfall shocks is provided in the data section below.

[2] See the data section for more discussion.

ciation between rainfall and conflict is robust to accounting for spatial dependence in weather patterns (Auffhammer et al. 2013) and the fact that conflicts may spill across borders (Aydin 2008). These contribute towards the cross-sectional dependence of countries. From an econometric perspective, cross-sectional dependence may confound regression's estimates. If one uses a panel estimator that is not robust to cross-sectional dependence, as is the two-way fixed effects estimator employed by MMS, the estimated effect of rainfall shocks on conflicts could be inconsistent. In this case, a more robust approach would be to use panel regression techniques that incorporate interactive fixed effects, such as the common correlated effects (CCE) estimator proposed by (Pesaran 2006), given that interactive fixed effects can capture cross-sectional dependence and take into account of its potentially confounding effects.

Finally, we revisit the effect of rainfall on conflicts when rainfall is modeled with various functional forms. In the literature, the question of how rainfall should be modeled has important implications and is subject to much debate (Miguel and Satyanath 2011). On one hand, Ciccone (2011) and Sarsons (2015) argue that the model to estimate the effect of rainfall shocks on conflicts could be misspecified if rainfall is mean reverting, in which case, they suggest that rainfall should be modeled in log levels instead.[3] On the other hand, Dell, Jones and Olken (2014) suggest that rainfall should be modeled in its mean deviation form instead as rainfall data does not follow a normal distribution.[4]

Generally, we find that the statistical significance of the effect of rainfall shocks on conflicts is not robust when revised rainfall and/or conflict datasets are used. For example, based on the same 41 countries and the period from 1980 to 1999 as considered by MMS, we find that the effect of rainfall shocks on conflicts is statistically significant when the GPCP 2.0 rainfall dataset and the ACD 2004 conflict

[3]Mean reversion indicate that there is a long-run equilibrium or trend in the rainfall data and that negative rainfall shocks in time t-1 are followed by positive rainfall shocks or vice versa in time t or t+1.

[4]The definition of mean deviation rainfall variable is properly discussed in the variable section below. Hidalgo et al. (2010) also implement mean deviation form in the rainfall variable.

dataset are used. However, with the same countries and time period, the statistical significance mostly disappears when we employ the GPCP 2.1 or GPCP 2.2 rainfall datasets, or the ACD 2010 and ACD 2015 conflict datasets. Therefore, we cannot rule out the possibility that the statistical significance of the effect of rainfall shocks on conflicts is an artifact of measurement errors.

Secondly, we have evidence that rainfall shocks are cross-sectionally dependent and the cross-border spillover of civil conflict is prevalent. This suggests that panel regressions that take care of cross-sectional dependence should be employed when modeling the effects of rainfall on conflicts. By using Pesaran (2006)'s CCE estimator to deal with cross-sectional dependence, we find that the effect of rainfall is indeed statistically significant on reducing conflicts. Finally, we extend our CCE estimation to different rainfall functional forms such as logarithm and mean deviation. As rainfall are by these two functional forms, the effect of rainfall on conflicts still remain statistically significant in the CCE estimation.

Although the literature on civil conflict is rapidly expanding, whether weather conditions affect conflict incidence is still under much debate. For example, there is a major group of studies (e.g.Burke et al. (2009); Hsiang, Meng and Cane (2011); O'Loughlin, Linke and Witmer (2014); Couttenier and Soubeyran (2014)) showing that weather conditions, such as precipitation or temperature levels have statistically significant effects on conflict outbreaks in African countries. However, this is contested by another group of studies (e.g. Buhaug (2010); Ciccone (2011); Slettebak (2012)) arguing that the link between weather conditions and conflicts is weak or may not even be present. This paper shows that more work on estimating the effect of rainfall on conflicts would be useful.

The rest of this study is organized as follows. Section 2 discusses the data sources and shows that measurements among different rainfall and conflict data versions are substantially different. Section 3 outlines the empirical model with emphasis on the problems of conventional two-way fixed effect model and improvements of CCE estimator in the estimation. Section 4 presents the results followed by conclusion in

Section 5.

## 3.2 Data and Variables

### 3.2.1 Data

Since MMS, the rainfall data provider Global Precipitation Climatology Project (GPCP),[5] and the conflict data provider Armed Conflict Dataset (ACD) of Uppsala Conflict Data Program have updated their datasets.[6] The purpose of updates is not only to extend the data to the later years but also correct erratas.[7] In this study, we explore the implications of using three different versions of rainfall and conflict data, namely the GPCP 2.0, 2.1 and 2.2 datasets for the rainfall variable, and the ACD 2004, 2010 and 2015 datasets for the conflict variable. GPCP 2.0 and 2.1 are past rainfall datasets and ACD 2004 and 2010 are past conflict datasets. These past datasets are obtained in the published studies. For instance, we obtain GPCP 2.0 and ACD 2004 from the study of MMS.[8] Additionally, GPCP 2.1 and ACD 2010 are obtained from Ciccone (2011). GPCP 2.2 and ACD 2015 are the most recent rainfall and conflict datasets. These most recent datasets are sourced from the GPCP and ACD websites.

For our results to be comparable to MMS, we use the same 41 African countries and the same period from 1981 to 1999 as used by MMS. From there, we explore the sensitivity of the estimates if the sample period is extended to 2009, as considered by Ciccone (2011).

[5]Please see Adler et al. (2003) or GPCP (2018) for more details about this dataset.

[6]Please refer to Gleditsch et al. (2002) or ACD (2018) for more discussion about this dataset.

[7]The conflict and rainfall data providers have listed out all erratas in the previous data version as the revised version is available.

[8]One of the authors in MMS, Edward Miguel, also offers GPCP 2.0 and ACD 2004 dataset in his personal website.

### 3.2.2 Variables

We follow MMS to model rainfall shocks, denoted by $\Delta R_{it}$, as

$$\Delta R_{it} = \frac{R_{it} - R_{it-1}}{R_{it-1}},$$

where $R_{it}$ is the rainfall level at year $t$ and $R_{it-1}$ is the rainfall level at $t-1$. We also follow MMS to construct three related dummy variables to indicate three different aspects of conflict. The first dummy variable indicates the incidence of civil conflict. For each country, it is coded as 1 for the year (or years) when an episode of armed conflict that has resulted in at least 25 battle related deaths has taken placed. The second dummy variable indicates the incidence of war. For each country, it is coded as 1 for the year (or years) when an episode of armed conflict that has resulted in at least 1000 battle related deaths has taken placed. The third dummy variable indicates civil conflict onset. For each country, it is coded as 1 for the year during which there is an outbreak of a new civil conflict or war incidence (for the second and the subsequent years of same conflict or war, the onset dummy is coded as zero).

For the same country and year, rainfall could be recorded differently in different versions of the rainfall datasets. As Table 3.1 shows, the mean and standard deviation of rainfall shocks based on the GPCP 2.0, 2.1 and 2.2 datasets differ even if we focus on the same set of countries and years. For specific countries, what is recorded by GPCP may vary significantly across the different versions. For instance, for Cameroon between 1981 to 2009, the mean of its rainfall growth is reported as 0.0061 in GPCP 2.0, -0.0076 in GPCP 2.1 and -0.0016 in GPCP 2.2. For Uganda between 1981 and 2009, the mean of its rainfall growth is reported as -0.0089 in GPCP 2.0, 0.0222 in GPCP 2.1 and 0.0025 in GPCP 2.2.

The same consequences can be seen in the revisions of conflict datasets. Table 3.2 provides summary about the disparity from different conflict data versions in 1981-1999. We can take some specific countries out Table 3.2. Take Zaire as an example. In Table 3.2, Zaire's civil incidence is reported by ACD 2004 as 12 times. Subsequently, this is revised to 6 times in ACD 2010, then 4 times in ACD 2015.

Another example is Senegal. In Table 3.2, Senegal's civil onset is reported as 4 times by ACD 2004. Subsequently, this is revised to 5 times in ACD 2010 and 1 time in ACD2015.

Table 3.1: Variation of mean and standard deviation in rainfall growth

| Country | GPCP 2.0 (1981-1999) | GPCP 2.1 (1981-1999) | GPCP 2.2 (1981-1999) |
|---|---|---|---|
| Angola | 0.0137 (0.1766) | -0.0061 (0.1104) | 0.0090 (0.0905) |
| Benin | 0.0173 (0.1512) | 0.0174 (0.1716) | 0.0084 (0.1191) |
| Botswana | 0.0462 (0.3742) | 0.0622 (0.3783) | 0.0752 (0.3891) |
| Burkina Faso | 0.0144 (0.157) | 0.0111 (0.1551) | 0.0157 (0.1441) |
| Burundi | 0.0157 (0.1604) | 0.0008 (0.1591) | 0.0106 (0.1432) |
| Cameroon | 0.0061 (0.0957) | -0.0076 (0.1075) | -0.0016 (0.0950) |
| Central African | 0.0041 (0.0816) | -0.0078 (0.0786) | -0.0023 (0.0687) |
| Chad | 0.0134 (0.2400) | 0.0109 (0.2250) | 0.0064 (0.1506) |
| Congo | 0.0040 (0.1150) | -0.0067 (0.1144) | 0.0040 (0.0874) |
| Djibouti | 0.0234 (0.2434) | 0.0129 (0.2598) | 0.0193 (0.2353) |
| Ethiopia | 0.0177 (0.1641) | -0.0147 (0.1317) | -0.0079 (0.1127) |
| Gabon | 0.0104 (0.1204) | -0.0093 (0.1356) | 0.0082 (0.1363) |
| Gambia | 0.0171 (0.1765) | 0.0268 (0.2192) | 0.0264 (0.2006) |
| Ghana | 0.0135 (0.1782) | 0.0026 (0.1779) | 0.0064 (0.1506) |
| Guinea | -0.0078 (0.1159) | 0.0038 (0.1530) | 0.0015 (0.1177) |
| Guinea-Bissau | 0.0106 (0.1481) | 0.0134 (0.1586) | 0.0067 (0.1379) |
| Ivory Coast | -0.0003 (0.1189) | -0.0017 (0.1480) | 0.0008 (0.1335) |
| Kenya | 0.0430 (0.3388) | 0.0322 (0.3945) | 0.0426 (0.3496) |
| Lesotho | 0.0268 (0.2262) | 0.0183 (0.2448) | 0.0402 (0.2526) |
| Liberia | -0.0084 (0.1365) | -0.0140 (0.1630) | -0.0115 (0.1310) |
| Madagascar | 0.0090 (0.1290) | -0.0028 (0.1575) | 0.0081 (0.1579) |
| Malawi | 0.0242 (0.2616) | 0.0105 (0.2210) | 0.0213 (0.2122) |
| Mali | 0.0137 (0.2005) | 0.0172 (0.2099) | 0.0151 (0.1837) |
| Mauritania | 0.0256 (0.2838) | 0.0522 (0.2991) | 0.0466 (0.2806) |
| Mozambique | 0.0254 (0.2138) | 0.0092 (0.2183) | 0.0150 (0.1951) |
| Namibia | 0.1114 (0.5845) | 0.1081 (0.4890) | 0.1445 (0.5489) |
| Niger | 0.0319 (0.3173) | 0.0323 (0.2951) | 0.0290 (0.2883) |
| Nigeria | 0.0084 (0.0831) | -0.0025 (0.0909) | 0.0016 (0.0880) |
| Rwanda | 0.0182 (0.1466) | -0.0052 (0.1113) | 0.0037 (0.0904) |
| Senegal | 0.0155 (0.1791) | 0.0271 (0.2142) | 0.0244 (0.1901) |
| Sierra Leone | -0.0128 (0.1265) | -0.0089 (0.1624) | -0.0107 (0.1164) |
| Somalia | 0.0872 (0.4106) | 0.0676 (0.4534) | 0.0682 (0.4049) |
| South Africa | 0.0237 (0.2412) | 0.0208 (0.2721) | 0.0395 (0.2722) |
| Sudan | 0.0202 (0.1774) | -0.0038 (0.1404) | -0.0010 (0.1366) |
| Swaziland | 0.0318 (0.3119) | 0.0262 (0.3134) | 0.0497 (0.3161) |
| Tanzania | 0.0143 (0.2288) | 0.0048 (0.2210) | 0.0154 (0.2162) |
| Togo | 0.0161 (0.1673) | 0.0071 (0.1573) | 0.0107 (0.1397) |
| Uganda | -0.0089 (0.1249) | 0.0222 (0.1918) | 0.0025 (0.1123) |
| Zaire | 0.0132 (0.1153) | -0.0095 (0.0801) | 0.0005 (0.0576) |
| Zambia | 0.0110 (0.1836) | 0.0031 (0.1781) | 0.0147 (0.1639) |
| Zimbabwe | 0.0416 (0.2907) | 0.0271 (0.2972) | 0.0363 (0.2806) |

The value without parentheses is mean and standard deviation is in parentheses. The observational year is 1981-2009 and observational country is 41 African countries.

Table 3.2: Sum of conflicts (1981-1999)

| | Civil Incident | | | Onset | | | War Incident | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | ACD 2004 | ACD 2010 | ACD 2015 | ACD 2004 | ACD 2010 | ACD 2015 | ACD 2004 | ACD 2010 | ACD 2015 |
| Angola | 19 | 19 | 19 | 0 | 0 | 1 | 17 | 16 | 15 |
| Bennin | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Botswana | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Burkina Faso | 3 | 1 | 1 | 2 | 1 | 1 | 1 | 0 | 0 |
| Burundi | 8 | 8 | 8 | 2 | 2 | 0 | 1 | 1 | 0 |
| Cameroon | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| Central Africa | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Chad | 17 | 15 | 15 | 1 | 3 | 0 | 11 | 5 | 2 |
| Congo | 3 | 5 | 4 | 1 | 2 | 1 | 3 | 2 | 2 |
| Djibouti | 1 | 5 | 5 | 1 | 2 | 1 | 0 | 0 | 0 |
| Ethiopia | 15 | 17 | 18 | 1 | 2 | 2 | 11 | 10 | 10 |
| Gabon | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Gambia | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Ghana | 2 | 2 | 2 | 2 | 2 | 0 | 0 | 0 | 0 |
| Guinea | 2 | 2 | 0 | 1 | 1 | 0 | 1 | 0 | 0 |
| Guinea-Bissau | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 0 | 0 |
| Ivory Coast | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kenya | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Lesotho | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Liberia | 3 | 2 | 2 | 1 | 1 | 0 | 1 | 1 | 0 |
| Madagascar | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Malawi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mali | 2 | 2 | 2 | 2 | 2 | 1 | 0 | 0 | 0 |
| Mauritania | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mozambique | 12 | 12 | 12 | 0 | 0 | 0 | 12 | 11 | 11 |
| Namibia | 2 | 2 | 0 | 1 | 1 | 0 | 2 | 2 | 0 |
| Niger | 6 | 5 | 5 | 3 | 3 | 3 | 0 | 0 | 0 |
| Nigeria | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Rwanda | 9 | 9 | 9 | 2 | 2 | 1 | 5 | 6 | 3 |
| **Senegal** | 7 | 8 | 6 | 4 | 5 | 1 | 1 | 0 | 0 |
| Sierra Leone | 9 | 9 | 9 | 1 | 1 | 1 | 2 | 2 | 3 |
| Somalia | 11 | 14 | 14 | 1 | 2 | 1 | 3 | 4 | 4 |
| South Africa | 13 | 9 | 8 | 0 | 1 | 1 | 13 | 6 | 6 |
| Sudan | 16 | 17 | 17 | 1 | 1 | 0 | 14 | 15 | 15 |
| Swaziland | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tanzania | 0 | 4 | 0 | 0 | 1 | 0 | 0 | 4 | 0 |
| Togo | 2 | 4 | 1 | 2 | 4 | 1 | 0 | 0 | 0 |
| Uganda | 17 | 18 | 18 | 2 | 1 | 0 | 12 | 13 | 10 |
| **Zaire** | 12 | 6 | 4 | 1 | 3 | 0 | 11 | 6 | 4 |
| Zambia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Zimbabwe | 2 | 8 | 0 | 1 | 2 | 0 | 2 | 8 | 0 |
| Total | 199 | 207 | 185 | 38 | 48 | 20 | 124 | 112 | 85 |

### Two-sample Kolmogorov-Smirnov Test

To further investigate the extent to which the data revisions affect the data itself, we conduct a two-sample Kolmogorov-Smirnov (K-S) test to compare the shape of empirical distribution in the rainfall variable across three data versions. To do so, we first construct the empirical cumulative distribution of rainfall from each version of the rainfall dataset (GPCP 2.0, 2.1 and 2.2) between 1981 and 1999. Then, we perform a pairwise comparison of the empirical distribution and test the null hypothesis that the empirical distributions are identical in this time period. A rejection of the K-S under conventional significance levels will indicate that the revisions made to the rainfall dataset have changed the distribution of rainfall in a statistically significant way.

The variable in the K-S test is rainfall shocks from 1981 to 1999. We obtain the data of rainfall shocks from three different data versions (GPCP 2.0, 2.1 and 2.2) and then compare the shape of empirical distribution in pairwise among these three versions. We start with GPCP 2.0 versus GPCP 2.1 and then move to GPCP 2.0 versus GPCP 2.2 and GPCP 2.1 versus 2.2.

Table 3.3: K-S Test (GPCP 2.0 vs 2.1)

| Test | D | P-value |
|---|---|---|
| (1) | 0.0572 | 0.08 |
| (2) | -0.0374 | 0.34 |
| (3) | K-S test | 0.16 |

(1): test the null hypothesis that GPCP 2.0 contains smaller values than for GPCP 2.1. The largest difference between the distribution functions is 0.0572. The p-value is 0.081, which is significant at 5%. (2): test the null hypothesis that GPCP 2.0 contains larger values than for GPCP 2.1. The largest difference between the distribution function is -0.0374. The p-value for this is 0.341 and the null hypothesis cannot be rejected. (3): test the null hypothesis is the empirical cumulative distributions of GPCP 2.0 and GPCP 2.1 is identical (K-S test). The p-value is 0.162 and the null hypothesis cannot be rejected.

Table 3.4: K-S Test (GPCP 2.0 vs 2.2)

| Test | D | P-value |
|---|---|---|
| (1) | 0.0589 | 0.02 |
| (2) | -0.0550 | 0.04 |
| (3) | K-S test | 0.05 |

] (1): test the null hypothesis that GPCP 2.0 contains smaller values than for GPCP 2.2. The largest difference between the distribution functions is 0.0589. The p-value for this is 0.027, which is significant at 5%. (2): test the null hypothesis that GPCP 2.0 contains larger values than for GPCP 2.2. The largest difference between the distribution function is -0.055. The p-value for this is 0.043, which is significant at 5%. (3): test the null hypothesis is the empirical cumulative distributions of GPCP 2.0 and GPCP 2.2 is identical (K-S test). The p-value is 0.054 and the null hypothesis is rejected at 5%.

Table 3.5: K-S Test (GPCP 2.1 vs 2.2)

| Test | D | P-value |
|---|---|---|
| (1) | 0.0587 | 0.02 |
| (2) | -0.0351 | 0.26 |
| (3) | K-S test | 0.05 |

(1): test the null hypothesis that GPCP 2.1 contains smaller values than for GPCP 2.2. The largest difference between the distribution functions is 0.0587. The p-value is 0.023, which is significant at 5%. (2): tests the hypothesis that GPCP 2.1 contains larger values than for GPCP 2.2. The largest difference between the distribution function is -0.0351.The p-value is 0.259 and the null hypothesis cannot be rejected. (3): test the null hypothesis that the empirical cumulative distributions of GPCP2.1 and GPCP2.2 are identical. The p-value is 0.046 and the null hypothesis is rejected at 5%.

The results of K-S test for each pair (GPCP 2.0 vs GPCP 2.1, GPCP 2.0 vs GPCP 2.2, GPCP 2.1 vs GPCP 2.2) are presented in the row (3) of Table 3.3, 3.4 and 3.5 above. The null hypothesis of K-S test is that the empirical cumulative distributions of each pair are identical.

For example, the p-value of K-S test that compares GPCP 2.0 and GPCP 2.1 is 0.162. Thus, the null cannot be rejected at the 10% level of significance (see Row (3) Table 3.3) . However, the p-value of K-S test that compares GPCP 2.0 and 2.2

is 0.05 (see Row (3) Table 3.4). This indicates that the null hypothesis is rejected at the 5% level and there is evidence that the empirical cumulative distributions of the rainfall shocks from the GPCP 2.0 and 2.2 datasets are not identical.

The final pair to be considered are GPCP 2.1 and 2.2. The p-value of the K-S test for this pair is 0.05 ((see Row (3) Table 3.5)). This indicates that null hypothesis is rejected at 5% and the empirical cumulative distributions between GPCP 2.1 and 2.2 are not identical.

Overall, the difference between GPCP 2.0 and 2.1 is not large enough for the K-S test to be rejected at standard significance level. However, the revision from GPCP 2.1 to 2.2 is significant enough for the K-S test to be rejected. Thus, it will be interesting to see if the statistically significant effect of rainfall on conflict in MMS still holds up with the revision.

## 3.3 Implication of Data Revisions

We first investigate how using the revised rainfall and conflict datasets may affect the estimates of rainfall shocks on conflict. As a benchmark, we estimate a two-way fixed effect model:

$$y_{it} = \sum_{k=0}^{2} \beta_k \Delta R_{it-k} + c_i + \mu_t + \epsilon_{it}, i = 1...N, t = 1...T \tag{3.1}$$

where $y_{it}$ represents one of the three indicators of conflict, i.e. conflict incidence, war incidence, or conflict onset, for country $i$ at year $t$, and $\Delta R_{it-k}$ represents rainfall shocks in country $i$ and year $t-k$ and is defined as the growth in rainfall levels (i.e. $\Delta R_{it-k} = (R_{it-k} - R_{it-k-1})/R_{it-k}$). In Eq. (3.1), we include rainfall shocks up to the second lag following MMS (i.e. $k = 0, 1, 2$) so as to capture the potential lagged effects of rainfall shocks on conflict. For the unobserved components in Eq. (3.1), $c_i$ represents the set of the country fixed effects that capture all the unobserved permanent differences across countries,[9] $\mu_t$ represents the set of year fixed effects

[9]Quality of governmental institute can be a time invariant factor.

that capture all macroeconomic shocks that have identical effects on countries,[10] and $\epsilon_{it}$ is the idiosyncratic error term. Our interest lies in estimating $\beta_k$. It reflects the change in the likelihood of civil conflict, war, or conflict onset when rainfall growth increases by one percentage point.

As a benchmark, we first estimate the effect that rainfall shocks have on conflicts using the datasets used originally by MMS. Then, we re-estimate this effect using a newer version of the rainfall dataset, conflict dataset, or both, for the same set of 41 countries and years from 1981 to 1999 as considered by MMS.

For the sake of presentation, the actual two-way fixed effects estimates of effect of rainfall shocks on conflicts, corresponding to each version of the GPCP rainfall and ACD conflict datasets, are relegated to Table 20 in the appendix. Instead, we summarize the statistical significance of the contemporaneous effects of rainfall shocks on conflict incidence (as the dependent variable in Eq. (3.1)), war incidence, and conflict onset in Table 3.6. The statistical significance of the lagged effect of rainfall shocks on conflict is summarized in Table 3.7.

[10]These macroeconomic shocks could be commodity price shocks.

Table 3.6: Significant level of $\Delta R_{it}$ on conflicts (1981-1999)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2004 | No | No | No |
| ACD 2010 | No | No | No |
| ACD 2015 | No | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2004 | No | No | No |
| ACD 2010 | No | No | No |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2004 | Yes(5%) | No | No |
| ACD 2010 | Yes(10%) | Yes(5%) | Yes(10%) |
| ACD 2015 | No | No | No |

Using the GPCP 2.0 rainfall and ACD 2004 conflict datasets, we have successfully replicated MMS' estimate of the impact of contemporary and lagged (first lag) rainfall shocks on conflict incidence, war incidence, and conflict onset (see panel A of Table 20 in the appendix). As Table 3.6 shows, the effect of contemporary rainfall shocks ($\Delta R_{it}$) on war incidence is statistically significant at 5%. Additionally, the estimated effect of lagged rainfall shocks ($\Delta R_{it-1}$) on conflict incidence, war incidence, and conflict onset are all statistically significant at least at the 5% level. Thus, if we estimate the effect of rainfall shocks on conflicts using the GPCP 2.0 and ACD2004 datasets, we would conclude that rainfall shocks, especially their first lag, can explain conflict in the SSAs.

Table 3.7: Significant level of $\Delta R_{it-1}$ on conflicts (1981-1999)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2004 | Yes(5%) | Yes(10%) | Yes(10%) |
| ACD 2010 | No | Yes(10%) | Yes(10%) |
| ACD 2015 | No | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2004 | Yes(10%) | No | No |
| ACD 2010 | No | No | No |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2004 | Yes(5%) | No | No |
| ACD 2010 | No | Yes(5%) | Yes(10%) |
| ACD 2015 | No | Yes(5%) | No |

However, when the updated rainfall and/or conflict datasets are used to estimate the impact of rainfall shocks in the contemporary and lagged one level on conflict, the impact estimates may become statistically insignificant. For example in Panel C Table 3.6, when we maintain the GPCP 2.0 rainfall dataset as MMS did, but use the revised conflict dataset ACD 2015, the estimated effect of rainfall shocks in contemporary level ($\Delta R_{it}$) on war incidence now become statistically insignificant. The second example is in Panel B and C Table 3.7. When we *maintain the ACD 2004 conflict dataset* as MMS did, but use the revised rainfall dataset (i.e. GPCP 2.1 or GPCP 2.2), the estimated effect of rainfall shocks in lagged one ($\Delta R_{it-1}$) on conflict onset and war incidence now become statistically insignificant (the effect on conflict incidence is still statistically significant). Likewise, when we *maintain the use of the GPCP 2.0 rainfall dataset* as MMS did, but use the revised conflict datasets (i.e. ACD 2010 and 2015), all the rainfall shock estimates in lagged one ($\Delta R_{it-1}$) that were once statistically significant, as reported in MMS, now become statistically insignificant on incidence, war, and onset (see Panel A, B and C Table 3.7).

Finally, when the latest conflict (ACD2015) and rainfall (GPCP2.2) datasets are employed jointly, the effect of rainfall shocks in contemporary and lagged one level ($\Delta R_{it}$ and $\Delta R_{it-1}$) on conflict incidence and onset and on war incidence are all statistically insignificant in Table 3.6 and 3.7. Therefore, the statistically significant effect of rainfall shocks on conflict, as found by MMS, is not robust to the revision of the rainfall and conflict datasets. Furthermore, compared to conflict data revision, rainfall data revision changes the estimated coefficients more in the estimation. This is because when the rainfall data version is revised to GPCP 2.1 and 2.2, more estimated coefficients turn to be statistically insignificant.[11]

### 3.3.1 Extending the Sample Period

We conduct a series of robustness checks toward previous results about how estimates of statistical significance in MMS disappears after conflict and rainfall data are revised. Firstly, we extend the observational year. Secondly, we add one more time-lagged rainfall variable in the estimation.

In the previous exercise, the sample period is restricted to 1981 to 1999 and is consistent with what MMS have considered. Here, we repeat the exercise with the same 41 countries but with data stretching from 1981 to 2009 in the two-way fixed effect model. For the sake of presentation, the estimates of the effect of rainfall shocks on conflicts corresponding to the most recent conflict data (ACD 2015) and each version of rainfall data (GPCP 2.0, 2.1 and 2.2) are documented in the appendix (see Table 21). We then summarize the statistical significance of the contemporaneous and lagged one effects of rainfall shocks ($\Delta R_{it}$ and $\Delta R_{it-1}$) on conflict incidence, conflict onset and war incidence in Table 3.8 and 3.9.

As Table 3.8 shows, the contemporary rainfall shocks ($\Delta R_{it}$) on all conflict variables (incident, onset and war) are not statistically significant when conflict data

[11]Please refer to Table 3.6 and 3.7 above.

is ACD 2015 and rainfall data is varied from GPCP 2.0 to GPCP 2.1 and GPCP 2.2. For the estimates of lagged one rainfall shocks ($\Delta R_{it-1}$) on all conflict variables (incident, onset and war), Table 3.9 shows that they are statistically insignificant as conflict data is ACD 2015 and rainfall data is GPCP 2.0, 2.1 and 2.2.

Table 3.8: Significance level of $\Delta R_{it}$ on conflicts (1981-2009)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2015 | No | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2015 | No | No | No |

Table 3.9: Significance level of $\Delta R_{it-1}$ on conflicts (1981-2009)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2015 | No | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2015 | No | No | No |

### 3.3.2 Including the Second Lag of Rainfall Shocks

In this subsection, we follow Ciccone (2011) and Miguel and Satyanath (2011) to add the second lag of rainfall shocks $\Delta R_{it-2}$ and estimate the effect of rainfall shocks on conflicts (conflict incident, onset and war incident) with the same 41 countries and time span (1981-2009) in the two-way fixed effect model. The detail about the estimates of the effect of rainfall shocks on conflicts are recorded in Panel B

Table 21 in appendix. We then summarize the significance level of these estimates in Table 3.10, 3.11 and 3.12 and find that the significance level of these estimates disappears when rainfall data is revised from GPCP 2.0 to GPCP 2.1 and 2.2 and conflict data is ACD 2015. Take conflict incident as an example, the impacts of rainfall shocks in time lagged one and two ($\Delta R_{it-1}$ and $\Delta R_{it-2}$) on conflict incident becomes statistically insignificant when rainfall data is revised from GPCP 2.0 to GPCP 2.1 or 2.2 and conflict data is ACD 2015 (see Table 3.11 and 3.12). When the newest rainfall and conflict datasets are jointly used (GPCP 2.2 and ACD 2015), the contemporary, time lag one and two of rainfall shocks ($\Delta R_{it}$, $\Delta R_{it-1}$ and $\Delta R_{it-2}$) on three conflict variables (conflict incident, onset and war incident) remain statistically insignificant.

Table 3.10: Significance level of $\Delta R_{it}$ on conflicts (1981-2009)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2015 | No | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2015 | No | No | No |

Table 3.11: Significance level of $\Delta R_{it-1}$ on conflicts (1981-2009)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2015 | Yes(5%) | Yes(10%) | No |
| Panel B: Conflict Onset | | | |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2015 | No | No | No |

Table 3.12: Significance level of $\Delta R_{it-2}$ on conflicts (1981-2009)

| Panel A: Civil Conflict Incident | | | |
|---|---|---|---|
| | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| ACD 2015 | Yes(5%) | No | No |
| Panel B: Conflict Onset | | | |
| ACD 2015 | No | No | No |
| Panel C: War Incident | | | |
| ACD 2015 | No | No | No |

## 3.4 Cross-Sectional Dependence

The two-way fixed effects estimator above does not take into account of potential cross-sectional dependence. However, cross-sectional dependence may arise due to the fact that rainfall shocks are spatially dependent and conflicts may spill across borders. Therefore, estimated coefficients in the two-way fixed effects estimator are expected to be upward biased, which leads to over-rejection of the null hypothesis if cross-sectional dependence is not controlled for in the panel model.

### 3.4.1 Are Rainfall shocks and Conflict Cross-Sectionally Dependent?

To test if rainfall shocks are cross-sectionally dependent, we apply the cross-sectional dependence (CD) test of Pesaran (2004). CD test is a simple test to examine error term cross section dependence in the panel model. In the cross section dependence literature, spacial dependence test of Moran (1948) and Lagrange Multiplier approach of Breusch and Pagan (1980) or LM Test are commonly used. However, there are problems in these tests. For instance, spatial information is required to construct a spatial weight matrix in the Moran (1948)'s test.[12] But, this spatial

[12]This spatial information could be economic distance information such as trade or output patterns. For more information, please see Baltagi, Song and Koh (2003).

information is hard to obtain and it is not accurate to use this spatial information to justify the dependence in the panel model even though spatial weight matrix is constructed (Pesaran 2004). In the LM test, panel models must have a fixed number of N and T must be very large. If T is small, LM test is not applicable (Pesaran 2004). However, the CD test is applicable to the panel model that is with short T and does not require spatial information. Given there is only 28 years in my panel model, CD test is more suitable for this study. Specifically, the CD test is based on average of pair-wise correlation coefficients of the OLS residuals in the panel model. In this study, the CD tests evaluates the null hypothesis that the contemporaneous or lagged rainfall shocks are cross sectionally *independent*. A rejection of the CD test (at some conventional level of significance) suggests that rainfall shocks are cross-sectionally dependent.

From Table 3.13, the CD test for the cross-sectional dependence of rainfall shocks, both their contemporaneous values and lags, can be rejected at the 1% level. This is not surprising as the literature suggests that rainfall is spatially dependent (Auffhammer et al. 2013).

Table 3.13: Cross-section Independence Test on rainfall shocks(1981-2009)

| Variable | CD-test | p-value |
|---|---|---|
| $\Delta R_{it}$ | 29.52 | 0.000 |
| $\Delta R_{it-1}$ | 28.23 | 0.000 |
| $\Delta R_{it-2}$ | 31.05 | 0.000 |

The rainfall data is GPCP 2.2. The CD-test is proposed by Pesaran (2004).

In the SSAs, there are significant cross-border conflict spillovers. To demonstrate this, we follow Bosker and de Ree (2014) to use ACD 2015 conflict dataset and to construct a conflict spillover index for country $i$ based on:

$$spillover_i = \frac{\sum_{t=1981}^{t=2009} c_{it}^*}{\sum_{t=1981}^{t=2009} c_{it}} \tag{3.2}$$

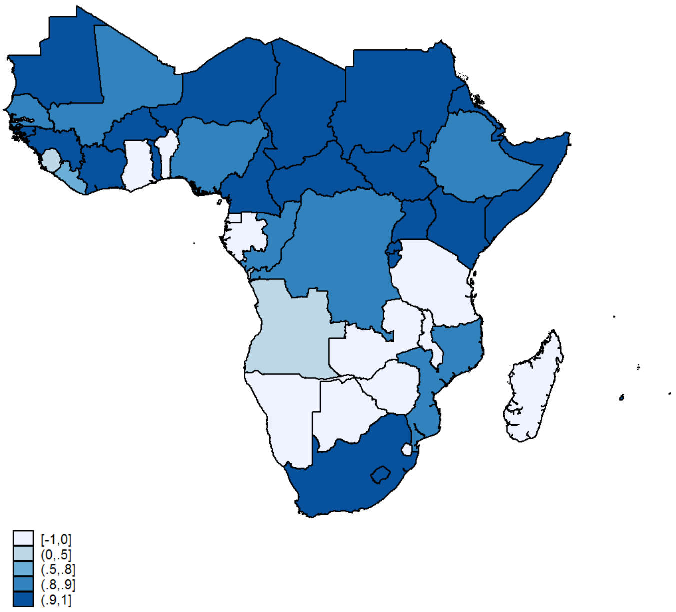
The denominator of this index is $\sum_{t=1981}^{t=2009} c_{it}$ and represents the total number of conflict in country $i$ from 1981 to 2009. The numerator of spillover index is $\sum_{t=1981}^{t=2009} c_{it}^{*}$ and is summing up the conflict in country $i$ and year $t$ conditional on whether its any neibhbouring countries have experienced conflicts in $t-3$.[13] Take Niger as an example, there are 7 civil conflict incidents from 1981 to 2009 according to ACD 2015 conflict dataset and then $\sum_{t=1981}^{t=2009} c_{it}$ is 7. If 6 out of these 7 conflicts were happening when any Niger's neighbouring countries had also experienced conflict in the last three year,[14] $\sum_{t=1981}^{t=2009} c_{it}^{*}$ is 6. Then, the spillover index for Niger is about 0.86 (6/7). This index is ranged from 0 to 1 and captures the conditional probability that conflict from one country spreads to another. If this index is equal to 1 (0), this indicates that a civil conflict incident in one country can spill over to other neighbouring countries with a probability of 1 (0).

For the sake of presentation, we document the result in Figure 3.1 below. Countries like Benin, Botswana, Gabon, Madagascar, Malawi, Namibia, Swaziland and Tanzania getting -1 in the spillover index and -1 indicates that there is no conflict from 1981 to 2006 for these countries. The rest of SSA countries has experienced at least one civil conflict incident from 1981 to 2009 according to ACD 2015 conflict dataset. For example, Ghana experienced 2 civil conflict incidents (one was in 1981 and another one was in 1983). As neighbouring countries of Ghana (Ivory Coast, Togo and Burkina Faso ) had not encountered any civil conflict incident three years before Ghana experienced these two civil conflicts, the spillover index for Ghana is 0. Nearly half countries in SSA that has experienced civil conflicts from 1981 to 2009 scores 0.5 above in the spillover index. Countries like Liberia, Central African Republic, Somalia, Kenya, Uganda, Democratic Republic of Congo, Sudan, Chad, Nigeria, South Africa and Lesotho score close to or even equal to 1 in the spillover index. To sum up, it may be common to see conflicts spilling over across border and countries are cross-sectionally dependent to each other according to the computation of the spillover index.

[13]Neighbouring countries are defined as countries share the same border with country $i$

[14]Neighbouring countries of Niger are Nigeria, Mali, Chad, Burkina Faso and Benin.

Figure 3.1: Conflict spillover in SSA




*Note*: -1 means no conflicts; 0 means no spillover effect. Higher spillover index in country $i$ indicates conflicts from neighboring countries spillover to country $i$ with a higher probability.

In the presence of cross-sectional dependence, it will be more appropriate to employ panel regressions with interactive fixed effects. Thus, we estimate:

$$y_{it} = \sum_{k=0}^{2} \beta_k' \Delta R_{it-k} + \gamma_i' f_t + v_{it}, \quad i = 1...N, \ t = 1...T \tag{3.3}$$

where $f_t$ represents the set of unobserved common factors and $\gamma_i$ represents the set of factor loadings possibly unique to each country $i$. $v_{it}$ is the idiosyncratic error term. The term $\gamma_i' f_t$ represents what is known as interactive fixed effects. Pesaran (2006) argues that these interactive fixed effects are more suitable than the additively structured two-way fixed effects, in that they can absorb all confounding country permanent differences, as well as common (i.e. macroeconomic) factors and country-specific policy shocks regardless of their stationarity properties and whether they have impact countries homogeneously or heterogeneously.

Interactive fixed effects are powerful. They can absorb all confounding country permanent differences, common (i.e. macroeconomic) factors and country-specific policy shocks regardless of their stationarity properties and their homogeneous/heterogeneous impacts on countries (Chudik, Pesaran and Tosetti, 2011; Chudik and Pesaran, 2013). They may also address the confounding influence of dependence across space (Pesaran and Tosetti, 2011), which, in our context, may arise because of spatial dependence in weather patterns and therefore in rainfall shocks, or because of cross-border conflict spillovers.[15] Importantly, the CCE estimator subsumes the two-way fixed effects estimator as a special case (Pesaran, 2006). Therefore, panel regressions with interactive fixed effects will be consistent if the two-way fixed effects estimator is consistent, and may still be so even if the two-way fixed effects estimator is not.

To estimate $\beta_k'$ in a panel regression with interactive fixed effects, we employ the Common Correlated Effects (CCE) estimator of Pesaran (2006). The CCE approach is based on the idea that the observable covariates of the model (in this case, $y_{it}$, $\Delta R_{it-k}$) are correlated with the unobserved factors captured by the vector $f_t$ in Eq. (3.3). Because of their correlation, we may use the observable covariates to construct proxies for $f_t$ and control for it.

To do so, observe that the covariates (i.e. $y_{it}$, $\Delta R_{it-k}$) have both cross-sectional and time variation, while unobservable factors (i.e. $f_t$) only have time variation. Thus, we first transform the observable covariates into variables that only have time variation. This is done by averaging them across space, i.e. $\overline{y}_{\cdot t} = \sum_{i=1}^{N} y_{it}/N$, $\overline{\Delta R}_{\cdot t} = \sum_{i=1}^{N} \Delta R_{it}/N$. Then, we use these cross-sectional averages as proxies for $f_t$ by including these averages as control variables. Pesaran (2006) shows that under mild regularity conditions,[16] $\beta_k'$ can be estimated using the pooled mean-group OLS estimator. He also shows that inference can be implemented using the approach of Newey and West (1986) to correct for heteroskedasticity and autocorrelated standard errors.[17]

[15] To appreciate how cross-sectional dependence can be captured by interactive fixed effects, consider an event in time $t$. This could be a macroeconomic event, or an event arising from a country. Different countries are exposed differently to this event, as reflected by each country's factor loading. However, as all countries are affected by it, although with varying intensities, this unobserved event would cause the countries to be cross-sectionally dependent.

[16] For these conditions, see page 972 to 975 in Pesaran (2006).

[17] The CCE estimator requires both large $N$ and $T$. Through a Monte Carlo exercise, Pesaran (2006) shows that the CCE estimator works well with N=30 and T=20. This is easily satisfied by

### 3.4.2 CCE Estimation Results

The conclusion in the previous section about the effect of rainfall shocks on conflicts is based on the conventional two-way fixed effect panel model as MMS that overlooks the problem of cross-sectionally dependence arising from spatial weather pattern and conflict spillovers. Therefore, we change our estimator from two-way fixed effect model to CCE estimator that is designed to tackle cross-sectional dependence while the observational years is between 1981 and 2009 with the same observational countries as MMS to study the effect of rainfall shocks on conflicts. Details about results from CCE estimation are shown in the Panel A, Table 22 of Appendix and then significant level of these estimates are summarized in Table 3.14 and 3.15. As we can see, the effect of lagged rainfall shock $\Delta R_{it-2}$ on war incident is statistically significant at 10% level.

Table 3.14: Significant level of rainfall shocks on conflicts in CCE (1981-2009)

| | GPCP 2.2 and ACD 2015 | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $\Delta R_{it}$ | No | No | No |
| $\Delta R_{it-1}$ | No | No | No |

Table 3.15: Significant level of rainfall shocks on conflicts in CCE (1981-2009)

| | GPCP 2.2 and ACD 2015 | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $\Delta R_{it}$ | No | No | No |
| $\Delta R_{it-1}$ | No | No | No |
| $\Delta R_{it-2}$ | No | No | Yes(10%) |

our sample of N=41 and T=29. However, Totty (2017) reports that the CCE would produce nearly identical $t$-statistics with or without bootstrapping. Therefore, we decide to report Newey-West robust standard errors in this paper.

## 3.5 The Functional Form of Rainfall

In MMS, the rainfall variable that enters into the econometric model of conflict is rainfall shock, which is defined as the growth in rainfall. This specification of rainfall has been a subject of much debate. For example, Ciccone (2011) argues that the relationship between rainfall and conflicts is spurious when the rainfall functional form is rainfall shocks as MMS due to the property of mean reversion in the rainfall data and suggests to use log rainfall to address the problem of mean reversion.[18] Moreover, Dell, Jones and Olken (2014) and Hidalgo et al. (2010) suggest to use rainfall functional form of mean deviation in order to address substantial variations arising from extreme weather.

In the baseline, as MMS, rainfall shocks are our main regressor. Here, we consider using different functional forms of rainfall. First, we consider using the log of rainfall, denoted by $\log R_{it}$, Second, we consider the mean deviation of rainfall ($MdR_{it}$), which is computed as,

$$MdR_{it} = \frac{R_{it} - \bar{R}}{\sigma},$$

where $R_{it}$ is same as before as rainfall level for country $i$ and year $t$, $\bar{R}$ and $\sigma$ are the mean and standard deviation of rainfall for country $i$ in the whole observational years (1981-2009).

Table 3.16: Significant level of log(rainfall) on conflicts in CCE

| | GPCP 2.2 and ACD 2015 (1981-2009) | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $\log(R_{it})$ | No | No | No |
| $\log(R_{it-1})$ | No | No | No |

[18] Mean reversion of rainfall data implies that there is a long run equilibrium in the rainfall data and temporarily deviation from the mean at any period will return to normal in the future. In other words, a negative (positive) rainfall shock in year t is followed by positive (negative) rainfall shock in the future.

Table 3.17: Significant level of log(rainfall) on conflicts in CCE

| | GPCP 2.2 and ACD 2015 (1981-2009) | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $\log(R_{it})$ | No | No | No |
| $\log(R_{it-1})$ | No | No | No |
| $\log(R_{it-2})$ | No | No | Yes(10%) |

Table 3.18: Significant level of mean deviation rainfall on conflicts in CCE

| | GPCP 2.2 and ACD 2015 (1981-2009) | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $MdR_{it}$ | No | No | No |
| $MdR_{it-1}$ | No | No | No |

Table 3.19: Significant level of mean deviation rainfall on conflicts in CCE

| | GPCP 2.2 and ACD 2015 (1981-2009) | | |
|---|---|---|---|
| | Civil conflict incident | conflict onset | War incident |
| $MdR_{it}$ | No | No | No |
| $MdR_{it-1}$ | No | No | No |
| $MdR_{it-2}$ | Yes(10%) | No | Yes(10%) |

We document all the details about estimates of the effect of rainfall when the estimator is CCE and the main regressors are log and mean deviation rainfall in Table 22 and summarize the significant levels of these estimates in Table 3.16 to 3.19. As we can see, the effect of time-lagged two rainfall in log and mean deviation forms remain statistically significant at 10% level on civil conflict incident and war incident.

Furthermore, we find that the difference between estimated coefficients in CCE estimator (Table 3.16-3.19) with different function forms (log and mean deviation) and the ones in traditional two-way fixed effect panel model (Table 3.10-3.12) is small. This may indicate that the bias due to cross-sectional dependence in the panel model is small. However, the CCE estimator is more suitable than the traditional two-way fixed effect panel model to understand the link between rainfall and conflict even though the role of cross-sectional dependence may be trivial.

## 3.6 Conclusion

In their seminal work, Miguel, Satyanath and Sergenti (2004) have shown that rainfall shocks have a statistically significant effect in increasing the incidence of civil conflict in sub-Saharan Africa. Their result was obtained based on the ACD 2004 conflict and GPCP 2.0 rainfall datasets, which had since been revised twice. In this article, we explore if the statistical significance of their impact estimates is robust to using the revised rainfall and conflict datasets. For the same set of 41 countries and 1981-1999 period considered by Miguel, Satyanath and Sergenti (2004), we find that using the most recently revised rainfall and conflict datasets (i.e. GPCP 2.2 and ACD 2015) will drive out the statistically significance of rainfall shocks for civil conflict, civil war incidence, and civil conflict onset. The statistical insignificance of these estimates remains even as we consider various functional forms for rainfall, extend the dataset to 2009, and include a second lag of rainfall shocks as a regressor. Finally, we find that there is cross-sectional dependence in rainfall shocks and conflict. However, even when we take cross-sectional dependence into account, it does not restore the statistical significance of rainfall shocks seen in Miguel, Satyanath and Sergenti (2004). This calls into question if rainfall shocks do affect civil conflict in sub-Saharan Africa, as there is no evidence to suggest that this is true once the latest rainfall and conflict datasets are used.

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Table 20: Rainfall shocks on Conflict from 1981-1999 (Two-way Fixed Effects)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Rainfall Dataset | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| Dependent Variable | Civil Conflict Incident $\geq$ 25 deaths | | | Conflict Onset | | | War Incident $\geq$ 1000 deaths | | |
| Panel A: Conflict Dataset ACD2004 | | | | | | | | | |
| $\Delta R_{it}$ | -0.0238 | -0.0187 | -0.0295 | -0.0625 | -0.0776 | -0.0731 | -0.0625** | -0.0429 | -0.0438 |
| | (0.0432) | (0.0422) | (0.0415) | (0.0477) | (0.0487) | (0.0517) | (0.0299) | (0.0326) | (0.0348) |
| $\Delta R_{it-1}$ | -0.1219** | -0.1027* | -0.1140* | -0.1202* | -0.1035 | -0.1083 | -0.0687** | -0.0413 | -0.0193 |
| | (0.0518) | (0.0588) | (0.0605) | (0.0681) | (0.0746) | (0.0757) | (0.0316) | (0.0297) | (0.0313) |
| Panel B: Conflict Dataset ACD2010 | | | | | | | | | |
| $\Delta R_{it}$ | -0.0677 | -0.1168 | -0.1135 | -0.0648 | -0.0732 | -0.0704 | -0.0768* | -0.0939** | -0.0826* |
| | (0.0627) | (0.0751) | (0.0803) | (0.0596) | (0.0546) | (0.0564) | (0.0445) | (0.0364) | (0.0418) |
| $\Delta R_{it-1}$ | -0.0835 | -0.0909* | -0.1138* | -0.1009 | -0.0743 | -0.0880 | -0.0537 | -0.0730** | -0.0537* |
| | (0.0552) | (0.0503) | (0.0612) | (0.0625) | (0.0644) | (0.0674) | (0.0385) | (0.0316) | (0.0293) |
| Panel C: Conflict Dataset ACD2015 | | | | | | | | | |
| $\Delta R_{it}$ | -0.0251 | -0.0840 | -0.0784 | 0.0033 | -0.0021 | 0.0057 | -0.0327 | -0.0597 | -0.0466 |
| | (0.0629) | (0.0787) | (0.0834) | (0.0514) | (0.0341) | (0.0343) | (0.0411) | (0.0371) | (0.0428) |
| $\Delta R_{it-1}$ | -0.0444 | -0.0549 | -0.0766 | 0.0032 | 0.0194 | 0.0182 | -0.0264 | -0.0492** | -0.0288 |
| | (0.0502) | (0.0491) | (0.0590) | (0.0480) | (0.0474) | (0.0480) | (0.0305) | (0.0237) | (0.0216) |

The intercept and observation number are not reported. Country fixed effect and country specific time trend are included. Robust standard errors clustered at the country level are in the parentheses.
***p<0.01,**p<0.05,*p<0.1

Table 21: Rainfall Shocks on Conflict from 1981-2009 (Two-way Fixed Effects)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Conflict Dataset ACD2015 | | | | | | | | | |
| Rainfall Dataset | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 | GPCP 2.0 | GPCP 2.1 | GPCP 2.2 |
| Dependent Variable | Civil Conflict Incident >= 25 deaths | | | Conflict Onset | | | War Incident >= 1000 deaths | | |
| Panel A: One lag | | | | | | | | | |
| $\Delta R_{it}$ | 0.0458 | 0.0117 | 0.0299 | 0.0476 | 0.0252 | 0.0303 | -0.0111 | -0.0044 | 0.00357 |
| | (0.0485) | (0.0503) | (0.0509) | (0.0400) | (0.0212) | (0.0223) | (0.03360) | (0.0405) | (0.0439) |
| $\Delta R_{it-1}$ | -0.0286 | -0.0389 | -0.0400 | 0.0337 | 0.0297 | 0.0323 | -0.0040 | 0.0022 | 0.0115 |
| | (0.0424) | (0.0335) | (0.0394) | (0.0360) | (0.0253) | (0.0261) | (0.0256) | (0.0200) | (0.0253) |
| Panel B: Two lags | | | | | | | | | |
| $\Delta R_{it}$ | 0.0220 | 0.0034 | 0.0314 | 0.0153 | 0.0037 | 0.0263 | -0.0329 | -0.0194 | -0.0130 |
| | (0.0492) | (0.0479) | (0.0443) | (0.0395) | (0.0168) | (0.0203) | (0.0399) | (0.0422) | (0.0474) |
| $\Delta R_{it-1}$ | -0.0992** | -0.0829* | -0.0570 | 0.0060 | -0.0014 | 0.0379 | -0.0417 | -0.0225 | -0.0172 |
| | (0.0507) | (0.0482) | (0.0497) | (0.0305) | (0.0147) | (0.0255) | (0.0365) | (-0.0274) | (0.0399) |
| $\Delta R_{it-2}$ | -0.0909** | -0.0370 | -0.0384 | 0.0112 | 0.0105 | 0.0112 | -0.0554 | -0.0326 | -0.0438 |
| | (0.0416) | (0.0421) | (0.0413) | (0.0153) | (0.0205) | (0.0205) | (0.0448) | (0.0354) | (0.0386) |

The intercept is not reported.Robust standard errors clustered at the country level are in the parentheses.
***p<0.01,**p<0.05,*p<0.1

Table 22: Rainfall on Conflict from 1981-2009 (CCE estimator)

| | (1) | (2) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| Conflict Dataset: ACD 2015 and Rainfall Dataset:GPCP2.2 | | | | | | |
| Dependent Variable | Conflict Incident >= 25deaths | | Conflict Onset | | War Incident >= 1000death | |
| Panel A: Rainfall Shock | | | | | | |
| $\Delta R_{it}$ | 0.0294 | 0.0380 | 0.0259 | 0.0297 | -0.0051 | -0.0257 |
| | (0.0568) | (0.0634) | (0.0211) | (0.0228) | (0.0302) | (0.0328) |
| $\Delta R_{it-1}$ | -0.0482 | -0.0782 | 0.0217 | 0.0268 | 0.0052 | -0.0244 |
| | (0.0573) | (0.0695) | (0.0305) | (0.0310) | (0.0314) | (0.0380) |
| $\Delta R_{it-2}$ | | -0.0629 | | 0.0116 | | -0.0566* |
| | | (0.0649) | | (0.0206) | | (0.0334) |
| Panel B: log Rainfall | | | | | | |
| $\log(R_{it})$ | 0.0564 | 0.0640 | 0.0497 | 0.0466 | -0.0426 | -0.0386 |
| | (0.0640) | (0.0642) | (0.0330) | (0.0306) | (0.0390) | (0.0403) |
| $\log(R_{it-1})$ | -0.0389 | -0.0379 | 0.0188 | 0.0165 | -0.0424 | -0.0363 |
| | (0.0656) | (0.0705) | (0.0337) | (0.0366) | (0.0399) | (0.0417) |
| $\log(R_{it-2})$ | | 0.0285 | | 0.0079 | | -0.0694* |
| | | (0.0662) | | (0.0329) | | (0.0384) |
| Panel C: Mean Deviation Rainfall | | | | | | |
| $MdR_{it}$ | 0.0127 | 0.0051 | 0.0050 | 0.0041 | -0.0023 | -0.0019 |
| | (0.0105) | (0.0047) | (0.0048) | (0.0046) | (0.0064) | (0.0065) |
| $MdR_{it-1}$ | -0.0156 | -0.0192* | -0.0001 | -0.0001 | -0.0081 | -0.0093 |
| | (0.0109) | (0.0109) | (0.0060) | (0.0063) | (0.0075) | (0.0075) |
| $MdR_{it-2}$ | | -0.0021 | | 0.0024 | | -0.0121* |
| | | (0.0108) | | (0.0051) | | (0.0071) |

The intercept is not reported.Robust standard errors clustered at the country level are in the parentheses. ***p<0.01,**p<0.05,*p<0.1

# Chapter 4

# The Effect of Agricultural Innovation on Economic Development: Can Genetically-Modified Crops Abate Conflicts ?

WEIDONG LIANG
School of Economics, University of Adelaide

**Abstract:** This study investigates the new productivity-enhancing technology in agriculture– the adoption of Genetically-Modified (GM) soybeans– on internal conflicts. A conceptual model is constructed to show that an improvement in agricultural productivity induced by adoption of GM soybeans can reduce land value and mitigate land-related conflicts. Additionally, we employ the Difference-in-Differences (DD) estimation to capture variations from: 1) a policy experiment on the commercial legalization of GM soybean cultivation in 2003 in Brazil and 2) land suitability of cultivating this crop and examine the effect of these variations on land conflicts. Results in the DD estimation show that GM soybean cultivation is negatively associated with the number of land conflicts, the number of people and family participated in land conflicts.

# Statement of Authorship

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## Principal Author

| | | | |
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| Name of Principal Author (Candidate) | Weidong Liang | | |
| Contribution to the Paper | This paper is written by a sole author (the candidate) | | |
| Overall percentage (%) | 100% | | |
| Certification: | This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper. | | |
| Signature | Weidong Liang | Date | 12/01/2018 |

## 4.1 Introduction

In developing countries, internal conflicts are closely related to agricultural shocks. One possible explanation is that the incomes of developing countries tend to be highly dependent on the agricultural sector (Gollin 2010). Since conflicts are found to be associated with low incomes (Collier and Hoeffler 1998), a negative shock to the agricultural sector may give rise to conflicts in agriculturally dependent countries (Miguel, Satyanath and Sergenti 2004).[1] As such, technologies that lead to an improvement in agricultural productivity, and therefore income, may reduce the incidence of internal conflicts in developing countries.[2]

In this paper, we address the question of whether productivity-enhancing technologies in agriculture can help to mitigate internal conflicts. To do so, we exploit a policy experiment in Brazil – the legalization of Genetically-Modified (GM) soybean cultivation – to study how the adoption of a productivity-enhancing agricultural technology may affect land conflicts. In 2003, the Brazilian federal government legalized the cultivation of GM soybeans that are more robust and therefore more productive than traditional soybeans. Since the inception of this policy, the adoption rate of GM soybeans in soybean harvest areas in Brazil rose quickly from 46.4% in 2005 to 93% in 2016 (IBGE 2006; USDA 2016). According to FAO (2013), Brazil is the second largest soybean producer in the world with a production of 86.8 million metric tons in 2013. After the legalization of GM soybean cultivation in 2003, Brazil has also become the second biggest GM crop producer in the world with 44.2 million hectares of land being used to cultivate GM crops (James 2015).

Over the past decades, Brazil has experienced numerous internal conflicts associated with land invasions. According to Girardi (2015), there have been over 9,400

[1] Miguel, Satyanath and Sergenti (2004) show that a reduction in agricultural income that is approximated by a decrease in rainfall leads to a higher conflict likelihood in countries where incomes heavily rely on the agricultural sector.

[2] The enhancement of agricultural productivity can expand income and sustain long-run economic growth (Gollin, Parente and Rogerson 2002; Self and Grabowski 2007). This is because, according to Johnston (1951), improvement of agricultural productivity can release labor from the agriculture sector to the non-agriculture sectors and encourage capital formation. Thereby, structural transformation and industrialization can be initiated (Johnston and Mellor 1961). Consequently, agricultural productivity improvement can increase income.

land conflicts in Brazil, involving several million people and over 1,300 deaths. Our contribution is to show that the adoption of GM soybean cultivation could help to mitigate this problem, and thus, the GM technologies in agriculture could help to reduce internal conflicts in agriculturally dependent countries in general. The idea is that the adoption of GM soybeans would help to increase agricultural productivity by improving labor and land use efficiency (Bustos et al. 2016).[3] Given that the demand for agricultural products is inelastic (Van Driel, Nadall and Zeelenberg 1997), agricultural productivity enhancement would in turn lead to a fall in agricultural prices and therefore in agricultural land value (Iyigun, Nunn and Qian, 2015). In the context of Brazil, Barrows, Sexton and Zilberman (2014*b*) show that the agricultural productivity improvement arising from the commercial legalization of GM soybean cultivation is followed by a decline in the soybean price. If this causes agricultural land to depreciate as theory suggests,[4] and agricultural land is the reward for winners in land conflicts, then land conflicts could decline in major soybean cultivation regions once GM soybean cultivation was legalized.

Empirically, we employ the Difference-in-Differences (DD) estimation approach to examine the effect of GM soybean farming on land conflicts. Our estimation design makes use of two sources of variations: 1) the legalization of GM soybean cultivation in 2003 in Brazil, and 2) the cross-sectional differences arising from the size of suitable land for soybean cultivation in Brazilian states. Specifically, our approach exploits the legalization of GM soybean cultivation in Brazil as the treatment, where states with large tracts of suitable land for cultivating soybeans are the treatment group, and states with smaller tracts are the control group. If GM soybean cultivation as an agricultural productivity-enhancing technology is irrelevant for land conflicts, the policy should not affect land conflicts in both treatment and control groups differently. However, if it is relevant, land conflicts should be reduced

[3]Land productivity is improved because GM soybean cropping enables farmers to do double-cropping (Sharma et al. 2002 and Barrows, Sexton and Zilberman 2014*a*).

[4]Huang et al. (2004) provide empirical evidence to show that the prices of agricultural land that is used for cultivating GM crops decline while the crop prices reduce after the GM crops are adopted in China.

in major soybean cultivation states after the legalization of GM soybeans.

Our DD estimation results show that adopting GM soybeans as an agricultural productivity-enhancing technology can abate land conflicts. Its mitigating impact on land conflicts is sizable. For example, states that owns 1% more land that is suitable for growing GM soybeans can reduce land conflicts by about 0.12% after the legalization of GM soybean cultivation in 2003. Furthermore, a 1% increase in the size of suitable land for GM soybean cultivation can lessen the number of people and families participated in land conflicts by about 0.17% and 0.14% respectively. These results remain robust after placebo tests, confounding factors and different measures of land suitability are considered in the estimation. Hence, the agricultural innovation from adopting GM soybean cultivation can alleviate the land conflict problem and promote economic development.

Our study contributes to the following literature. Firstly, this study is closely related to the literature about the effect of agricultural productivity-enhancing technology on conflicts. For example, Iyigun, Nunn and Qian (2015) argue that agricultural productivity improvement due to the adoption of potatoes can reduce conflicts. Jia (2014) shows that the adoption of potatoes is able to lessen peasant revolts in historical China.[5] Both studies explore the historical event of "The Columbian Exchange" and establish the impact of this event on economic and political development.[6] However, the purpose of this study is to investigate the effects of the new and ongoing agricultural productivity shocks induced by the cultivation of GM soybeans on land conflicts.

Secondly, this study links to the literature on the determinants of land conflicts. On one hand, the literature suggests that land reforms and the effectiveness of property right are determinants on land conflicts. For example, Alston, Libecap

[5]The reason is that potatoes are a drought-resistant crop and the cultivation of this crop can play a mitigating effect on production loss in the occurrence of extreme weather. In other words, the adoption of potatoes is able to maintain income growth and enhance the opportunity cost of participating conflicts. This leads to a reduction in conflicts. Collier and Hoeffler (1998) and Axbard (2016) discuss about the relationship between opportunity cost, income and conflicts.

[6]Nunn and Qian (2010) provide in-depth discussion about "The Columbian Exchange". For more information on its impact on economic development, refer to Nunn and Qian (2011).

and Schneider (1996) explain that the national land reform implemented by the National Institute for Colonization and Agrarian Reform (or INCRA) helps landless people in securing land titles, thus reducing land inequality and conflicts in Brazil. Fetzer and Marden (2017) argue that weak property rights in Brazil increase land contestability and land conflicts. On the other hand, the literature argues that economic performance and inequality are sources of land conflicts in Brazil. For instance, Hidalgo et al. (2010) find that economic conditions approximated by rainfall are negatively associated with land conflict incidence in Brazil. Additionally, social grievance arising from acute land inequality in Brazil can play an important role in land conflicts (Albertus, Brambor and Ceneviva 2016). This study, however, examines the determinants of land conflict from the perspective of agricultural development. In particular, this study, to the best of our knowledge, is the first study to attempt to seek a solution for reducing internal conflicts from the perspective of agricultural productivity improvement induced by the adoption of GM soybeans.

Thirdly, this study is associated with literature on the impact of agricultural productivity and innovation on a series of economic consequences. Matsuyama (1992) and Gollin, Parente and Rogerson (2002) argue that agricultural productivity improvement can sustain economic growth. Kassie, Shiferaw and Muricho (2011) provide evidence to show that the adoption of high-yield varieties of rice and maize can substantially reduce poverty in Uganda.[7] Emerick et al. (2016) demonstrate that agricultural innovation in terms of adopting flood-resistant crops can encourage farmers to modernize their cultivation practices and increase fertilizer and credit use. Nunn and Qian (2011) and Andersen, Jensen and Skovsgaard (2016) illustrate that the adoption of potatoes and heavy plows respectively are positively associated with urbanization. We differ from these studies by investigating the adoption of GM soybeans as a source of agricultural productivity enhancement, as well as their potential role in economic development in terms of conflict reduction.

Lastly, this study contributes to the ongoing and still early discussion about the

[7] Ravallion and Chen (2007) use China as an example to show that agricultural development can alleviate poverty.

effect of agricultural biotechnologies. GM crop cultivation is one of the most debatable topics in literature (Gaskell et al. 1999; Hartl and Herrmann 2009; Canavari and Nayga Jr 2009).[8] So far, the literature on agricultural biotechnologies mainly focuses on yield improvement from the adoption of GM crops (Qaim and Zilberman 2003; Qaim and Traxler 2005). However, studies on the effect of adopting GM crops on economic development is scarce.[9] This study aims to establish and explore the link between the cultivation of GM crops and economic development.

The rest of this study is organized as follows. Section 2 describes the background about the cultivation of GM soybeans and land conflicts in Brazil. In particular, Section 2 introduces knowledge on GM soybeans and its benefits. Section 3 introduces the conceptual framework. The conceptual framework includes two parts. Part one explains how the adoption of GM soybeans can reduce land value. Part two shows how the reduction of land value in part one can reduce land conflicts. The data for this study is discussed in Section 4. More importantly, Section 4 explains the construction of the variable that is used to measure land suitability for cultivating soybeans in this study. Section 5 discusses the empirical model. Main results are presented in Section 6 and are followed by robustness checks in Section 7. Section 8 is the conclusion.

## 4.2 Background

In this section, we offer some background on the benefits of cropping GM soybeans, GM soybean production and land conflicts in Brazil.

[8] Huang et al. (2004) discuss the welfare implications of GM cotton in China. Furthermore, Huang, Pray and Rozelle 2002 and Barrows, Sexton and Zilberman (2014*b*) offer better insight into the prospect of GM crops.

[9] The exception is Bustos et al. (2016) who investigate the effect of GM soybean adoption on urbanization in Brazil.

### 4.2.1 The Benefits of Cultivating GM Soybeans

Genetically-Modified crops refer to Genetically-Engineered or transgenic crops. These are crops that incorporate genes from other species to achieve desirably agricultural traits. There are three main types of GM technologies – herbicide tolerant, insect resistant or strait traits – which are mainly applied to soybean, maize, cotton and canola crops. GM soybean seeds were initially released commercially in the US in 1996 and are characterized by a gene from the soil bacterium Agrobacterium Tumefaciens (Qaim and Traxler 2005). In turn, GM soybean cultivation is compatible with using, Glyphosate, the broad-spectrum herbicide.[10] This herbicide is safer to consumers and farmers, more environmental friendly and more efficient in terms of weed eradication than other herbicides that are used in traditional soybean cultivation (Qaim 2009).[11] As Glyphosate is not applicable to traditional soybean cultivation, there are several advantages in cultivating GM soybeans over the cultivation of traditional soybeans.[12]

Firstly, the cultivation of GM soybeans would result in improving land productivity. In traditional soybean cultivation, if farmers apply the tillage method in land preparation, they must till soil repeatedly to remove weeds.[13] In GM soybean cultivation, farmers can take advantage of Glyphosate, a broader-spectrum herbicide that is compatible with GM soybean cropping. In doing so, GM soybean can be seeded directly along with the use of Glyphosate for weed control, and tillage

[10]This herbicide is strictly regulated by the US Environmental Protection Agency (EPA) and is registered in June 1986 by EPA. The toxicity level is considered to be second lowest by EPA. WHO (2010) also make similar categorization in the International Classification of Pesticides for Glyphosate.

[11]Many studies provide empirical evidence to show that, compared to traditional soybean cultivation, growing GM soybean can significantly substitute the use of highly toxic herbicides (Qaim and Traxler 2005). This can be beneficial for farmers, consumers and animals (Huang et al. 2003; Cerdeira and Duke 2006). Additionally, GM soybean cultivation can also lead to a decrease in release of greenhouse gas emission and preserve cropland (Barrows, Sexton and Zilberman 2014*b*; Brookes and Barfoot 2015).

[12]The difference between GM and conventional soybean cultivation is herbicide use only. If conventional soybeans were grown along with GM soybeans, their performance would be identical as long as the presence of weeds and other related adverse factors are considered in the conventional soybean plantation (Rocha and Villalobos 2013). For climate, land and soil level that are needed during cultivation, GM soybeans and traditional soybeans are the same.

[13]Otherwise, unwanted weeds would crowd out other crops and absorb water and nutrients that are needed by other crops.

is not required (Rocha and Villalobos 2013). Consequently, the cultivation of GM soybeans saves time and enables farmers to practice the double-cropping of GM soybeans in the same piece of land, which is often infeasible with traditional soybean farming (Sharma et al. 2002; Barrows, Sexton and Zilberman 2014*a*).[14]

Secondly, the cultivation of GM soybeans can help to enhance labor productivity. Specifically, by using Glyphosate, a broader-spectrum herbicide, the process of weed eradication will be simplified and less ongoing effort on weed management will be required (Qaim and Traxler, 2005). For example, Huang et al. (2002) show that GM technology adopters can save about 67% of labor time in weed management. Bustos et al. (2016) find that, due to the legalization of GM soybean cultivation in 2003, soybean production per worker in Brazil rises from fewer than 100 tons in the 1980s to 300 tons in 2010.

Thirdly, GM soybean farmers are able to enjoy higher yields than traditional soybean cultivators. If traditional soybean planters apply the tillage method during land preparation, plowing the land repeatedly can cause low outputs as consecutive plowing can stifle the positive characteristics of organic contents, destabilize the structure of soil and increase soil erosion (Rocha and Villalobos 2013). However, GM soybean cultivation does not present these problems as GM soybean adopters can avoid the tillage method and use the direct seed method in the weed management, which is advantageous in preserving soil conditions and augmenting crop yield (Motavalli et al. 2004). Farmers who cultivate GM soybeans can also double-crop in the same piece of land and this can significantly increase crop outputs (Trigo and Cap 2004).[15] Therefore, GM soybean cultivators can result in higher yields (Benthem 2013).[16]

[14]The practice of double-cropping is planting two, instead of just one, crops in the same piece of land in different growing seasons within a year. Farmers can produce one crop in the early season and another one in the late season per year. In double-cropping, crop combinations can be wheat and soybeans or only soybeans in both growing seasons. For more detail, please see Rocha and Villalobos (2013).

[15]Trigo and Cap (2004) provide empirical evidence to show that double-cropping induced by the adoption of GM technologies can increase crop outputs by about 3 times in Argentina.

[16]Benthem (2013) used data from two large soybean cultivators in Brazil–Mato Grosso and Parana and found that soybean yields increased by at least 9 percent on average in 2010 after the legalization of GM soybean cultivation. Qaim and Zilberman (2003) and Qaim (2003) focused on

Finally, production costs can be reduced by switching from cultivating traditional soybeans to GM soybeans. If traditional soybeans planters choose direct seeding in weed management, they have to purchase costly chemicals for weed removal. However, GM soybean cultivators would require less chemicals due to its efficiency in weed eradication and therefore incur lower production costs (Qaim 2009). Quantitatively, Qaim and Traxler (2005) argue that GM technologies can reduce production costs by about 10%, which is approximately equivalent to a saving of USD 7.57 per ton of soybean production. Moreover, fertilizer input is lower in GM soybean cultivation. In Brazil, James et al. (2010) reveals that the production costs in terms of fertilizer use in GM soybean plantation is about 50% less than conventional soybean cropping and that the total direct production costs for GM soybean cultivation are about 5.1% lower than conventional soybean cropping.

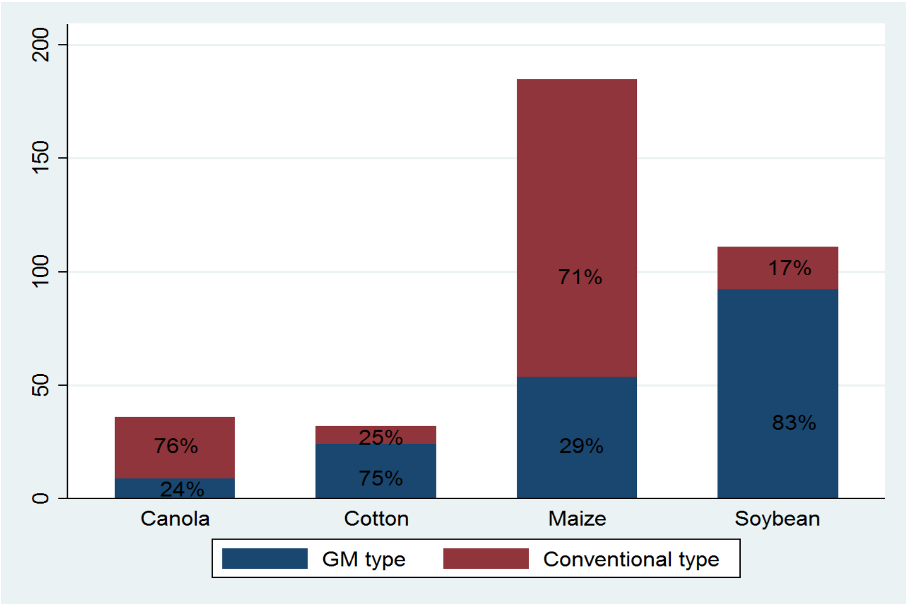
### 4.2.2 GM Soybean Production in Brazil

Traditionally, Brazil has been a large producer of soybeans. According to FAO (2013), Brazil is the second largest soybean producer in the world with 86.8 million metric tons, or 30% of global production, produced in 2013.[17] However, traditional soybeans are significantly replaced by GM soybeans. According to Figure 4.1, GM soybeans account for 83% of soybean harvest area. This high replacement rate is due to the policy change on legalizing GM soybean cultivation.

another type of GM crop Bacillus thuringiensis (bt) cotton and show that GM cotton improved yields remarkably in India.

[17]USA is the biggest soybean producer in the world and about 108 million metric tons were produced in 2013.

Figure 4.1: Comparison in harvest area
(GM vs conventional soybeans)




*Note*: Data is extracted from James (2015)

In 2003, commercial farming of GM soybeans was legalized in Brazil.[18] Following this, a large proportion of traditional soybeans production was replaced by the production of GM soybeans. For example, GM soybean seeds cover 46.4% of Brazil's soybean cultivation in 2005, just two years after the policy was in place (IBGE 2006). This figure rises rapidly to 85% in 2011-2012 (USDA 2012), and 93% in 2016-2017 (USDA 2016). Brazil has now become a major GM crop cultivator in the world. As Table 4.1 shows, Brazil is the second biggest GM crop cultivator in the world, with 44.2 million hectares of land harvests being GM crops (James, 2015).[19]

[18] Initially, the Brazilian government announced the Law 10.688 which only allowed one harvest season. In 2005, the Brazilian government passed a second law, Bio-Safety Law, and this resulted in large scale production and consumption of GM soybeans.

[19] James (2015) also reveals that 28 countries have adopted GM crops in 2015. These 28 countries are USA(70.9), Brazil(44.2), Argentina(24.5), India(11.6), Canada(11.0), China(3.7), Paraguay(3.6), South Africa(2.3), Uruguay(1.4), Bolivia(1.1), Philippines(0.7), Australia(0.7), Burkina Faso(0.4), Myanmar(0.3), Mexico(0.1), Spain(0.1), Colombia(0.1), Sudan(0.1), Honduras(<0.05), Chile(<0.05), Portugal(<0.05), Vietnam(<0.05), Czech Republic(<0.05), Slovakia(<0.05), Costa Rica(<0.05), Bangladesh(<0.05), Romania(<0.05). The figures in bracket are harvest area (unit is million hectares).

Table 4.1: Top 10 GM crops cultivation countries in 2015

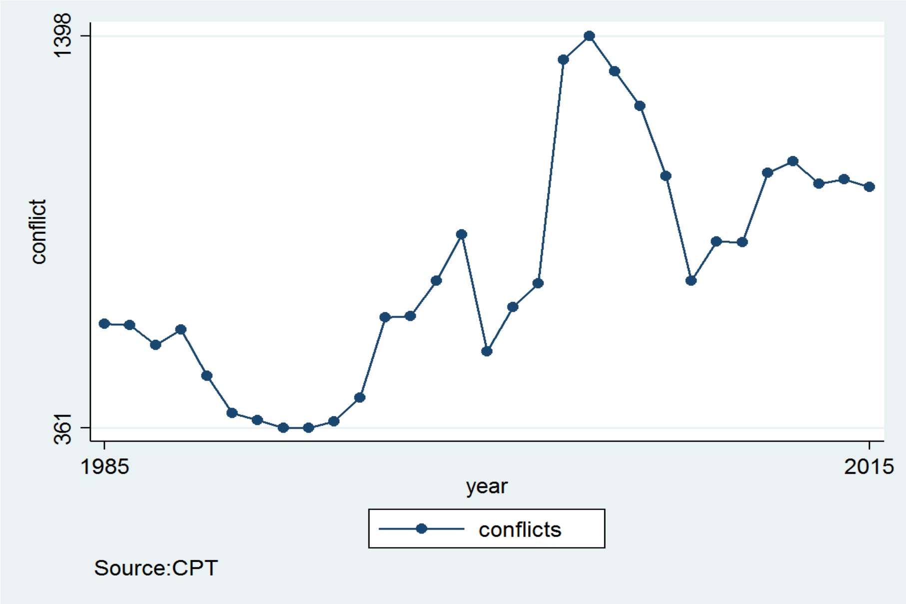
| Rank | Country | GM crop cultivation size (Unit is million hectare) |
|---|---|---|
| 1 | U.S.A. | 70.9 |
| 2 | Brazil | 44.2 |
| 3 | Argentina | 24.5 |
| 4 | India | 11.6 |
| 5 | Canada | 11.0 |
| 6 | China | 3.7 |
| 7 | Paraguay | 3.6 |
| 8 | Pakistan | 2.9 |
| 9 | South Afirca | 2.3 |
| 10 | Uruguay | 1.4 |

*Note*: Data is extracted from James (2015)

### 4.2.3 Land-related Conflicts in Brazil

Land-related conflicts are severe in Brazil. According to FAO (2005), Brazil is one of the most unequal countries in the world in terms of land distribution. For instance, more than two-thirds of total arable land are owned by 3.5% of landlords (Hidalgo et al., 2010), and the Gini coefficient of landholding consistently exceeds 0.8, which is one of the highest in the world (Albertus, Brambor and Ceneviva, 2016). The severity of land inequality is accompanied by land conflicts in Brazil. According to CPT (2014) and Girardi (2015), there are over 9,400 land conflicts in 2014, which involve more than 1.4 million families and several million individuals. Figure 4.2 shows the number of land conflicts in Brazil from 1985 to 2015. As we can see in Figure 4.2, the number of land conflict increases remarkably from 1985 to 2002. Particularly, it reached the peak in 2002. Conversely, the number of land conflict drops dramatically after legalizing GM soybean cultivation in 2003.

Figure 4.2: Number of land conflicts in Brazil




As a result of land conflicts, they resulted in the deaths of more than 1,300 people over this period (1985-2015). Moreover, there are numerous social movements and national land reforms in Brazil due to the severity of land conflicts. For example, the Landless Workers Movement (Movimento dos Trabalhadores Rurais sem Terra or MST) is a highly active social movement on land invasions (Hammond and Rossi 2013). The purpose of this organization is to organize or hire unemployed and landless farmworkers or poor rural people to take over private or government idle land collectively. Problems with land conflicts have also forced the Brazilian government to initiate national land reform by establishing the National Institute of Colonisation and Agrarian Reform or INCRA to help squatters or landless people secure land titles legally. For example, Robles (2018) illustrates three national land reforms across Brazil. The first one is Sarney's Agrarian Reform from 1985 to 1989. The second one is Collor-Franco's Agrarian Reform from 1990 to 1994. The last one is Cardoso's Agrarian Reform from 1995 to 2002. These agrarian reforms successfully help many landless people resolving land disputes and possessing land legally.

Figure 4.3: Control vs Treatment Group

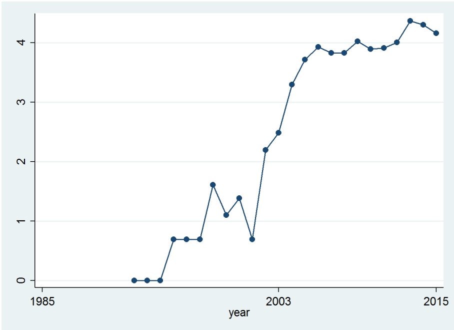



Figure 4.4: Amapa


Figure 4.5: Pernambuco

*Note*: Vertical axis is the number of land conflict (in log) and horizontal axis is year.

Implementing the policy of legalizing GM soybean cultivation in 2003 in Brazil may play a nontrivial role in the reduction of land conflicts. To better understand its impact on different Brazilian states, we select a state from the control and treatment group.[20] For example, the state of Amapa represents the control group and the state of Pernambuco is the treatment group.

As we can see in Figure 4.4 and 4.5 above, the same policy of legalizing GM soybean cultivation in 2003 affects the control (Amapa) and treatment (Pernambuco) group differently. Specifically, Figure 4.4 shows that Amapa experienced a remarkably rise in the number of land conflicts after 2003. Conversely, there is a steady decline in the state of Pernambuco after GM soybeans were legalized in 2003. Through the comparison between the control and treatment group, the policy impact is heterogeneous in terms of land conflicts.

## 4.3 Conceptual Framework

In this section, we provide the conceptual framework to explain how the adoption of GM soybeans lessens land conflicts. In the first part of the conceptual framework, we follow Iyigun, Nunn and Qian (2015) in using a simple model to demonstrate

[20]The construction and distinction between the treatment and control group are discussed below in Section 4.4.1.

that the productivity-enhancing technology induced by the GM soybean cultivation can reduce agricultural land value. In the second part of the conceptual framework, we show that the reduction of land value driven by the adoption of GM soybeans can reduce land conflicts, if agricultural land is the return for winners in land conflicts.

### 4.3.1 The Effect of GM Soybean Cultivation on Land Value

The adoption of GM soybeans can improve agricultural productivity by enhancing land and labor efficiency in the GM soybean cultivation. We follow Iyigun, Nunn and Qian (2015) and use a simple two-sector model to show that the agricultural productivity improvement induced by the adoption of GM soybeans can reduce agricultural land value. The key insight is that the adoption of GM soybeans can reduce soybean price (Barrows, Sexton and Zilberman 2014*b*). Since agricultural products are price inelastic, the price reduction would be greater than demand expansion for agricultural products (Van Driel, Nadall and Zeelenberg 1997). Farmers own land. They use it to produce agricultural goods and sell them for income at market price. This implies that agricultural land value is reflected by soybean price levels. Thus, as soybean price decreases due to the adoption of GM soybeans, the value of agricultural land is reduced. The reduction of agricultural land value can lessen land conflicts if agricultural land is the return for winners in land conflicts.

#### Impact of Adoption of GM Soybeans on Land Value

Following the simple two-sector model from Iyigun, Nunn and Qian (2015), there are two sectors: agriculture (A) and manufacturing (M) sectors and two players: landlords and landless workers in our model. The production of these two sectors are expressed in the Cobb-Douglas function forms as:

$$Y_A = A_A^* L_A^{\alpha} \tag{4.1}$$

where: $A_A^* \equiv A_A N^{1-\alpha}$

$$Y_M = A_M L_M \tag{4.2}$$

In Eq.(4.1) and (4.2), $Y_A$ and $Y_M$ are production from the agriculture and manufacturing sector. $L_A$ is labor input for the agriculture sector and $L_M$ is labor input for the manufacturing sector. Total labor supply is normalized to one.[21] $A_A^*$ is total factor productivity in the agriculture sector and consists of agricultural technology development $(A_A)$ and the total fixed supply of arable land $(N)$. As $N$ is in $A_A^*$, this can capture land use efficiency. For GM soybean cultivation, $A_A^*$ is enhanced as GM soybean cultivation can encourage farmers do double-cropping. $\alpha$ is the output elasticity of labor in the agriculture sector. $A_M$ is the total factor productivity in the manufacturing sector. There are some differences between output setups in Eq.(4.1) and (4.2). Firstly, land is required only in the agriculture but not in the manufacturing sector. Secondly, as the supply of land is fixed, marginal product of labor in the agricultural sector is decreasing whereas it is constant in the manufacturing sector.

Labor is perfectly mobile across the two sectors and the wage $w$ is in the competitive equilibrium. Additionally, $w$ is decided by the marginal productivity of labor in the manufacturing sector:

$$w = A_M \tag{4.3}$$

The price of agriculture products is $P_A$ and the price of manufacturing products is normalized to one. The landlord faces the following problem:

$$\pi = \max_{L_A} P_A A_A^* L_A^\alpha - w L_A \tag{4.4}$$

From Eq.(4.4), we can see that the landlord uses the land to produce agriculture products $Y_A$, which is equal to $A_A^* L_A^\alpha$ and sells them at the price of $P_A$. The cost of producing these agriculture products is labor cost $wL_A$. The difference between income and cost is $\pi$, which is equal to the value of owning land. Take the first order

[21] $L_A + L_M = 1$

condition in Eq.(4.4) with respect to $L_A$ and set it to zero. This implies that

$$\alpha P_A A_A^* L_A^{\alpha-1} = w \tag{4.5}$$

Combing Eq.(4.5) with Eq.(4.3), we then obtain

$$L_A = (\frac{\alpha P_A A_A^*}{A_M})^{\frac{1}{1-\alpha}} \tag{4.6}$$

Eq.(4.6) is the equilibrium labor in the agriculture sector, which is a function of $P_A$, $A_A^*$ and $A_M$. We then also use Eq.(4.6) to replace $L_A$ in Eq.(4.1). It gives:

$$Y_A = A_A^*[(\frac{\alpha P_A A_A^*}{A_M})^{\frac{1}{1-\alpha}}]^{\alpha} \tag{4.7}$$

Simplify Eq.(4.7), we get:

$$Y_A = [(\frac{\alpha P_A}{A_M})^{a} A_A^*]^{\frac{1}{1-\alpha}} \tag{4.8}$$

Next, we consider the landless worker's problem as:

$$\begin{gathered}\max_{C_A,C_M} \frac{1}{1-\sigma}(C_A)^{1-\sigma} + C_M \\ \text{s. t.} P_A C_A + C_M = w\end{gathered} \tag{4.9}$$

where $C_A$ and $C_M$ are consumption of agricultural and manufacturing goods. $\sigma$ is the elasticity of demand for agricultural products. Taking the first order-condition with respect to $C_A$, we have:[22]

$$(C_A)^{\frac{-1}{\sigma}} = P_A \tag{4.10}$$

We assume that the goods market is in a competitive environment, therefore aggre-

[22]In order to get Eq.(4.10), we also need to take the first order condition with respect to $C_M$.

gate production is equal to aggregate consumption:

$$C_A = Y_A \tag{4.11}$$

We use Eq.(4.8) to re-write Eq.(4.11):

$$C_A = [(\frac{\alpha P_A}{A_M})^a A_A^*]^{\frac{1}{1-\alpha}} \tag{4.12}$$

We then combine Eq.(4.12) and Eq.(4.10):

$$\begin{aligned} P_A &= \left\{[(\frac{\alpha P_A}{A_M})^a A_A^*]^{\frac{1}{1-\alpha}}\right\}^{\frac{-1}{\sigma}} \\ &= [(\frac{\alpha P_A}{A_M})^a A_A^*]^{\frac{1}{(\alpha-1)\sigma}} \end{aligned} \tag{4.13}$$

Re-write Eq.(4.13) as:

$$P_A^{(\alpha-1)\sigma-\alpha} = \alpha^\alpha(\frac{1}{A_M})^\alpha A_A^* \tag{4.14}$$

We can simplify Eq.(4.14) further and obtain the equilibrium price of agriculture products $P_A^*$ as :

$$P_A^* = [(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{\sigma(1-\alpha)+\alpha}} \tag{4.15}$$

From Eq.(4.15), we can see that $P_A^*$ is a function of $A_M$, $A_A^*$, $\sigma$ and $\alpha$. We can also see that an increase of $A_A^*$ can lead to a reduction of $P_A^*$. Use $P_A^*$ above to replace $P_A$ in Eq.(4.6). It gives:

$$\begin{aligned} L_A &= \alpha^{\frac{1}{1-\alpha}} \underbrace{\left\{[(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{\sigma(1-\alpha)+\alpha}}\right\}^{\frac{1}{1-\alpha}}}_{\mathrm{P}_A^*} (A_A^*)^{\frac{1}{1-\alpha}} (\frac{1}{A_M})^{\frac{1}{1-\alpha}} \\ &= \alpha^{\frac{1}{1-\alpha}} \left\{[(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{(\sigma(1-\alpha)+\alpha)(1-\sigma)}}\right\} (A_A^*)^{\frac{1}{1-\alpha}} (\frac{1}{A_M})^{\frac{1}{1-\alpha}} \end{aligned} \tag{4.16}$$

We then use Eq.(4.16), Eq.(4.15) and Eq.(4.4) to construct the equilibrium land value to see how agricultural productivity enhancement can reduces land value.

$$\pi^* = \underbrace{[(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{\sigma(1-\alpha)+\alpha}}}_{\mathrm{P}_A^*} \underbrace{A_A^* \, \alpha^{\frac{1}{1-\alpha}} \left\{[(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{(\sigma(1-\alpha)+\alpha)(1-\sigma)}}\right\} (A_A^*)^{\frac{1}{1-\alpha}} (\frac{1}{A_M})^{\frac{1}{1-\alpha}}}_{\mathrm{L}_A}$$
$$- w \star \underbrace{\alpha^{\frac{1}{1-\alpha}} \left\{[(\frac{A_M}{\alpha})^\alpha \frac{1}{A_A^*}]^{\frac{1}{(\sigma(1-\alpha)+\alpha)(1-\sigma)}}\right\} (A_A^*)^{\frac{1}{1-\alpha}} (\frac{1}{A_M})^{\frac{1}{1-\alpha}}}_{\mathrm{L}_A}$$
$$= (1-\alpha) A_M^{\frac{\alpha(1-\sigma)}{\sigma(1-\alpha)+\alpha}} (\frac{1}{A_A^*})^{\frac{(1-\sigma)}{\sigma(1-\alpha)+\alpha}} \tag{4.17}$$

In Eq.(4.17) above, the equilibrium land value $\pi^*$ is a function of $A_A^*$, $A_M$,$\sigma$ and $\alpha$. Many empirical studies show that the demand for agriculture products is inelastic (Tobin 1950 and Tolley, Wang and Fletcher 1969).[23] This means that $\sigma$ is greater than 0 but small than 1. This implies that an increase in agriculture productivity ($A_A^* \uparrow$ ) can result in a reduction of land value ( $\pi^* \downarrow$ ).[24]

### 4.3.2 Impact of Adoption of GM Soybeans on Land Conflicts

The simple two-sector model above shows that the value of agricultural land is depreciated when agricultural productivity is enhanced (Iyigun, Nunn and Qian 2015). As the adoption of GM soybeans can improve agricultural productivity by increasing land and labor efficiency during cultivation, the agricultural land value can fall. In this section, we use similar settings from the gun-or-butter model or the appropriate-or-production model from Powell (1993), Grossman (1994) and Acemoglu et al. (2012) to demonstrate that land conflicts can be deterred when land value is decreased. Specifically, we presume landless workers can spend effort on illegal activities for seizing the contestable land from the landlord. If landless workers win, the return of a land conflict is land itself. Therefore, landless workers solve the

[23] The price elasticity of agriculture products is between 0.2 and 0.8. For more discussion, please seeVan Driel, Nadall and Zeelenberg (1997).

[24] $\frac{1-\sigma}{\sigma(1-\alpha)+\alpha}$ is always $> 0$ as $\sigma$ and $\alpha$ are $> 0$, $1-\sigma > 0$ and $\sigma(1-\alpha)+\alpha > 0$

following problem:

$$\max_{m} P(m)\pi^* - l(m) \tag{4.18}$$

where $m$ is the effort spent on taking land in conflicts by the landless people; $P(m)$ is the probability of winning in land conflicts and $P(.)$ is an increasing and concave function; $l(m)$ is the cost to win in land conflicts and $l(.)$ is an increasing and convex function. The landless worker's problem is to choose the optimal level of $m$ such that he can win the $\pi^*$ ( the land) in conflicts. Taking the first order condition with respect to $m$ in Eq.(4.18), we have

$$\pi^* = \frac{l'(m)}{P'(m)} \tag{4.19}$$

From Eq.(4.19), we can see the negative relationship between land value and land conflict likelihood. If the value of agricultural land is diminished ($\pi^* \downarrow$), this results in less effort spent on taking land ($m \downarrow$) and reduced probability of land conflicts ($P(m) \downarrow$).

The conceptual framework in this sector explains that productivity-enhancing technology induced by the adoption of GM soybeans can devalue agricultural land. This would reduce land conflicts if land is the winning price for winners.

## 4.4 Data

Our dataset consists of a panel of 27 Brazilian states from 1985 to 2015.[25] We consider the following dependent variables (in log form) that capture various aspects of land conflicts: the number of land conflicts ($\log(\mathit{Conflict})$), the number of people and families who participated in land conflicts ($\log(\mathit{People})$) and $\log(\mathit{Family})$) and the hectares of land affected by land conflicts ($\log(\mathit{Area})$).

Our main independent variable is the interaction of two variables (see Section 4.5): 1) $I_t^{post}$, the GM soybean policy treatment dummy and 2) $\log(\mathit{SoybeanSuitability})$, a measure of exposure to this treatment. $\log(\mathit{SoybeanSuitability})$ measures the size

[25] One of these states, Distrito Federal, is a federative units.

of suitable land (in log form) for cultivating soybeans at the state level. A larger value in log(*SoybeanSuitability*) indicates that the state has a larger land area that is suitable for cultivating soybeans. Thus, log(*SoybeanSuitability*) reflects the capacity of the state to produce soybeans.

Our main control variables are the log of rainfall (log(*Rainfall*)), the log of population (log(*Population*)), and the *Gini* coefficient. Summary statistics are provided in Table 4.2 below.

Table 4.2: Summary statistics

| Variable | (1) obs. | (2) mean | (3) sd | (4) min | (5) max |
|---|---|---|---|---|---|
| log(*SoybeanSuitability*) | 837 | 10.01 | 3.11 | 0 | 12.98 |
| log(*Conflict*) | 810 | 2.84 | 1.13 | 0 | 5.41 |
| log(*People*) | 774 | 9.22 | 1.59 | 1.61 | 12.57 |
| log(*Family*) | 676 | 7.58 | 1.41 | 0 | 10.76 |
| log(*Area*) | 751 | 10.64 | 1.99 | 3.61 | 16.00 |
| log(*Rainfall*) | 805 | 7.27 | 0.37 | 6.07 | 8.11 |
| log(*Population*) | 837 | 15 | 1.16 | 11.28 | 17.54 |
| *Gini* | 830 | 0.56 | 0.04 | .42 | 0.67 |

### 4.4.1 Soybean Suitability

We consider Nunn and Qian (2011) to construct the land suitability variable, log(*soybeansuitability*), to capture the difference in soybean cultivation in Brazilian states. The data on land suitability for cultivating soybeans (or log(*soybeansuitability*)) is taken from The Food and Agriculture Organization (FAO)'s GAEZ project, version 3.0, where the GAEZ project provides measures on suitability for cultivating a variety of crops including soybeans.[26]

The FAO constructs the measures of land suitability for cultivating a crop based on the following procedure. Firstly, the FAO collects information about growing characteristics of the crop in question.[27] In particular, they obtain information

[26]The GAEZ project provides measures of cultivation suitability for the crop in question during different periods. These periods are 1960-1990, 2020-2029, 2050-2059 and 2080-2089. 1960-1990 is the baseline period. We follow Nunn and Qian (2011) to use the baseline period in our main estimation and the 2020-2029 period in the robustness check.

[27]The information about the growing characteristics of the crop includes length of growth cycle,

from agronomic literature and agricultural research stations about the crop under consideration to determine what physical environment conditions are essential for its cultivation.

Secondly, the FAO's GAEZ project assesses the physical environment in the global coverage. Specifically, the FAO splits the entire globe into 2.2 million grid cells, which is about six kilometers by fifty-six kilometers each. Then, the FAO collects data about climate,[28] land features and soil characteristics in each grid cell.[29] Then, climatic conditions such as moisture and temperature levels are assessed against minimum requirements for growing the crop under consideration in each grid cell and the cell becomes *unsuitable* to cultivate the crop if the climatic conditions are not met. If this minimum requirement is met, the GAEZ project takes land and soil conditions into account to further determine cultivation suitability for the given crop in the given grid cell.

Thirdly, a series of assumptions about irrigation methods and input intensity are considered. For instant, the GAEZ project can estimate the potential yields when the irrigation system is rain-fed and when the intensity of input level is high, medium or low.[30] In this study, we select the rain-fed irrigation method with the input intensity at intermediate as Nunn and Qian (2011).

At this stage, all of this information is combined with the assumptions mentioned above to determine the constraint-free crop yields or the maximum possible yield for the crop in question. Then, the GAEZ project estimates the suitability in the chosen geographical level for the crop as a percentage of the maximum possible yield that can be achieved in the chosen geographical level.

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length of yield formation period, maximum rate of photosynthesis and so on. The user's guide of Global Agro-Ecological Zones (GAEZ v 3.0) provides more discussion about this.

[28]The climatic data is from Climate Research Unit at the University of East Anglia. The GAEZ project considers nine variables from the climatic database. These nine variables are precipitation, frequency of wet days, mean temperature, diurnal (daily) temperature range, vapor pressure, cloud cover, sunshine, ground-frost frequency, and wind speed.

[29]Land characteristics are types of land. They are farmland, cropland, pasture and rangeland. This data in each cell is from the FAO's Digital Soil Map of the World. Some soil characteristics are drainage, texture of soil or soil erosion. Information about soils is obtained from the GTOPO30 Database. This database is constructed by the U.S. Geological Survey EROS Data Center.

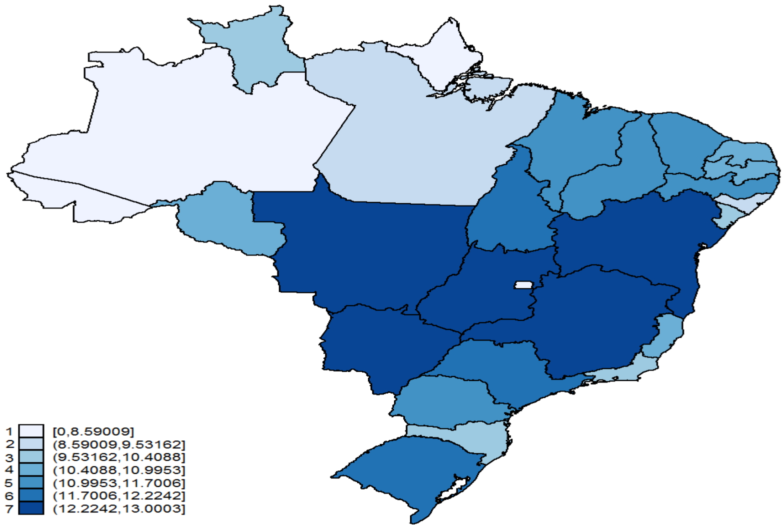
[30]Other irrigation methods in the GAEZ project are the sprinkler, gravity, and drip irrigation systems.

Finally, the GAEZ project produces eight mutually exclusive classes in regards to the suitability of the land in different geographic levels for growing the crop in question. These classes are constructed on the basis of the percentage of the maximum yield estimated by the GAEZ project that can be achieved in the selected geographic levels. The eight land classes and their associated percentage of the maximum yield are: (i) Very High (85-100%), (ii) High (70-84%), (iii) Good (55-69%), (IV) Medium (40-54%), (V) Moderate (25-39%), (VI) Marginal (10-24%), (VII) Very Marginal ( 0-9%, but 0 is exclusive in this class), (VIII) Not Suitable ( 0%).

Following a similar approach as Nunn and Qian (2011), we define suitable land for soybean cultivation as land that is classified as "Medium", "Good", "High", and "Very High". In other words, land is suitable for soybean cultivation if the land can achieve 40% or above the maximum yield of the soybean crop as estimated by the GAEZ project. Our variable $\log(SoybeanSuitability)$,[31] therefore, measures (in log) the size of suitable land for cultivating soybeans at the state level. In our robustness checks, we vary this 40% cut-off point to 25% or 55%, and show that our conclusion about the impact of legalization of GM soybean cultivation on land conflicts is not sensitive to various selections of cut-off values that define the land suitability for cultivating soybeans (or $\log(SoybeanSuitability)$).

[31] The unit of $SoybeanSuitability$ is square kilometer.

Figure 4.6: Land suitability for cultivating soybean in Brazil



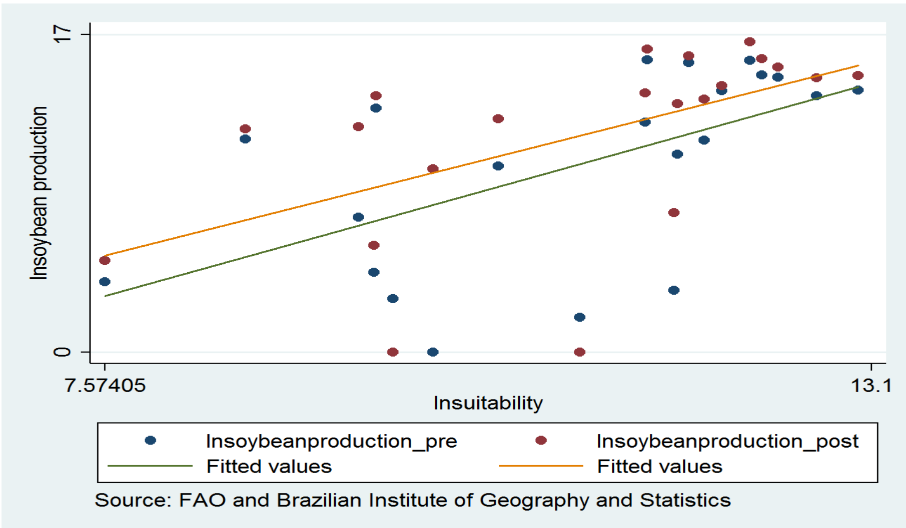

*Notes:*1=not suitable+ very marginal; 2=marginal; 3=moderate; 4=medium; 5=good; 6=high; 7=very high.

Figure 4.6 shows the distribution of suitable land for cropping soybeans at the state level (or $\log(SoybeanSuitability)$) based on the assessment by the GAEZ project. States that are shaded in darker colors are those that have larger tracts of suitable land for cultivating soybeans. Given that each state owns different sizes of suitable land for soybean cultivation, the policy on commercial legalization of of GM soybean cultivation in 2003 would affect each state differently. For example, the states in Northeastern and Southeastern regions would benefit more than the ones in the Northern regions from this policy change. This is because, according to Figure 4.6, the Northeastern and Southeastern regions are more productive in soybean production than the Northern region is as the former owns more land that is suitable for growing soybeans. We will exploit this cross-sectional differences in the size of suitable land for soybean cultivation for our Difference-in-Differences approach discussed in Section 4.5 below.

**The Relationship between Land Suitability Measure and Production for Soybeans**

To examine the validity of log($SoybeanSuitability$), our measure of land suitability for cultivating soybeans, we explore the relationship between log($SoybeanSuitability$) and the production of soybeans. To do this, we collect data on soybean production from 1989 to 2010 for each Brazilian states from the Brazilian Institute of Geography and Statistics (BIGS) and present the relationship between log($SoybeanSuitability$) provided by the GAEZ project and the soybean production in Brazilian states from 1989 to 2010 in Figure 4.7.

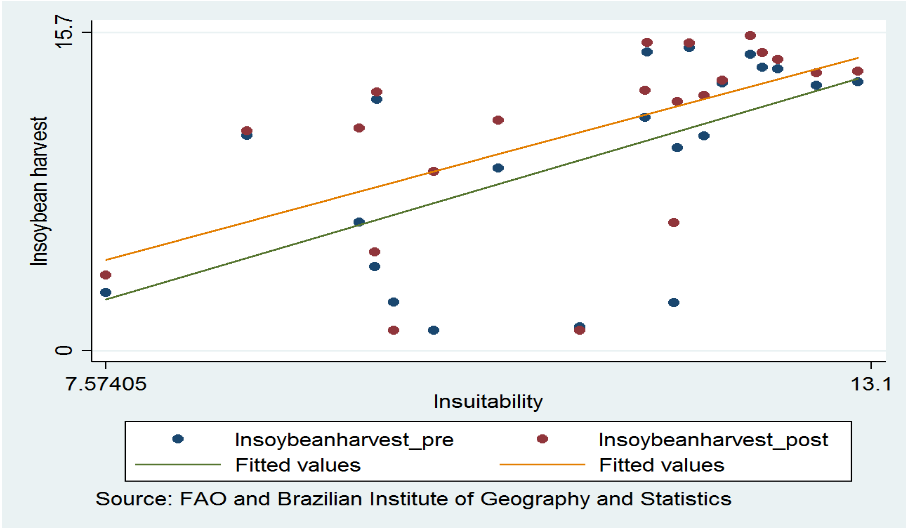
Figure 4.7: Soybean production and soybean suitability in Brazilian states




In Figure 4.7, we plot the average soybean production (in log form) from 1989 to 2010 against log($SoybeanSuitability$) for each state. The upward-slope lines indicate a positive correlation between log($SoybeanSuitability$) and the production of soybeans across Brazilian states.

Additionally, we collect data on the size of soybean harvest area in Brazil from BIGS for 1989 to 2010. We plot the average size of soybean harvest area in log against log($SoybeanSuitability$) in Figure 4.8. From Figure 4.7 and 4.8, we can argue that the states marked as having more land considered suitable for cultivating soybeans by the GAEZ project (or higher log($SoybeanSuitability$)) are producing more soybeans. Therefore, we can view the variable log($SoybeanSuitability$) in this study as a valid proxy to measure land suitability for cultivating soybeans.

Figure 4.8: Soybean harvest area and soybean suitability




Lastly, there are two upward-slope lines in both Figures 4.7 and 4.8. The top line represents average production amount and average size of harvest area after the GM soybean cultivation was legalized (from 2003 to 2010) and the bottom line indicates average production amount and average size of harvest area before the legalization of GM soybean cultivation (from 1989 to 2002) in Figures 4.7 and 4.8 respectively. These two upward-slope lines indicate that the production amount and harvest area of soybeans have increased after GM soybean cultivation was legalized in 2003.

### 4.4.2 Land Conflict

Data on land conflicts is taken from Brazil's Pastoral Land Commission (Comissao Pastoral da Terra, CPT). CPT (2004) defines land-related conflicts as "collective action by landless families or peasants that, by entering rural properties, claim lands that do not fulfill the social function".[32] Since 1985, CPT has compiled information from all available sources and has published annual reports (Conflitos no Campo) about land-related conflicts.[33] These reports widely document the number

[32]The definition of land-related conflicts is directly translated by the study of Hidalgo et al. (2010) from CPT (2004).

[33]The sources are local, national and international news articles, state and federal government reports, reports from churches, rural unions, political party, NGOs, reports from CPT offices and citizen depositions. For more details, please see Hidalgo et al. (2010).

of conflicts, the number of family and people involved, hectares of affected area, land-related murders, attempted murders, death threats and other disputes (water and labor) at municipal, state and national levels in Brazil. As the land conflict data is survey data, it may be subject to under-reporting. However, the conflict dataset in this study is viewed as the most comprehensive by Albertus, Brambor and Ceneviva (2016) and is used by many studies (see Alston, Libecap and Schneider 1996; Hidalgo et al. 2010; Albertus, Brambor and Ceneviva 2016; Fetzer and Marden 2017). The data collector, CPT, has widely considered all available sources and has systematically compiled reports since 1985. Therefore, the problem of under-reporting in the conflict data is marginal.

### 4.4.3 Other Control Variables

The rainfall data is from INMET which belongs to the Ministry of Agriculture in Brazil. INMET is the official meteorology statistics provider for other government and research organizations, owns 270 weather stations across Brazil and records daily precipitation from these stations. To construct log annual rainfall variable, log(*Rainfall*), we first compute annual levels by summing up daily data for all weather stations. In some states, there is more than one weather station.[34] If that is the case, we take the average of annual rainfall from all stations in the same state. For the variable of log(*Population*) and the *Gini* coefficient, the data is obtained from the Institute for Applied Economic Research (Instituto de Pesquisa Economica Allicada, IPEA).[35]

## 4.5 Empirical Model

Our main identification strategy is to exploit a quasi-natural experiment based on the legalization of GM soybean cultivation in 2003 by the Brazilian federal gov-

[34] All the states except Amapa have more than one weather states.

[35] Population data in IPEA is not year-wise and is only available in 1980, 1991, 1996, 2000, 200, 2010. Therefore, missing years during the observational period are interpolated.

ernment, and then observe the impact of this policy on land conflicts for states that own more suitable land for soybean cultivation vis-a-vis states that own less. Empirically, to estimate the effect of this quasi-natural experiment, we adopt a Difference-in-Differences (DD) approach and estimate:

$$y_{it} = \beta_1 \log(\mathit{SoybeanSuitability}_i) \cdot I_t^{post} + \boldsymbol{\gamma}'\mathbf{x}_{it} + a_i + \mu_t + \epsilon_{it} \tag{4.20}$$

This approach captures (if any) the difference in land conflict intensity between states that have more suitable land for soybean cultivation versus states that have less after GM soybean cultivation was legalized. The dependent variable $y_{it}$ represents one of the four conflict variables in their log form: the number of land conflicts ($\log(\mathit{Conflict})$), the number of people ($\log(\mathit{People})$) and families ($\log(\mathit{Family})$) that participated in conflicts and the area affected by land conflicts ($\log(\mathit{Area})$) in state $i$ and year $t$. $\log(\mathit{SoybeanSuitability}_i)$ is the log size of suitable land for soybean cultivation in state $i$ (as determined by the GAEZ project). $I_t^{post}$ is a dummy variable that is equal to one for the years when GM soybean cultivation was legalized. Thus, it takes the value of one from 2003 onward (i.e. from 2003 to 2015) and zero if otherwise (i.e. from 1985 to 2002).

The vector $\mathbf{x}_{it}$ is other control variables in state $i$ and year $t$. We consider three control variables in this study. The first one is $\log(\mathit{Rainfall})$, which aims to control the effects of economic conditions on land-related conflicts (Hidalgo et al. 2010). The second one is $\log(\mathit{Population})$, which controls the effect of population on land conflicts (Dow, Mitchell and Reed 2017). The third one is the *Gini* coefficient, which captures the effect of social grievance on land conflicts (Muller et al. 1989; Albertus, Brambor and Ceneviva 2016). For the unobserved components of the model, $a_i$ is the state fixed effect and $\mu_t$ is the year fixed effect. $\epsilon_{it}$ is the idiosyncratic error term clustered at the state level.

$\beta_1$ is the coefficient of interest and represents the impact of the interactive variable between the land suitability for cultivating soybeans and years of legalization on cultivating GM soybeans in Brazil on the dependent variables. Using one of the dependent variable $\log(\mathit{Conflict})$ as an example, the estimated coefficient $\hat{\beta}_1$ is the impact of GM soybean cultivation on the number of land conflicts. A negative $\hat{\beta}_1$ indicates that states with 1% more land that is suitable for cultivating GM soybeans experience $\hat{\beta}_1$% fewer land conflicts after GM soybean cultivation was legalized in 2003.

### 4.5.1 Further Remarks

We argue that our main regressor – $\log(\mathit{SoybeanSuitability}_i) \cdot I_t^{post}$ – is plausibly exogenous for two reasons. Firstly, the announcement of legalization of GM soybean cultivation in 2003 is unexpected and therefore, the timing of implementing this policy, which is captured by $I^{post}$ in the empirical model, is plausibly exogenous (Bustos et al. 2016). Secondly, climatic, land and soil characteristics in the physical environment, which are used for measuring land suitability for soybeans cultivation as reflected by $\log(\mathit{SoybeanSuitability})$, are predetermined. The literature argues that variation of these characteristics is exogenous and considers to be a good identification strategy (see Carranza (2014) as an example). Our argument that the variable $\log(\mathit{SoybeanSuitability}_i) \cdot I_t^{post}$ in the empirical model is plausibly exogenous is not new. Nunn and Qian (2011) made a similar argument when they interacted the years of adopting potato cultivation with a variable that is constructed to measure land suitability for cultivating potato under the same method as this study.

Nonetheless, there are two potentially confounding issues that we need to take care of. The first one is omitted variable bias. The coefficient of interest is $\beta_1$ and captures the impact of the interactive variable between $\log(\mathit{SoybeanSuitability}_i)$ and $I_t^{post}$ on the dependent variables. If there are variables that are correlated with the interactive variable and the dependent variable but are not controlled for, $\hat{\beta}_1$ would be biased. For example, rainfall may be positively correlated with $\log(\mathit{SoybeanSuitability}_i)$. Moreover, rainfall as a proxy of income is negatively associated with land conflicts (Hidalgo et al. 2010).[36] So, $\hat{\beta}_1$ is overestimated. Population

[36] Hidalgo et al. (2010) argue that income rises when $\log(\mathit{Rainfall})$ increases, income growth can heighten the cost of participating in land invasion and then land conflicts reduce.

growth can intensify resource scarcity, which leads to conflict outbreaks (Brückner 2010).[37] Social grievance due to unequal land distribution can trigger land conflicts (Albertus, Brambor and Ceneviva 2016).

To address the omitted variable bias issue, we add the control variables, namely $\log(\textit{Rainfall})$, $\log(\textit{Population})$ and the *Gini* coefficient to control the effect of incomes arising from weather variations, population and social grievance on land conflicts. Additionally, we include state fixed effects ($\alpha_i$) to control all time-invariant state level factors and unobserved permanent differences across states.[38] We also include year fixed effects ($\mu_t$) to capture all time-varying macroeconomic factors such as national land reforms in Brazil (Alston, Libecap and Schneider 1996), and commodity price shocks (Brückner and Ciccone 2010; Dube and Vargas 2013).[39]

The second potential threat is reverse causality. If the dependent variables in this study (i.e. $\log(\textit{Conflict})$, $\log(\textit{People})$, $\log(\textit{Family})$ and $\log(\textit{Area})$) are positively or negatively associated with the interactive variable $\log(\textit{SoybeanSuitability}_i) \cdot I_t^{post}$ in the empirical model above, $\hat{\beta}_1$ would either be overestimated or underestimated, respectively. However, the construction of the variable, $\log(\textit{SoybeanSuitability})$, measuring land suitability for cultivating soybeans in this study is time-invariantly based on the climate, land and soil conditions of each state $i$ in Brazil and is not directly as a function of any dependent variable. Additionally, $I_t^{post}$ is exogenous (Bustos et al. 2016). Therefore, reverse causality may not be a threat in our empirical model.

## 4.6 Main Results

In this section, we present the main results. To examine the inclusion of main control variables on the estimated effect of GM soybean cultivation on land conflicts ($\hat{\beta}_1$), we first present our estimates of the regression model without control variables in

[37]However, Dow, Mitchell and Reed (2017) argue that a bigger population can deter attacks in land conflicts.

[38]These time invariant factors could be the quality of government institutes (Fearon and Laitin 2003) and the property rights (Fetzer and Marden 2017 ).

[39]Adding $\mu_t$ can also control the effect of financial crisis that could potentially has on land conflict.

Table 4.3, and then with control variables in Table 4.4.

### 4.6.1 Baseline Results without Control Variables

Table 4.3 presents the baseline regression results with state and year fixed effects but without controls. We find that there is a negative association between GM soybean cultivation and land conflicts. Specifically, Column (1) shows that states that are more suitable for GM soybean cultivation have experienced fewer land conflicts after the legalization of GM soybean cultivation in 2003, where a 1% increase in the size of suitable land for GM soybean cultivation is associated with a 0.115% decline in land conflicts on average.

Table 4.3: Baseline results without control variables

| | (1) log(*Conflict*) | (2) log(*People*) | (3) log(*Family*) | (4) log(*Area*) |
|---|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.115** | -0.170*** | -0.137** | -0.117 |
| | (0.0528) | (0.0310) | (0.0516) | (0.1090) |
| Observations | 810 | 774 | 676 | 751 |
| R-squared | 0.278 | 0.327 | 0.249 | 0.100 |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Additionally, Columns (2) and (3) in Table 4.3 show that states that are more suitable for GM soybean cultivation experience a reduction in the number of people and families participating in land conflicts. For instance, after the legalization of GM soybean cropping, we find that a 1% increase in area of suitable land for GM soybean cultivation is associated with a 0.170% and 0.136% decline in the number of people and families participating in land conflicts on average respectively. However, GM soybean cultivation is not statistically significant to the size of the areas affected by land conflicts (measured by log(*Area*)). This suggests that while the number of people and families affected by conflicts have declined with the legalization of soybean cultivation, there is no evidence at this point that the area affected by land conflicts has declined.

### 4.6.2 Baseline Results with Control Variables

We explore the sensitivity of our baseline regression results to the inclusion of control variables, namely, the log of rainfall ($\log(Rainfall)$), the log of population ($\log(Population)$), and the Gini coefficient ($Gini$). Firstly, we add the rainfall variable to control the effect of economic conditions due to weather changes on land conflicts (Hidalgo et al. 2010). Secondly, we include the population variable to control the impact of population on conflicts (Brückner 2010). Thirdly, the $Gini$ coefficient variable is added to control the effect of social grievance arising from land inequality on land conflicts (Muller et al. 1989; Albertus, Brambor and Ceneviva 2016).

The estimation results with controls are reported in Table 4.4. In general, we find that the sign and statistical significance of the treatment (i.e. $\log(SoybeanSuitability_i) \cdot I_t^{post}$) are the same as what we have found in the baseline regression without controls (see Table 4.3). As such, the mitigating effect that the legalization of GM soybean cultivation has on land conflict incidence, and the number of people and families participating in land conflicts is not driven by the effects of rainfall, population and social grievance.

Interestingly, compared with the treatment, the effect of the controls appear to be weak. For instance, rainfall, population and the Gini coefficient are all statistically insignificant for conflict incidence. While the effect of rainfall on the four measures of conflict has the expected negative sign, which is consistent with the literature that rainfall is negatively associated with land conflicts (Hidalgo et al. 2010), this effect is only statistically significant when conflict is measured by the number of participants. Likewise, population and the Gini coefficient are only statistically significant when conflict is measured by the area affected by land conflicts. These suggest that the association of these controls and land conflicts, especially when it is measured by conflict incidence, is weak.

Table 4.4: Baseline results with control variables

| | (1) log(*Conflict*) | (2) log(*People*) | (3) log(*Family*) | (4) log(*Area*) |
|---|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.114** | -0.151*** | -0.115** | -0.143 |
| | (0.0522) | (0.0256) | (0.0428) | (0.1102) |
| log(*Rainfall*) | -0.234 | -0.751*** | -0.187 | -0.234 |
| | (0.2767) | (0.1267) | (0.2741) | (0.4369) |
| log(*Population*) | -0.136 | -0.367 | 1.167 | -2.161** |
| | (0.4085) | (0.7834) | (0.7622) | (0.8729) |
| *Gini* | 1.071 | 2.383 | -1.0632 | 6.558* |
| | (2.385) | (2.8208) | (1.9898) | (3.5565) |
| Observations | 774 | 743 | 662 | 722 |
| R-squared | 0.291 | 0.347 | 0.257 | 0.134 |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 4.7 Robustness Checks

Our baseline results have shown that the legalization of GM soybean cultivation is associated with a reduction in land conflicts. In this section, we conduct several checks to investigate the robustness of these results.[40]

### 4.7.1 Placebo Test

The DD approach relies on the assumption that the pre-treatment trends (i.e. in land conflicts) of the treatment and control groups (i.e. soybean cultivation suitable versus less suitable states, respectively) are the same. If not, the deviation in land conflicts between the soybean cultivation suitable and less suitable states after 2003 could be due to not only the legalization of GM soybean cultivation, but also other confounding factors that we may not be aware of. To see if this assumption is violated, we consider Waldinger (2010) and conduct a series of placebo tests.

In each placebo test, we keep only the pre-legalization period (1985 to 2002) and

[40]As the coefficient of interest, $\beta_1$, is not statistically significant when the dependent variable is log(*Area*) in the main results, robustness checks to the case of log(*Area*) is excluded in this section. I also conducted the same robustness checks for the case of log(*Area*. The results are not shown here. However, excluding the case of log(*Area*) do not affect our conclusion.

randomly select a false treatment period. Then, we create a new treatment variable by interacting the false treatment year with the suitability measure of soybean cultivation for each state (i.e. $\log(SoybeanSuitability_i)$). In principle, the false treatment should not have any effect on conflicts. As such, we would expect the effect of this treatment to be statistically insignificant, or has the wrong (positive) sign. If false treatment is statistically significant and has the same negative sign as reported in the baseline regressions, then what we believe to be the effect of the legalization of GM soybean cultivation could be an artifact of an unobserved shock.

Table 4.5: Placebo test 1

| | (1) $\log(Conflict)$ | (2) $\log(People)$ | (3) $\log(Family)$ |
|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{1993}$ | 0.024 | 0.029 | 0.091** |
| | (0.0272) | (0.0456) | (0.043) |
| $\log(Rainfall)$ | -0.420 | -1.076*** | -0.268 |
| | (0.2981) | (0.2149) | (0.4179) |
| $\log(Population)$ | -0.927 | -1.034 | 0.322 |
| | (0.6420) | (1.287) | (1.318) |
| *Gini* | -1.116 | 1.361 | -1.721 |
| | (2.5162) | (4.6626) | (3.3580) |
| Observations | 428 | 397 | 316 |
| R-squared | 0.178 | 0.325 | 0.225 |
| State FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The first false treatment year is 1993. In this case, the false treatment can be constructed as $\log(SoybeanSuitability_i) \cdot I_t^{1993}$, where $I_t^{1993}$ is a dummy variable that takes a value of one for the year 1993 (zero if otherwise). Using this new interactive term as the main regressor, we estimate our model with the sample from 1985 to 2002 (pre-legalization of GM soybean cultivation period). Table 4.5 shows that the estimated coefficient of the effects of $\log(SoybeanSuitability_i) \cdot I_t^{1993}$ on $\log(Conflict)$ and $\log(People)$ are statistically insignificant and very close to zero (Columns (1) and (2)). Although $\log(SoybeanSuitability_i) \cdot I_t^{1993}$ is statistically significant for $\log(Family)$ in Column (3) Table 4.5, the sign of this effect is (positive)

Table 4.6: Placebo test 2

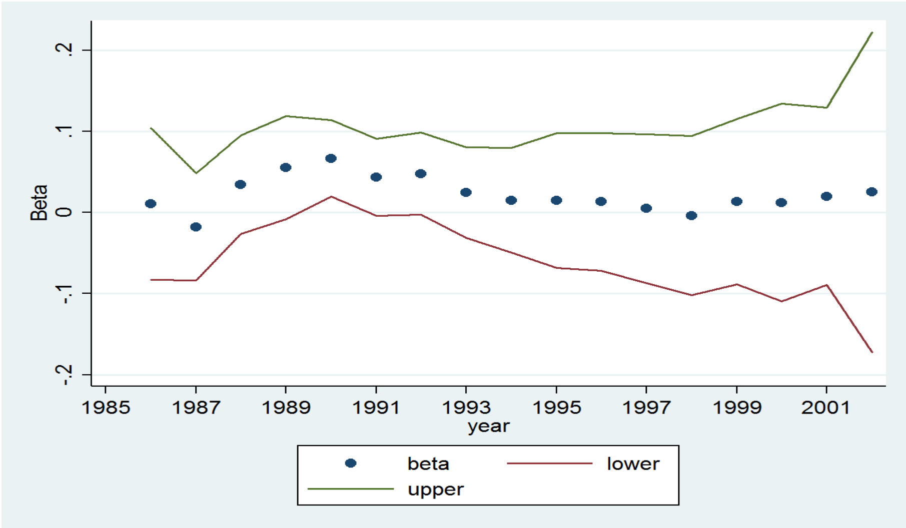
| | (1)<br>log(*Conflict*) | (2)<br>log(*People*) | (3)<br>log(*Family*) |
|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{2000}$ | 0.012 | -0.012 | -0.006 |
| | (0.0594) | (0.1087) | (0.0994) |
| $\log(Rainfall)$ | -0.428 | -1.083*** | -0.284 |
| | (0.2998) | (0.2140) | (0.4073) |
| $\log(Population)$ | -0.963 | -1.152 | -0.005 |
| | (0.6498) | (1.2480) | (1.1784) |
| $Gini$ | -1.467 | 1.035 | -3.052 |
| | (2.5287) | (4.5737) | (2.9888) |
| Observations | 428 | 397 | 316 |
| R-squared | 0.176 | 0.325 | 0.217 |
| State FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

wrong. This provides some support that our regression design does not erroneously report the presence of a treatment effect where there is none.

The second false treatment year is 2000. We construct $\log(SoybeanSuitability_i) \cdot I_t^{2000}$, where $I_t^{2000}$ indicates that the year 2000 is one (zero if otherwise), and use it to replace $\log(SoybeanSuitability_i) \cdot I_t$ as the main regressor in the estimation. In Table 4.6, we find that the estimated coefficient of the effect of $\log(SoybeanSuitability_i) \cdot I_t^{2000}$ is not statistically significant for all our dependent variables and are close to zero. This may suggest that the link between soybean cultivation and conflict reduction is weak before the policy of legalizing GM soybean cultivation was implemented in 2003.

Figure 4.9: False treatment year on log(*Conflict*)



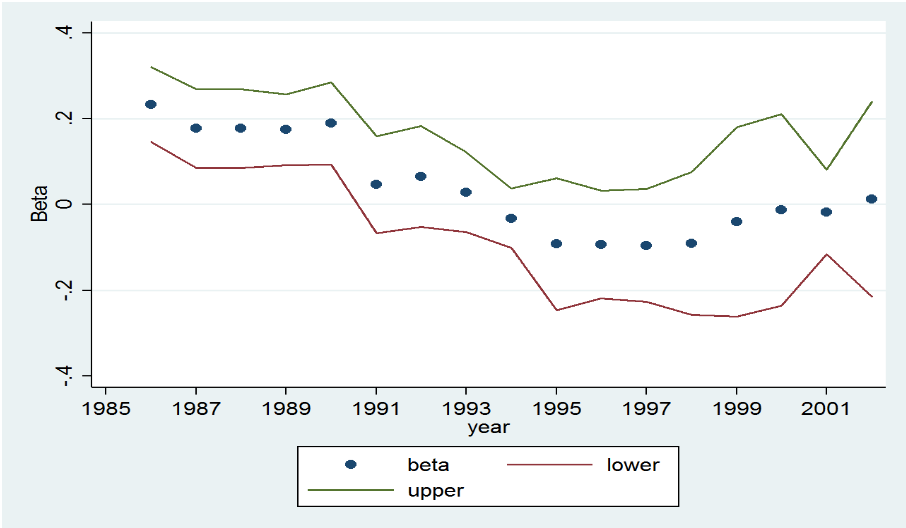

Tables 4.5 and 4.6 present the results of the placebo test based on the false treatment years of only 1993 and 2000 respectively. In order to check the common trend assumption completely, we hypothesize that each year in the period of pre-legalization of GM soybeans (1985 to 2002) is a false treatment year and false treatment variables are created by interacting the log($SoybeanSuitability_i$) with these false treatment years. We then summarize the estimated coefficients of these false treatment variables on log(*Conflict*), log(*People*) and log(*Family*) and their corresponding confidence intervals in the Figures 4.9, 4.10 and 4.12 separately.

In the Figure 4.9, the x-axis represents the period of pre-legalization of GM soybeans and the y-axis represents the estimated coefficients of the interactive variable between log($SoybeanSuitability_i$) and the false treatment year moving from 1986 to 2002 when the dependent variable is log(*Conflict*). These estimated coefficients are represented by dots between two solid lines in the Figure 4.9. The top and the bottom solid lines in the Figure 4.9 are the upper and lower bounds of corresponding confidence intervals of these estimates.

Three results are observed in the Figure 4.9. Firstly, if log($SoybeanSuitability_i$) interacts with the false treatment years from 1988 to 2002, the estimated coefficients are positive. This suggests that the cultivation of soybeans on log(*Conflict*) in the treatment groups were not already on a downward trend before the legalization of

GM soybean cultivation. Secondly, the estimated coefficient is negative when the false treatment year is 1987, but is statistically insignificant as zero is included in its confidence intervals. This demonstrates that the effect of soybean cultivation is not statistically associated with log(*Conflict*) before 2003. Thirdly, these estimated coefficients are close to zero. This indicates that the effect of soybean cultivation on log(*Conflict*) is very small before 2003.

Figure 4.10: False treatment year on log(*People*)




In Figure 4.10 and Figure 4.12, we plot the estimated coefficients of log(*SoybeanSuitability$_i$*) interacted with false treatment years from 1985 to 2002 when the the dependent variables are log(*People*) and log(*Family*). These estimated coefficients have the positive sign or are close to zero or are statistically insignificant (except the estimated coefficient when the false treatment year is 2002). Generally, the results that can be observed in the dependent variable log(*Conflict*) in Figure 4.9 can also be found in the dependent variable log(*People*) and log(*Family*) in Figure 4.10 and Figure 4.12 respectively.

To summarize, the placebo tests in this section show that the impact of soybeans cultivation in the pre-legalization of GM soybean cultivation is very small and not statistically significant on the dependent variables (i.e. log(*Conflict*), log(*People*) and log(*Family*)). The cultivation of soybeans in the treatment groups were not already on a downward trend before 2003 (or the pre-legalization of GM soybeans).

This suggests that the common trend assumption may not be violated in our DD estimation.

Figure 4.11: False treatment year on log(*Family*)

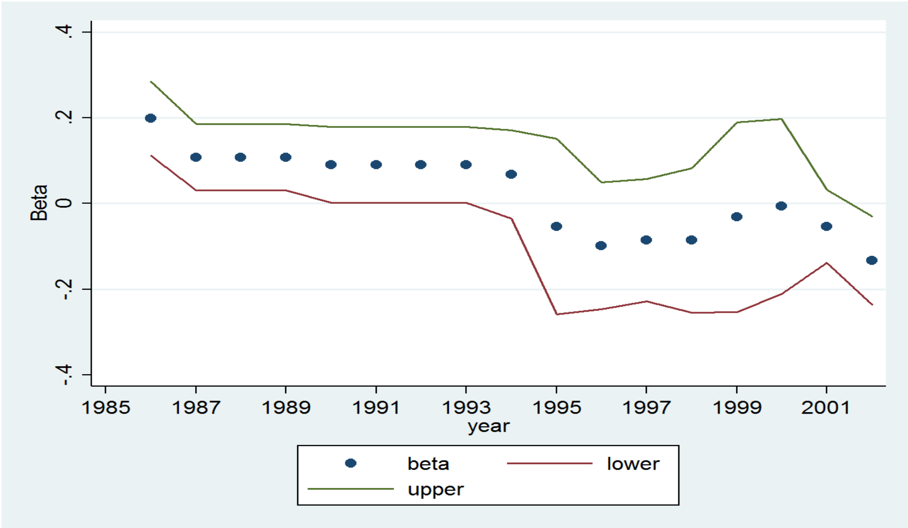
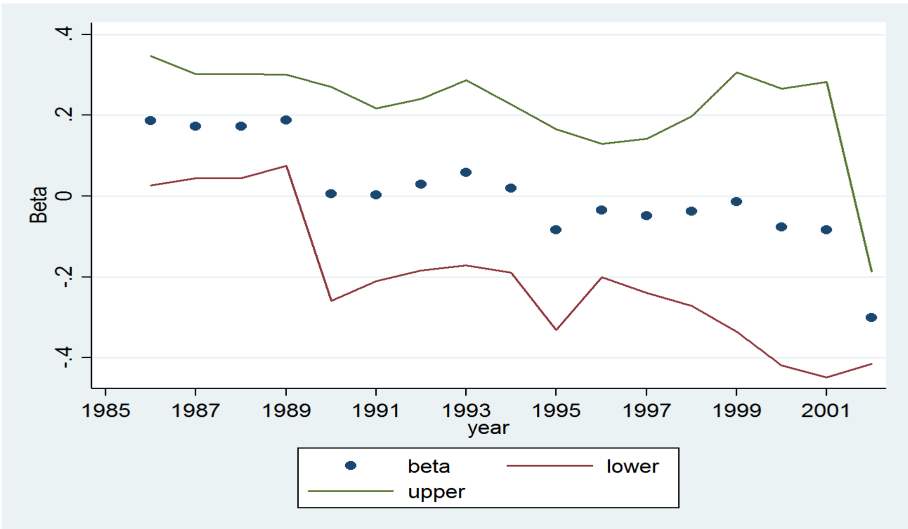



Figure 4.12: False treatment year on log(*Area*)




### 4.7.2 Confounding Factors in the Estimation of the Effects of GM Soybean Cultivation on Conflicts

In the main results section above, we suggest that states owning a greater size of suitable land for cultivating GM soybeans are negatively associated with land conflicts after GM soybean cultivation was legalized in 2003. This indicates that states with land that is suitable for cultivating *only soybeans* should get the treatment effect because of policy change in 2003.

However, states with land that is suitable to cultivate soybeans could be also suitable to grow other crops when GM soybean cultivation was legalized in 2003. It is important to know that the cultivation of other crops does not confound the estimation of the effects of GM soybean cultivation on the dependent variables in the empirical model. To determine this, we select some staple crops that are not genetically-modified. These non-GM crops are cassava, coffee and wheat. Since they are non-GM crops, the policy change in 2003 should not have affected the regions that are suitable to cultivate these non-GM crops and the reduction of land conflicts should not be linked to the cultivation of these non-GM crops. If so, we may argue that other factors (i.e. the cultivation of other non-GM crops) do not confound the effect of GM soybean cultivation on land conflicts after GM soybean cultivation was legalized in 2003.

To this end, we extract data about land suitability for cultivating these non-GM crops mentioned above (cassava, coffee and wheat) from the FAO's GAEZ project. We use the same way as section 4.4.1 above to define land that is suitable for cultivating these non-GM crops,[41] and create three new variables in log form: $\log(CassavaSuitability_i)$, $\log(CoffeeSuitability_i)$ and $\log(WheatSuitability_i)$ to approximate cultivation suitability for these non-GM crops in each state $i$. Then, we interact these three variables with the dummy variable $I_t^{post}$. So, three new interactive variables $\log(CassavaSuitability_i) \cdot I_t^{post}$, $\log(CoffeeSuitability_i) \cdot I_t^{post}$ and $\log(WheatSuitability_i) \cdot I_t^{post}$ are created and included in our empirical model.

The inclusion of these three new variables in the empirical model can capture the fact that regions that are suitable for cultivating GM soybeans could also be suitable for cultivating these non-GM crops when GM soybean cultivation was legalized in 2003. The related information about the estimated coefficient of $\log(SoybeanSuitability_i) \cdot I_t^{post}$ in the empirical model with the new variables of

[41] Land is defined as suitable to plant the crop in question if the land can achieve 40% or above of maximum yield.

$\log(CassavaSuitability_i) \cdot I_t^{post}$, $\log(CoffeeSuitability_i) \cdot I_t^{post}$ and $\log(WheatSuitability_i) \cdot I_t^{post}$ is helpful to explore the potential threat of confounding effects in the estimation of the impact of GM soybean cultivation on the dependent variables.

Table 4.7: Checking confounding factors in the empirical model

| | (1)<br>$\log(Conflict)$ | (2)<br>$\log(People)$ | (3)<br>$\log(Family)$ | (4)<br>$\log(Area)$ |
|---|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.122* | -0.147*** | -0.105** | -0.108 |
| | (0.0651) | (0.0303) | (0.0498) | (0.1163) |
| $\log(CassavaSuitability_i) \cdot I_t^{post}$ | 0.006 | 0.041 | -0.048 | -0.196 |
| | (0.1050) | (0.0929) | (0.0911) | (0.1542) |
| $\log(CoffeeSuitability_i) \cdot I_t^{post}$ | 0.060 | 0.082** | 0.066** | 0.039 |
| | (0.0366) | (0.0287) | (0.0230) | (0.0349) |
| $\log(WheatSuitability_i) \cdot I_t^{post}$ | 0.001 | -0.011 | 0.013 | -0.004 |
| | (0.0221) | (0.0211) | (0.0193) | (0.0276) |
| $\log(Rainfall)$ | -0.214 | -0.709*** | -0.175 | -0.217 |
| | (0.273) | (0.1308) | (0.2803) | (0.4249) |
| $\log(Population)$ | -0.290 | -0.091 | -0.941 | -2.205** |
| | (0.419) | (0.6686) | (0.7691) | (0.9449) |
| *Gini* | 0.925 | 1.879 | -1.373 | 5.757* |
| | (2.309) | (2.816) | (1.895) | (3.4122) |
| Observations | 774 | 743 | 662 | 722 |
| R-squared | 0.306 | 0.356 | 0.267 | 0.138 |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Firstly, we estimate our empirical model with these three new interactive variables and show the estimation results when the dependent variable is $\log(Conflict)$ in Column (1) Table 4.7. As we can see, the estimated coefficient of $\log(Soybean\text{-}Suitability_i) \cdot I_t^{post}$ is -0.122 and remains statistically significant at 10% level when three new interactive variables are included in the estimation. However, the estimates of $\log(CassavaSuitability_i) \cdot I_t^{post}$, $\log(CoffeeSuitability_i) \cdot I_t^{post}$ and $\log(WheatSu\text{-}itability_i) \cdot I_t^{post}$ are not statistically significant at any conventional level. Additionally, GM soybean cultivation is still negatively associated with $\log(Conflict)$ as the baseline results above suggest (see Column (1) Table 4.4). Therefore, the results in Column (1) Table 4.7 show that among soybeans, cassava, coffee and wheat, only the cultivation of soybeans can reduce the number of land conflicts after the policy of legalizing GM soybean cultivation was implemented in 2003.

Secondly, we apply the same strategy as above and add the variables of log($CassavaSuitability_i$) $\cdot$ $I_t^{post}$, log($CoffeeSuitability_i$) $\cdot$ $I_t^{post}$ and log($WheatSuitability_i$) $\cdot$ $I_t^{post}$ to conduct robustness checks for the second dependent variable log($People$). Results are presented in Columns (2) Table 4.7. They show that the estimated effect of log($SoybeanSuitability_i$) $\cdot$ $I_t^{post}$ on log($People$) is -0.147 and is statistically significant at 1% level. However, the estimates of log($CassavaSuitability_i$) $\cdot$ $I_t^{post}$ and log($WheatSuitability_i$) $\cdot$ $I_t^{post}$ are not statistically significant at any conventional level. Even though the estimate of log($CoffeeSuitability_i$) $\cdot$ $I_t^{post}$ is statistically significant, the sign is (positive) wrong. This indicates that, even though the states with land that is suitable for cultivating GM soybeans could also be the states with land that is suitable for planting other non-GM crops, only the cultivation of soybeans reduces the number of people that participated in land conflicts after GM soybeans cultivation was legalized in 2003. So, our results in this exercise align with what we find in the main results section above (see Column (2) Table 4.4 above).

Thirdly, we include log($CassavaSuitability_i$) $\cdot$ $I_t^{post}$, log($CoffeeSuitability_i$) $\cdot$ $I_t^{post}$ and log($WheatSuitability_i$) $\cdot$ $I_t^{post}$ in the empirical model when the dependent variable is log($Family$) and present the new results in Column (3) Table 4.7. As we can see, the estimated coefficient of log($SoybeanSuitability_i$) $\cdot$ $I_t^{post}$ is -0.105 and remain statistically significant at 5% level as the baseline results suggest (see Column (3) Table 4.4). However, the estimates of log($CassavaSuitability_i$) $\cdot$ $I_t^{post}$ and log($WheatSuitability_i$) $\cdot$ $I_t^{post}$ are not statistically significant at any conventional level. The estimate of log($CoffeeSuitability_i$) $\cdot$ $I^{post}$ is statistically significant at 5% level with the wrong (positive) sign.

To summarize, this section explores some potential confounding factors that may challenge the estimation of the impact of GM soybean cultivation on the dependent variables in the empirical model. In particular, we consider the fact that states that are suitable for cultivating soybeans could also have land that is suitable for cultivating other non-GM crops when GM soybeans were legalized in 2003. We added three new interactive variables: $\log(\textit{CassavaSuitability}_i) \cdot I_t^{post}$, $\log(\textit{CoffeeSuitability}_i) \cdot I_t^{post}$ and $\log(\textit{WheatSuitability}_i) \cdot I_t^{post}$ to the empirical model and find that, as the main results section suggests, the estimated coefficient of $\log(\textit{SoybeanSuitability}_i) \cdot I_t^{post}$ is negative and remains statistically significant. This indicates that only soybean cultivation has a negative association with land conflicts after GM soybean cultivation was legalized in 2003.

### 4.7.3 Alternative Definitions of Land Suitability

In Section 4.4.1 above, we construct a variable, $\log(\textit{SoybeanSuitability}_i)$, to define the size of land that is suitable to cultivate soybeans in state $i$. According to the FAO's GAEZ project, land in each state is categorized into eight land classes on the basis of what percentage of the land in each state can achieve the estimated maximum yield for the crop in question. In our baseline regressions, land is defined as suitable for soybean cultivation if it can achieve 40% or above of maximum yield of the soybean crop as estimated by the GAEZ project (see Section 4.4.1 for details).

As discussed, the selection of this 40% cut-off point, while it follows a similar approach as Nunn and Qian (2011), is nonetheless arbitrary. Therefore, we check if our conclusions are robust to using different cut-off points to construct the definition of suitable land for soybean cultivation. To this end, we will create two new suitability variables by adjusting the cut-off point from land that can achieve above 40% of maximum yield to land that can achieve above 55% or 25%. Then, we estimate the effect of GM soybean cultivation on the dependent variables with these new suitability variables and access its result sensitivity.

#### First Alternative Definition of Land Suitability

In this section, we use a different cut-off point to define land that is suitable for cultivating soybeans. The new cut-off point is land that can achieve 55% or above of the maximum yield estimated by the GAEZ project. Then, we re-estimate the effect of GM soybean cultivation ($\hat{\beta}_1$) on log(*Conflict*), log(*People*) and log(*Family*) with this new suitability variable and present the results in Table 4.8 below. As Table 4.8 shows, our conclusions in the main result sector above are not sensitive to the change of cut-off point in log($SoybeanSuitability_i$). Specifically, the sign, size and significant levels of $\hat{\beta}_1$ on log(*Conflict*), log(*People*) and log(*Family*) in Table 4.8 are similar to what Table 4.4 suggests in the main result section above when the cut-off point is 40% or above .

Table 4.8: First alternative definition of land suitability

| | (1) log(*Conflict*) | (2) log(*People*) | (3) log(*Family*) | (4) log(*Area*) |
|---|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.112** | -0.155*** | -0.115** | -0.141 |
| | (0.0521) | (0.0258) | (0.0428) | (0.1094) |
| log(*Rainfall*) | -0.236 | -0.754*** | -0.191 | -0.238 |
| | (0.2772) | (0.1259) | (0.2746) | (0.4378) |
| log(*Population*) | -0.123 | -0.357 | 1.175 | -2.146** |
| | (0.4107) | (0.6749) | (0.7640) | (0.8761) |
| *Gini* | 1.047 | 2.281 | -1.115 | 6.527* |
| | (2.3977) | (2.8022) | (1.9943) | (3.556) |
| Observations | 774 | 743 | 662 | 722 |
| R-squared | 0.290 | 0.348 | 0.257 | 0.133 |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

### Second Alternative Definition of Land Suitability

We further check the main results in terms of the selection of cut-off point in the construction of the suitability variable for soybean cultivation or log($SoybeanSuitability_i$). The cut-off point for log($SoybeanSuitability_i$) here is land that can achieve 25% or above of the maximum yield estimated by the FAO's GAEZ project. The results are presented in Table 4.9 below. Once again, $\hat{\beta}_1$ (which denotes the estimated coefficient of GM soybean cultivation on log(*Conflict*), log(*People*) and log(*Family*) is statistically significant in Table 4.9. The results here still suggest that states with a greater area of land that is suitable for cultivating GM soybeans experience fewer land-related conflicts after the GM soybean cultivation was legalized in 2003.

Table 4.9: Second alternative definition of land suitability

| | (1) log(*Conflict*) | (2) log(*People*) | (3) log(*Family*) | (4) log(*Area*) |
|---|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.107** | -0.143*** | -0.113** | -0.323** |
| | (0.0509) | (0.0249) | (0.0420) | (0.1638) |
| log(*Rainfall*) | -0.228 | -0.743*** | -0.189 | -0.243 |
| | (0.2738) | (0.1285) | (0.2747) | (0.4298) |
| log(*Population*) | -0.030 | 0.531 | 1.277* | -1.829* |
| | (0.4250) | (0.6943) | (0.7688) | (1.0829) |
| *Gini* | 1.136 | 2.436 | -1.135 | 5.890* |
| | (2.3020) | (2.7094) | (1.9337) | (3.363) |
| Observations | 774 | 743 | 662 | 722 |
| R-squared | 0.291 | 0.347 | 0.260 | 0.132 |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, through this exercise, our main results are not sensitive to the selection of the cut-off point that is used to define $\log(SoybeanSuitability_i)$ in the DD estimation. As the cut-off point in $\log(SoybeanSuitability_i)$ is to determine whether land is suitable for cultivating soybeans. In the main results, we select that land is suitable to crop soybean if land can achieve 40% or above of the maximum yield. We have varied the cut-off point from 40% to 55% and 25% above here. We find that the variations of this cut-off point slightly change the size of $\hat{\beta}_1$ but do not change the sign and significance level of $\hat{\beta}_1$. Therefore, our findings on the negative association between GM soybean cultivation and log(*Conflict*), log(*People*) and log(*Family*) in the main results section remain robust.

### 4.7.4 Alternative Suitability Variable: 2020s

In our baseline results, we use the FAO's data on soybean suitability for the years 1960 to 1990 to construct our measure of soybean suitability (i.e. log(*SoybeanSuitabi-*

*lity*)).[42] One concern is that land invasions could be driven not only by the historical productivity of a piece of land, but also expectations about its future productivity. As a robustness check, we choose measures of land suitability for soybean cultivation projected to the 2020-2029 period by the FAO. We re-estimate our model with our new land suitability index for soybean cropping and present our new results in Table 4.10. We find that $\hat{\beta}_1$ (the estimated coefficient of $\log(SoybeanSuitability) \cdot I_t^{post}$) is still statistically significant on $\log(Conflict)$, $\log(People)$ and $\log(Family)$ even when the variable, $\log(SoybeanSuitability)$, to measure the soybeans cultivation suitability is for the 2020-2029 period.

Table 4.10: Alternative suitability variable (2020s period)

| | (1)<br>$\log(Conflict)$ | (2)<br>$\log(People)$ | (3)<br>$\log(Family)$ |
|---|---|---|---|
| $\log(SoybeanSuitability_i) \cdot I_t^{post}$ | -0.110** | -0.150*** | -0.114** |
| | (0.0526) | (0.0259) | (0.0432) |
| $\log(Rainfall)$ | -0.237 | -0.754*** | -0.189 |
| | (0.2780) | (0.1274) | (0.2743) |
| $\log(Population)$ | -0.118 | 0.398 | 1.192 |
| | (0.4109) | (0.6766) | (0.7608) |
| $Gini$ | 1.094 | 2.420 | -1.031 |
| | (2.3843) | (2.850) | (1.9960) |
| Observations | 774 | 743 | 662 |
| R-squared | 0.291 | 0.346 | 0.257 |
| State FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

Robust standard errors clustered in the state level in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 4.8 Conclusion

This study has examined the effect of GM soybean cultivation on land conflicts in Brazil. We argue that the legalization of GM soybean cultivation in 2003 in Brazil has remarkably improved agricultural productivity in terms of land and labor use efficiency. The agricultural productivity enhancement induced by GM soybean

[42]There are four time periods. They are 1960-1990, 2020-2029, 2050-2059 and 2080-2089. 1960-1990 is the baseline time period.

cultivation can not only reduce soybean price but also land value. A devaluation of land in return can result in a reduction of land conflicts. We employ a difference-in-differences estimation and explore two sources of variation. This first source of variation is the commercial legalization of GM soybean cultivation in 2003 in Brazil and the second source of variation is the cross-sectional differences in the size of land that is suitable for cultivating soybeans. Our study has found that states that are more suitable for cultivating GM soybeans tended to experience fewer land conflicts and fewer people and families participated in conflicts after cultivation of GM soybeans was legalized in 2003. Our findings remain robust after placebo tests, confounding factors and different measures of land suitability and functional forms of variable were taken into account in the estimation. The discussion about the legalization of GM crop cultivation is one of the most debated questions for policy makers and the effect of agricultural innovation arising from the GM soybean cultivation on economic development is still scarce. This study can provide some insight into this controversial crop and its impact on internal conflict reduction.

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# Chapter 5

# Conclusion

This dissertation has explored the relationship between agriculture, income and conflicts. There are five chapters in this dissertation. Chapters one and two are the introduction and overview respectively. Chapter three and four are the main studies. Chapter five is the conclusion of this dissertation. The purposes and results of these five chapters are presented as below.

In the first chapter, we provided extensive information on conflicts. In particular, we presented statistics on the number of armed conflicts, information regarding their geographic distribution, variations in conflict frequencies and the number of battle-related deaths. All of this information is imperative to understanding the severity and impact of conflicts.

The overview is a summary of the related literature on the link between agriculture, income and conflicts. Specifically, we discussed reasons to study conflicts, the methods used to estimate the effect of income on conflicts, potential issues in the prevailing estimation methods in the literature and the role of agriculture in the occurrence of conflicts.

In the first main study, we thoroughly examined the claim about the negative relationship between rainfall shocks and conflicts in Miguel, Satyanath and Sergenti (2004) by considering: 1) new rainfall and conflict datasets in their estimation, 2) extended observational years, 3) more lagged rainfall variables, 4) cross-sectional dependence, 5) different functional forms of rainfall. In this main study, we found that the statistical significance in estimating the effect of rainfall shocks on conflicts vanished in Miguel, Satyanath and Sergenti (2004) when the revised rainfall and conflict datasets were implemented. This indicates that the negative association between rainfall shocks and conflicts are not robust in their study. Results remain the same even though larger sample years and more lagged rainfall shocks variables were considered. However, we found that the effect of rainfall on conflicts is indeed statistically significant after cross-sectional dependence and different functional forms of rainfall were taken into account even though the statistical significance in the estimation is relatively weaker than Miguel, Satyanath and Sergenti (2004). The implication of this chapter is that shocks in the agriculture sector are associated with conflict incidence. Therefore, better development in the agriculture sector could contribute to a reduction of conflicts.

Lastly, we further explore the role of agriculture on conflict and investigated the effect of productivity-enhancing innovation in agriculture on conflicts. Specifically, we exploited the event of legalization of Genetically-Modified (GM) soybean cultivation in Brazil and argued theoretically that the enhancement of agricultural productivity induced by GM soybean cultivation can reduce land prices and then mitigate land conflicts. Empirically, we have employed DD estimation and found that states that own more land that is suitable for cultivating GM soybeans after the legalization was negatively associated with land conflicts. We conducted a series of robustness checks on our empirical results and found them still robust after these checks.

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