Erasmus University Rotterdam
Erasmus School of Economics
Master Thesis International Economics

The Seeds of Stability: Analyzing the Causal Link Between Maize Prices and Political Violence in Brazilian Municipalities

Robin van den Akker (657853)

Supervisor:	Dr. J. Emami Namini
Second assessor:	To be determined
Date final version:	30th October 2023

Abstract

This thesis analyses the causal relationship between fluctuations in maize prices on political violence in Brazilian municipalities. Utilising a difference-in-difference strategy in combination with an instrumented variable approach mitigates the scope of relevant endogeneity and reverse causality concerns. This study finds that rising maize price differentially decrease both the intensity and the likelihood of political violence in relatively maize suitable municipalities compared to less suitable ones. This finding aligns with the relevant economic literature, specifically, the opportunity cost channel that suggests that higher labour-intensive commodity prices discourage participation in politically motivated violent events. The outcomes are tested using relevant robustness checks that can partially reproduce the findings with some sensitivity with regard to other crops, demographic heterogeneity, and the inclusion of the COVID-19 Stringency Index. Policymakers can use these findings to argue for price stabilisation schemes, social safety nets, and a diversification of the economy.

Contents

1 Introduction

Civil conflict is a major impediment to economic growth and social security (Bodea & Elbadawi, 2008). Since the establishment of the United Nations, global inter-country conflict has declined, but intra-country conflict has persisted and, is now causing more casualties than inter-country wars (United Nations, 2023; UCDP, 2023). Civil conflict hinders the economic development of countries and causes their citizens to live in poverty (Collier & World Bank, 2003). Thus, it is imperative to study and comprehend the mechanisms that underlie civil conflict. The empirical literature has investigated several causes of civil conflict occurrence and intensity. Most of these studies focus on macro-level data that lead to generalisable results but struggle to define causal relationships between the root causes of violent intra-country conflict. The aim of this paper is to investigate the causal relationship between the labour-intensive agricultural commodity maize and political violence in Brazilian municipalities.

While there exists a vast literature on the determinants of civil conflicts, economists seem to struggle to identify causal relationships between determinants and outcomes. Moreover, the empirical literature is inconclusive and incomplete as it lacks fundamental micro-analyses to make causal inferences. Most of the published research uses macro-level data and finds statistically significant results that are subsequently used to make generalised claims about the effect of commodity price changes on civil conflict. However, these approaches often include fundamental identification challenges that hinder a causal interpretation of their results. A core problem in identifying these relationships is that they suffer from reverse causality; making a causal interpretation of the outcomes difficult or impossible. To alleviate these endogeneity concerns, economists use instrumental variables (IVs), such as exogenous harvest shocks (Winne & Peersman, 2021) and weather conditions (Dube & Vargas, 2013; Dube, García-Ponce & Thom, 2016). These studies find substantial differences regarding different types of commodities and how changes in their price affect civil conflict. Indeed, there seems to be a notable difference in the impact of price increases on civil conflict depending on the type of commodities involved. Specifically, a price increase in a labour-intensive good such as maize tends to reduce civil conflict, whereas a price increase in a capital-intensive good like oil likely leads to an increase in civil conflict (Dube & Vargas, 2013). The empirical literature defines three main mechanisms through which commodity price changes impact civil conflict: the opportunity cost effect (1), the rapacity effect (2), and the state capacity effect (3). In the scope of this paper, the opportunity cost effect is the main channel of interest as the literature expects labour-intensive goods to propagate through it.

This paper analyses the differential effect of international maize price changes on political violence in Brazilian municipalities using monthly micro-level data. The analysis aims to identify a causal relationship between fluctuations in the maize price and the intensity and occurrence of political violence. To do so, I utilise a difference-in-difference (DiD) estimation strategy in combination with a two-stage least squares regression (2SLS). The former is achieved by multiplying each municipality's maize suitability with the monthly maize price. This way, I account for the presumption that changes in the maize price differently affect a municipality's violence rate depending on its maize cultivation suitability. Furthermore, the 2SLS alleviates possible omitted variable and reverse causality concerns. In detail, I instrument the price of maize using exogenous monthly weather conditions of Brazilian municipalities and monthly absolute US maize exports to the world market. Moreover, I analyse civil conflict from a political violence perspective using two angles, the occurrence and the intensity of political violence. To estimate the former, maximum likelihood regressions are used and to estimate the latter, level regressions are used.

This research paper finds statistical evidence that the occurrence and the level of political violence in Brazilian municipalities are negatively affected by rising maize prices. Thereby, indicating that a labour-intensive agricultural good, like maize, likely propagates through the opportunity cost channel. Thus, high maize prices seem to discourage workers from joining politically violent uprisings. I test the validity of these results by performing various robustness tests. First of all, I repeat the regression for two more labour-intensive agricultural crops, specifically, coffee and soybean. Then, I conduct a test to (informally) verify the exclusion restriction assumption of the 2SLS approach. In addition, I test whether there is heterogeneity between rural and urban areas, which could indicate whether the opportunity cost channel is a logical propagation mechanism. Finally, I assess whether COVID-19 poses a threat to the identification method.

This research paper follows the structure outlined below. First, the empirical literature is analysed. Second, the data sources are described. Third, the identification strategy of this paper is outlined. Fourth, the regression results are presented and discussed with regard to the empirical literature. Fifth, multiple robustness checks to examine the validity of the results are conducted. Last, a conclusion summarises the findings of this paper together with policy implications, limitations and future research recommendations.

2 Literature Review

In this literature review, the initial aim is to identify the general relationship between economic factors and civil conflict. Building upon these insights, the scope is narrowed down to focus on specific attributes of economic factors that appear to be associated with heterogeneous effects on civil conflict. Finally, the main empirical identification challenges within the literature and their remedies are investigated.

2.1 Determinants of Civil Conflict

There is a vast literature regarding the root causes of civil conflict. However, research has long neglected the relationship between economic determinants and within-country conflict. The empirical literature started investigating economic determinants in the 1990s and focused on cross-country studies at the macro level. Sachs and Warner (1995) find that natural resource-abundant countries have lower GDP growth. Thereby, the authors make an initial connection between commodities and their effect on income which, indirectly, can affect civil unrest through GDP growth. Building on previous findings, Collier and Hoeffler (1998) created a cost-benefit framework that predicts the likelihood of conflict and applied it to African and other developing countries. The authors state four main indicators of civil unrest: initial income, ethnolinguistic fractionalisation, volume of natural resources, and the initial population size.

Collier and Hoeffler (1998) state that the relationship between the commodity endowment and the civil conflict risk of a country is non-monotonic. Thus, a rise in a natural resource endowment increases the risk of civil conflict at low levels of GDP but decreases it at high levels of GDP. The effects of income and natural resource endowment on civil conflict can be rationalised into three main mechanisms.

First, when there is a rise in the availability or profitability of natural resources, it creates an increased potential benefit for armed groups when capturing or controlling these natural resources. The empirical literature defines this mechanism as the rapacity effect. It describes the expected means by which armed groups can finance their rebellion (Collier & Hoeffler, 2004).

Second, the opportunity costs effects serves as a counterweight to the rapacity effect. In detail, it describes the missing income individuals face when leaving their licit labour market activity for illicit activities (Collier & Hoeffler, 1998). For instance, if the price of a commodity particular to a specific region decreases, farmers in that region might face difficulties sustaining themselves. Therefore, their opportunity cost of working in illicit markets diminishes as their legitimate wage decreases. This, in turn, increases their incentive to work for criminal organisations that offer higher relative wages.

Third, at higher levels of GDP, the state is likely to be more capable of financially gaining from an increase in the natural resource endowment as it has a higher initial ability to secure these natural resources. This way, a developed country can gain further capabilities to secure its natural resources through increased military or police expenditures financed by increases in the augmented tax revenues derived from the expansion in natural resource profitability. In other words, the more developed a state is, the more it is able to financially gain from the increase in the natural resource endowment and utilise the additional means to further secure the state against potential rebellions. In less developed states the government, thus, might not have the ability or capacity to discourage civil unrest or the creation of rebellions (Couttenier & Soubeyran, 2015). The empirical literature labels this mechanism as the state capacity effect.

Moreover, non-economic factors such as political rights, inequality, ethnic polarisation, or religious fractionalisation do not seem to be significant drivers of civil conflict; at most, they serve as moderators (Collier & Hoeffler, 2004; Fearon & Laitin, 2003). Nevertheless, most panel-data studies employ time and year-fixed effects to mitigate potential confounding factors. (Besley & Persson, 2008; Dube et al., 2016; Dube & Vargas, 2013).

There is a substantial body of contradictory empirical literature investigating the causality of the three mechanisms. According to Collier and Hoeffler (2004) and Brückner and Ciccone (2010), commodity dependence, specifically regarding primary export commodities, considerably increases the risk of civil conflict through the three mechanisms. However, Fearon and Laitin (2003) state that the previous research results are prone to slight adjustments in their methodology and hence, cannot be interpreted as causal. Moreover, Bazzi and Blattman (2014) agree that there is no robust relationship between civil conflict risk and commodity prices. Hence, the replication results provide no statistically significant evidence for the effect of primary commodity dependence on civil conflict. This empirical ambiguity calls for further specifications that clearly define which commodities are affected by the three mechanisms. This problem is rooted in most economists using macro-level data. Such data potentially produces generalisable results; however, it hinders causal identification and leads to ambiguous results as varying country and commodity specifications might lead to different outcomes. To disentangle the specific mechanisms and facilitate a causal interpretation of heterogeneous conditions, researchers need to apply more micro-level data (Bazzi & Blattman, 2014).

2.2 Heterogeneous Factor Intensity

The relative factor intensity of the commodities might change the impact of the opportunity, rapacity, and state capacity mechanisms. Specifically, whether a commodity is labour or capital-intensive can affect the direction of the relationship between the commodity price and civil conflict (Blair, Christensen & Rudkin, 2021; Dal Bó & Dal Bó, 2011). According to Bazzi and Blattman (2014), price shocks in labour-intensive goods disproportionately affect household incomes in relation to state revenue. This can be rationalised by the following logic. Labour-intensive commodities, like agricultural goods, are more difficult to capture and less extractable than immobile, highly concentrated capital-intensive commodities, such as oil. Thus, when the price of an agricultural good rises, the opportunity cost of farmers engaging in civil conflict increases. The increase in opportunity costs effect on the farmer is likely larger than the increase in the state capacity effect as the rise in tax revenue is diminished due to the difficulties when taxing labour-intensive goods. The same holds for criminal groups seeking to extort resources. Thus, it is likely that an increase in the price of a labour-intensive commodity increases the rapacity and the state capacity effect equally but less than the opportunity cost effect (Bazzi & Blattman, 2014). Hence, an increase in the profitability of a labour-intensive commodity is likely to decrease the risk of civil conflict (Blair et al., 2021)).

The effect of a price change works in a mirrored manner for capital-intensive commodities. In other words, for capital-intensive commodities, the rapacity dominates the opportunity effect. This can be seen in the study of Dube and Vargas (2013) in which the authors analyse the effect of oil and coffee price shocks in Colombian municipalities. On the one side, the authors conclude that price changes in oil primarily propagate through the rapacity effect and thus, increase conflict levels. On the other side, rises in the price of coffee decrease conflict in coffee-producing municipalities by propagating through the opportunity costs channel. Thus, Dube and Vargas (2013) argue that positive price shocks in labour-intensive commodities decrease conflict levels while an identical price shock to a capital-intensive commodity increases conflict levels. Dube et al. (2016) verify these results by investigating exogenous maize price shocks in Mexico. The authors find that decreases in the price of maize lead to increases in conflict levels in municipalities that predominantly produce maize; favouring the causality of the opportunity cost effect.

The empirical literature sparsely continued analysing the relationship between labour-intensive goods and changes in conflict level with varying results. Fjelde (2015) states that a decrease in agricultural prices increases the risk of violent events in Africa. In line with this, Berman and Couttenier (2015) find conflict to be negatively correlated with income using local data in sub-Saharan Africa. However, recently, some studies have found contradicting outcomes indicating that positive agricultural income shocks lead to more violence (Crost & Felter, 2020; Millán-Quijano & Pulgarín, 2023). These contradicting outcomes indicate that future research is necessary to identify the causal relationship between changes in commodity prices and civil conflict.

2.3 Empirical Identification Challenges

Identifying a causal relationship between changes in commodity prices and conflict levels is empirically challenging. The empirical literature yields several contradicting results. This part of the literature review will analyse the most important empirical challenges and their remedies as present in the current empirical literature. First, I discuss reverse causality issues. Second, I identify potentially omitted variables. Third, I discuss the use of the international crop price.

2.3.1 Endogeneity - Reverse Causality

The relationship between conflict and commodity prices is inherently endogenous as it suffers from reverse causality. The aim is to analyse how changes in commodity prices can affect local conflict levels. It is shortsighted to assume that commodity prices are exogenous to local municipalities. In detail, if local conflict levels rise due to reasons unrelated to price changes, the production of commodities will likely be negatively impacted by alleviated conflict levels. This, in turn, leads to lower supplies to markets which increases the commodity's price. Hence, the direction of the causality is ambiguous indicating a reverse causality issue.

A partial solution is to use international instead of local commodity prices (Winne & Peersman, 2021). By that, the effect of variation in local production levels on the price of the commodity is limited. However, this could also limit the strength price changes have on local conflict if international prices considerably differ from the amount local producers receive. To further resolve the reverse causality issue, economists utilise instrumental variable (IV) approaches. For example, Miguel, Satyanath and Sergenti (2004) use rainfall variation as an instrument for economic growth to analyse the conflict likelihood in Africa. Another example is Dube et al. (2016) who use exogenous changes in US weather conditions to instrument Mexican maize prices. This way, the reverse causality concern is alleviated given that the requirements of the IV approach are met.

2.3.2 Endogeneity - Omitted Variable Bias

As mentioned previously, there might be several unobserved differences between regions that facilitate or hinder conflict from arising. These include but are not limited to differences in institutional quality, systematic inequality, religious fractionalisation, political systems, and culture. While most studies find that they are not significant drivers of conflict, it is the conservative choice to control for these factors by using region and time-fixed effects (Besley & Persson, 2008; Collier & Hoeffler, 2004; Fearon & Laitin, 2003). The addition of region-fixed effects alters the interpretation of the regression outcomes by eliminating a common baseline effect. Specifically, by accounting for fixed effects, the baseline increase in violence that is common across regions is absorbed. This way, the regression analyses the differential effect of a commodity price change similar to a difference-in-difference strategy (Winne & Peersman, 2021). Additionally, to mitigate the effect of underlying region-specific trends, Dube et al. (2016) include region-specific time trends. This way, the scope of omitted variable bias is substantially limited and allows for a more causal interpretation of results. Lastly, by adopting a relevant and valid IV, omitted variable bias can be substantially reduced. When applying a relevant and valid IV omitted variables have to be related to the instruments to potentially bias the results (Erbahar, 2023).

2.3.3 Empirical Identification Challenges

A problem occurs when using international food prices, which are by definition common across all regions, and time-fixed effects, as the latter absorbs all variation necessary for inference (Winne & Peersman, 2021). Dube and Vargas (2013) and Dube et al. (2016) solve this by creating an interaction variable between the production of a commodity in a region by its price. The former uses production levels and the latter uses the suitability of the commodity of interest per region. This way, the economists create a difference-in-difference method with which they analyse the differential effect of price changes for regions that either produce more or are more suitable for producing a certain commodity. Nevertheless, the causality of this approach might be dubious as regions with a high dependency on a commodity might be systematically more sensitive to shocks that cause common price changes (Winne & Peersman, 2021). Moreover, the difference-in-difference method solely captures the effects of price changes for regions that also produce the commodity. According to Winne and Peersman (2021), if a price shock affects all regions in the same direction but commodity-producing regions disproportionately, the difference-in-difference method will only capture the latter effect. To facilitate a causal interpretation of results, common shocks to the international commodity price should be accounted for (Winne & Peersman, 2021). Dube et al. (2016) isolate the effect of international commodity prices by instrumenting with exogenous values of major global commodity exporters. This way, common global commodity price movements are accounted for.

3 Data

The descriptive statistics of all variables are illustrated in Table 3.1 and an overview of their sources and explanation in Table A.1 in Appendix A.1.

The aim of this thesis is to examine the differential impact of maize price changes on Brazilian municipalities that are heterogeneous with regard to their maize cultivation suitability. The maize suitability data is retrieved from the GAEZ database, provided by the Food and Agriculture Organisation (FAO) of the United Nations (GAEZv4, 2023). The suitability data includes historical soil suitability from 1981-2010. Therefore, it is determined before the sample period and thus, exogenous to the model. It provides comprehensive data regarding the suitability of growing a certain crop in a predetermined geographic area. In more detail, the suitability data represents the 'Agro-Ecological-Attainable Yield' for a specific crop in a predetermined geographic zone (GAEZv4, 2023). The measure takes the soil and terrain type of the region into account and thereby, computes an estimate of the attainable crop yield in that region. As different municipalities have different agricultural conditions, the data is downloaded in seven different variations. Each variation accounts for a different combination of input, irrigation, and fertilizer levels. The final data is a normalised index scaled from zero to five that represents the mean of the seven settings and thus, represents an average of the different specifications. A more detailed explanation of the suitability data can be found in the glossary of the GAEZ database (FAO, 2023). Initially, the suitability data is only available in a tagged-image-format (TIF). The TIF displays an image in which each pixel represents a unique local dataset. Using Python, I convert the necessary data into a comma-separated-value (CSV) file and generate a map indicating the maize cultivation suitability of each Brazilian municipality[1].

Moreover, the data for the weather conditions is available at the National Meteorological Institute of Brazil, INMET [2]. The institute provides a meteorological database for education and research purposes, BDMEP[3] (BDMEP, 2023). The institute provides monthly data recordings from 599 weather stations across Brazil. The data includes monthly recordings of the average temperature and total precipitation in millimetres from May 2000 until January 2021 with varying data availability per municipality. Initially, INMET provides the data in 599 single CSV files for each weather station. Moreover, the data was not usable at first as the files were not cleaned. For example, the data used Portuguese orthography which needed to be converted to standard Latin letters. Hence, I used Excel's VBA macros function to write a function that simultaneously cleans the 599 files, formats them identically, and finally creates one main database including all weather data[4].

Furthermore, the conflict data is retrieved from the ACLED conflict database (Raleigh, Linke, Hegre & Karlsen, 2010). Initially, the data is in daily intervals. To create a monthly violence count, I aggregate the daily into monthly violence counts. The database includes historical and

[1]The maize suitability data is illustrated in Panel A of Figure 4.1. The Python code is available on request.
[2]INMET is an abbreviation for 'Instituto Nacional de Meteorologia'.
[3]BDMEP is an abbreviation for Banco de Dados Meteorológicos para Ensino e Pesquisa.
[4]The VBA Macro code is available on request.

real-time conflicts and provides a detailed overview of political violence, protests, and other conflict-related events. In the context of this research, conflict is defined as political violence and thus, only civil conflict regarding battles, explosions, remote violence, and violence against civilians is used. Specifically, political violence is defined as "the use of force by a group with political purpose or motivation" (ACLED, 2019b). This definition aligns with the empirical framework of this paper, as it enables the measurement of politically motivated violent events that are likely the consequence of social unrest. Further details can be found in the ACLED Codebook (ACLED, 2019a). The ACLED data for Brazil is available in daily intervals from January 2018 to May 2023. Due to the daily data availability and vast municipalities covered in the dataset, there is enough variation for econometric analysis. Using Python, each in-sample event of political violence is visualised in Panel B of Figure 4.1.

Moreover, monthly US exports of maize and soybeans are downloaded from the Global Agriculture Trade System (GATS) of the United States Department of Agriculture (GATS, 2023). A further control variable in the likelihood regressions is the log of the population per municipality per year which is retrieved from the Brazilian census data uploaded by the Brazilian Institute of Geography and Statistics (SIDRA, 2023)[5].

Table 3.1: Summary Statistics

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
Cross-sectional variables					
Maize Suitability Index (Scale 0-5)	3,318	1.961	.804	0	5
Coffee Suitability Index (Scale 0-5)	3,318	2.658	1.232	0	5
Soybean Suitability Index (Scale 0-5)	3,318	2.858	.75	0	5
Monthly-level variables					
US Maize Exports (in ths Metric tons)	64	4,791	1,732	2,051	9,308
US Soybeans Exports (in ths Metric tons)	64	4,561	2,811	924	11,588
Log Maize Price (Brazilian Real per Metric ton)	64	6.89	.41	6.22	7.50
Log Soybean Price (Brazilian Real per Metric ton)	64	7.70	.38	7.13	8.22
Log Coffee Price (Brazilian Real per Metric ton)	64	2.70	.39	2.17	3.32
COVID - 19	36	48.45	17.21	1.04	1.95
Panel-data variables					
Total Rain (mm)	12,837	115.13	113.27	0	898.6
Average Temperature (°C)	14,700	23.61	3.71	6.62	35.47
Log Political Violence per 10,000 Inhabitants	159,696	.019	.12	0	3.36
Political Violence Indicator	225,160	.07	.25	0	1
Log Population (Yearly)	11,793	9.95	1.15	7.01	16.33

[5]The Portuguese name for the institute is: Instituto Brasileiro de Geografia e Estatística.

4 Methodology

To estimate the effect of maize price changes on civil conflict in Brazil in levels and likelihood, I use two approaches that are variations of the estimation strategy proposed by Dube and Vargas (2013) and Dube et al. (2016). Both methods use the same baseline framework; specifically, a difference-in-differences (DiD) approach that utilises an instrumental variable (IV) to alleviate endogeneity concerns. The aim of the methods is to analyse how variation in the price of maize differentially relates to the intensity and the occurrence of political violence relative to the maize suitability of Brazilian municipalities. By using two different methods, this paper gains important depth with regard to analysing the dynamics of civil conflict.

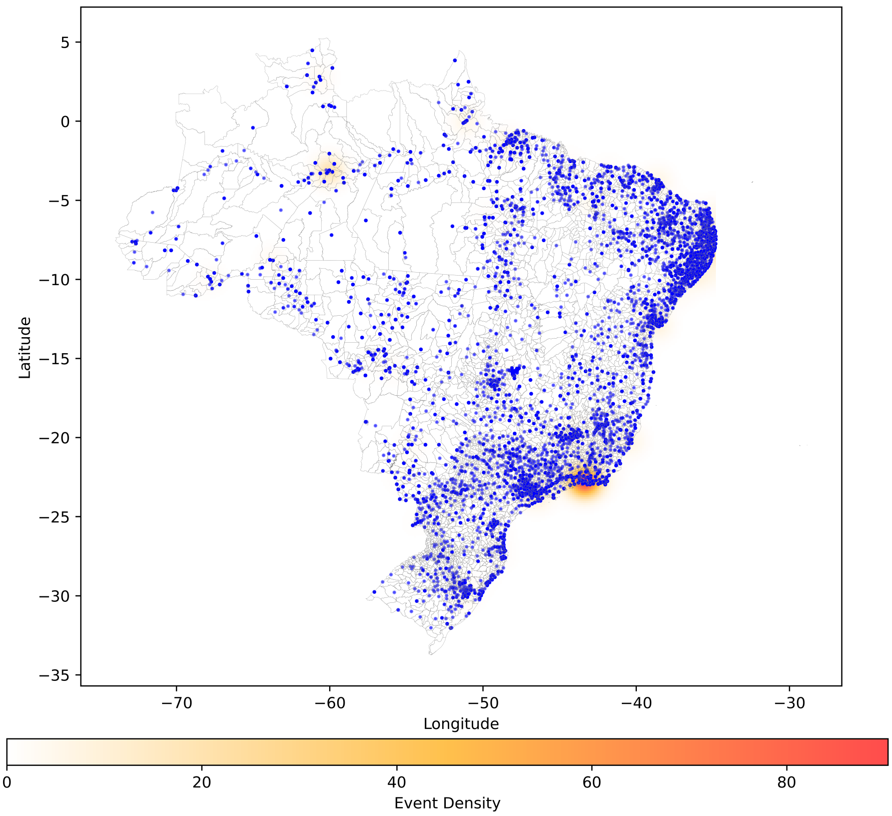
4.1 Political Violence Intensity

The level regression model aims to identify the causal relationship between maize price changes and the intensity of political violence in a Brazilian municipality. This is achieved through a panel data analysis, where the dependent variable measures the count of conflict per month per municipality. In this regression, the dependent variable is the conflict rate per 10,000 inhabitants for each Brazilian municipality. By incorporating a population-adjusted rate, the analysis accounts for differences in the annual population size among municipalities. Thereby, the regression provides a standardised measure of the conflict rate that facilitates a causal interpretation for heterogeneously populated municipalities. Panel A in Figure 4.1 illustrates each account of in-sample political violence. The map shows that political violence is not restricted to distinct municipalities. Therefore, a substantial proportion of municipalities appears to have accounts of political violence, making them suitable for inclusion in the analysis.

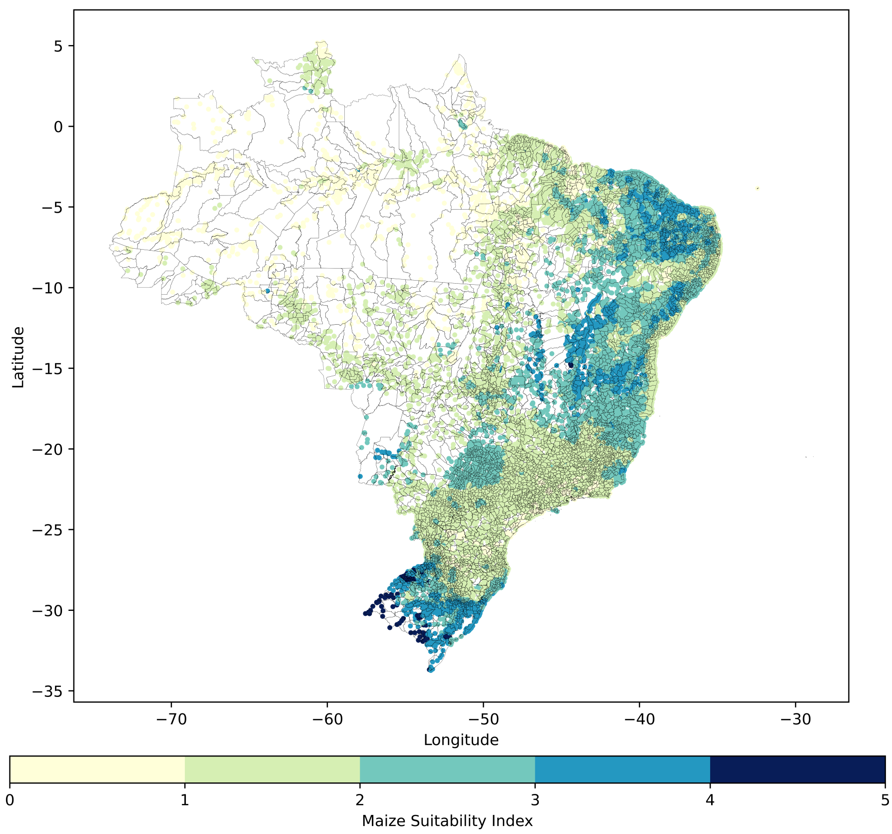
The model uses the maize suitability per Brazilian municipality and interacts it with the time-varying maize price. The Brazilian maize suitability is mapped in Panel B of Figure 4.1. Each dot represents the maize suitability of one municipality. Thus, white areas in the graph do not represent data unavailability but a lower density of municipalities. The figure indicates that all municipalities have considerable variation in maize suitability. Hence, the results cannot be attributed to a single geographic area.

Moreover, the interaction between price and maize suitability functions as a continuous treatment variable. As such, the maize price does not classify distinct treatment and control groups as all municipalities are exposed to the continuous maize price treatment. Therefore, the estimation strategy does not follow a traditional DiD method and the estimation strategy does not necessarily need to fulfil all the stringent requirements of the DiD approach. For example, the parallel trend test cannot be tested as all pre-sample observations are exposed to the continuous price treatment. By interacting the heterogeneous crop suitability of municipalities with the continuous price treatment, I capture the differential effect of commodity price changes between municipalities that differ with regard to their maize suitability.

Comparing Panel A and Panel B, there is no clear correlation between political violence and



(a) Panel A: Political Violence Events



(b) Panel B: Maize Suitability Index

Figure 4.1: This figure shows the maize suitability index per Brazilian municipality in Panel A and illustrates each in-sample case of political violence in Panel B.

maize suitability visible. This is not an unexpected result, as changes in the maize price will likely only explain a minor proportion of the total political violence in Brazilian municipalities. Thus, I expect the R-squared of the regressions to be small, irrespective of their statistical significance.

The main independent variable is the above-described interaction between crop suitability on a municipality level and the monthly international price of the crop. As explained in the literature review, using the international commodity price alleviates some of the potential endogeneity concerns because the international commodity price is most likely exogenous to local Brazilian producers. Due to the panel data structure, the estimation method can use municipality and month-fixed effects to mitigate potential omitted variables bias by accounting for unobserved municipality and time-invariant effects. Moreover, to account for potential endogeneity concerns, in the form of omitted variable bias and reverse causality, I instrument the commodity price with monthly rainfall and temperature data in Brazilian municipalities as well as the monthly US maize exports to the world market. The latter controls for common international commodity-specific price movements (Dube et al., 2016; Winne & Peersman, 2021). This way, the scope of omitted variable bias is considerably diminished as an omitted variable has to be related to the instruments to be considered endogenous. As weather conditions are by definition compellingly exogenous, potential confounders can solely exist with regard to US maize exports. In combination with the included fixed effects, this substantially limits the scope of omitted variable bias.

The second stage for the level regression is represented by Equation 4.1

$$\begin{aligned} PV_{i,t} &= \beta_0 + \alpha_{2,i} + \mu_{2,t} + \gamma_{2i} \times mt \\ &\quad + (\widehat{MAIZE_i \times Price_t})\beta_1 + \epsilon_{i,t}, \end{aligned} \tag{4.1}$$

where $PV_{i,t}$[1] measures the rate of political violence per 10,000 inhabitants in logs that occurred in municipality i, and time t. This way, the results will be comparable across municipalities with different population sizes which follows the recommendation of the literature review (Collier & Hoeffler, 1998).

Moreover, $MAIZE_i$ represents the suitability of growing maize in municipality i and, $Price_t$ is the natural logarithm of the international price of maize in Brazilian Real at time t. Following the literature review, the expected sign of the interaction term's coefficient is negative. This prediction stems from the notion that higher maize prices would decrease the incentive of farmers to engage with criminal organisations, thereby reducing the potential for political violence through the opportunity cost effect[2].

Additonally, β_0 is the constant, $\alpha_{2,i}$ captures the second stage municipality-fixed effects, $\mu_{2,t}$ the second stage time-fixed effects and, $\gamma_{2,i}$ the second stage municipality time trends. The municipality-fixed effects account for time-invariant municipality-specific characteristics such as a municipality's land size, elevation, distance to the sea, and ethnolinguistic fractionalisation (Collier & Hoeffler, 1998). Furthermore, the time-fixed effects account for common changes across all municipalities such as the business cycle, exchange rates, as well as federal political

[1] $PV_{i,t}$ is generated by dividing the monthly count of politically violent events by the total population of the municipality. The log rate is then constructed by adding one to each value and calculating the natural logarithm.

[2] The base terms of the interaction term are not included in the main regression as they are absorbed by time and municipality-fixed effects. Given that a specification does not use either time or municipality-fixed effects, the baseline term, $PRICE_t$, is included for the former and ($MAIZE_i$ for the latter.

and monetary policy changes.

Moreover, the municipality-specific time trends aim to account for the underlying time trends of a municipality. Due to the difficulty of gathering monthly Brazilian municipality-level data, potentially important variables, like income levels in municipalities, cannot be obtained. Hence, municipality time trends mitigate the effect of potential omitted variable bias. In detail, municipality-specific time trends can account for unobserved underlying trends like political radicalisation, inflation, climate change, changes in natural resource volumes, deforestation, or changes in soil suitability that could potentially affect political violence (Dube et al., 2016; Collier & Hoeffler, 1998).

Equation 4.1 is analysed using four different regression specifications. First, a simple ordinary least squares (OLS) with random effects is applied. Second, a fixed effects model is added. Both OLS regressions assume that international maize price movements are exogenous; in contrast to the empirical literature. It is difficult to predict the direction of the bias that the reverse causality issue is causing. On the one hand, high conflict levels likely increase the price of maize by diminishing harvest potential and thus limiting supply. This effect would indicate an overestimation of the coefficient when using OLS. On the other hand, a high maize price likely reduces conflict through the opportunity cost effect; thereby, potentially underestimating the coefficient's size (Erbahar, 2023). Depending on the relative strength of each effect, OLS can either under- or overestimate the coefficient of interest. The regression results will provide further detail on this matter. Third, the IV method is incorporated to alleviate the potential endogeneity concerns. Fourth, municipality time trends are added to account for any underlying unobserved municipality-specific time trends; thereby, mitigating potential omitted variable concerns.

Furthermore, all regressions use standard errors that are robust and clustered at the municipality level. Thereby, the standard errors are adjusted for potential serial correlation and heteroskedasticity. However, cluster-robust standard errors do not account for cross-sectional correlation (Wooldridge, 2020). Thus, time and municipality-fixed effects are included in all regressions, but the random effects regression, to provide further restrictions that facilitate causal interpretation.

4.2 Political Violence Occurrence

The maximum likelihood approach is used to identify the causal relationship between the variation in maize prices and the occurrence of political violence in Brazilian municipalities. The analysis applies a limited dependent variable model approach that will use linear and non-linear probability estimators. This approach aims to identify the likelihood of conflict in a Brazilian municipality following maize price changes. In this case, the dependent variable is a binary measure that equals 1 if there is conflict in a municipality and 0 if not. The likelihood regressions include four different regression models[3].

First, a linear probability model (LPM) is estimated with ordinary least squares. This regression model assumes that international maize price movements are exogenous. The linear dependent variable model is represented by Equation 4.2

$$\mathrm{PV}_{i,t} = \beta_0 + \alpha_{2,i} + \mu_{2,t} + (MAIZ\widehat{E_i \times P}rice_t)\beta_1 + Pop_{i,t}\beta_2 + \varepsilon_{i,t}, \tag{4.2}$$

where $PV_{i,t}$ indicates the occurrence of political violence in municipality i and time t. In contrast to the level regression, the likelihood regression includes the log of the yearly population per municipality as a control variable; $Pop_{i,t}$. This way, the heterogeneity in population size among municipalities is accounted for without adjusting the dependent variable. Consequently, the interpretation of the binary dependent variable is facilitated. The expected sign of the population variable is positive as more populated municipalities should have an increased violence potential. Besides this adjustment and the exclusion of municipality-specific time trends, the maximum likelihood regression follows the same specifications as the previously described level regression. LPMs have major drawbacks; especially for causal interpretation. These include potential predicted probabilities beyond zero and one, as well as the assumption of constant marginal effects (Wooldridge, 2020). The regression results of the LPMs are thus only used to give a first indication of the relationship between maize suitability, maize price changes, and political violence occurrence.

Second, a random-effects logistic regression is applied. This specification allows for control for potential heteroskedasticity and serial correlation while assuming a non-linear, S-shaped, relationship between the predictors and the binary outcome variable. The random effects specification assumes that the individual heterogeneity among municipalities is uncorrelated with the independent variables (Wooldridge, 2020). Moreover, by specifying the relationship between the dependent variable, the independent variable, and the error term, a causal interpretation of the results is facilitated. The logistic regression is illustrated in Equation 4.3

$$\mathbb{P}(PV_{i,t} = 1) = F[\beta_0 + \alpha_{2,i} + \mu_{2,t} + (MAIZ\widehat{E_i \times P}rice_t)\beta_1 + Pop_{i,t}\beta_2], \tag{4.3}$$

where each variable follows the same definition as previously.

Third, to verify if violating the random-effects assumption considerably affects the outcome, a conditional fixed-effects logistic regression is used. This specification assumes that municipality-specific effects are correlated with the independent variables. Both Logit models assume that the

[3]Given that a model does not use either time or municipality-fixed effects, the baseline term, $PRICE_t$, is included for the former and $MAIZE_i$ for the latter.

error term is logistically distributed (Wooldridge, 2020).

Fourth, the aforementioned IV is incorporated using a Probit regression[4]. The IV approach provides a more robust estimation of the causal relationship between maize prices and civil conflict by mitigating potential issues related endogeneity concerns. In the context of an IV-Probit model, it is required for the endogenous covariates to be continuous, which is the case in my dataset (Newey, 1987). Besides the assumption that the error term is independent of the independent variables, another crucial assumption of the Probit model is that its errors follow a normal distribution (Wooldridge, 2020). Since this assumption is likely not met, the regressions incorporate cluster-robust standard errors that allow for intra-group correlation. Moreover, Probit does not allow for municipality-fixed effects. Hence, $MAIZE_i$ is included in the regression and time-invariant municipality-specific variables are not accounted for; increasing the potential of omitted variable bias.

4.3 First Stage Regression

The first stage is represented by Equation 4.4

$$\begin{aligned} \widehat{MAIZE_i \times Price_t} = {} & \alpha_{1,i} + \mu_{1,t} + \gamma_{1,i} \times mt \\ & + (MAIZE_i \times Temp_{i,t})\theta \\ & + (MAIZE_i \times Temp_{i,t})^2\varphi \\ & + (MAIZE_i \times Rain_{i,t})\phi \\ & + (MAIZE_i \times Rain_{i,t})^2\vartheta \\ & + (MAIZE_i \times USExports_{i,t})\omega \\ & + \mathbf{X'}\delta + \varepsilon_{i,t}, \end{aligned} \tag{4.4}$$

where $Temp_{i,t}$ and $Rain_{i,t}$ represent the average temperature in Celsius and total rainfall in millimetres per time t and municipality i respectively[5]. Moreover, their squared terms are included to account for potential non-linear relationships. It is important to allow for non-linearity, as both droughts and flooding, along with extreme temperatures are detrimental to crop cultivation (Hidalgo, Naidu, Nichter & Richardson, 2010). Therefore, it is expected that both weather conditions follow a convex parabola-shaped relationship. Given optimal weather conditions, devoid of extremities, a crop's harvest yield is expected to increase. In this scenario, the market experiences an increase in supply, resulting in downward pressure on the price of the crop. Hence, the expected signs of the weather conditions are positive for the linear and squared variables. Moreover, $USExports_{i,t}$ represents the monthly US exports of maize to the world market in thousand Metric tons[6]. By including the US exports, common international commodity-specific price movements are accounted for (Dube et al., 2016; Winne & Peersman, 2021). Higher US exports of maize are expected to decrease the price of maize and hence, the coefficient is expected to be negative.

To align the first stage with the second stage, the former incorporates the same controls

[4]The function F in Equation 4.3 takes different forms given whether Logit or Probit is applied.

[5]The temperature and rainfall variables are illustrated in Figure 4.2.

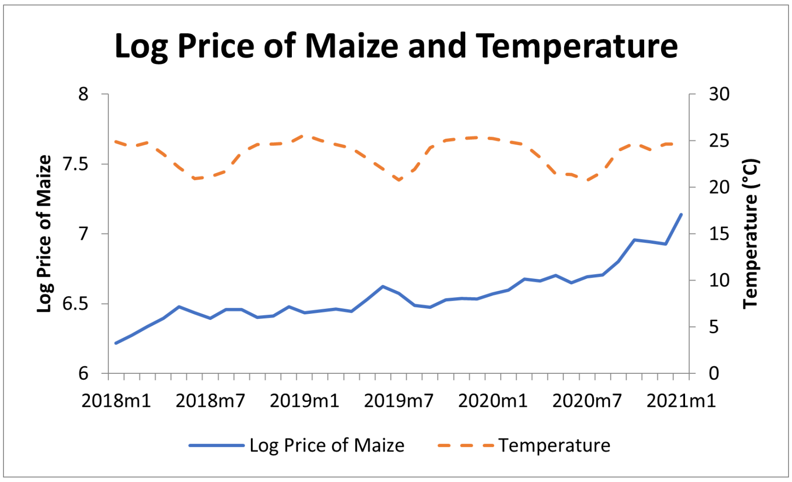
[6]The US maize exports are illustrated in Figure 4.2.

and fixed effects as the latter. Moreover, the first stage is appropriately adjusted to the second stage for each regression specification. For the maximum likelihood IV approach, the log of the population is thus added to the first-stage equation. Lastly, the first stage uses cluster-robust standard errors and, $\varepsilon_{i,t}$ shows its error term.

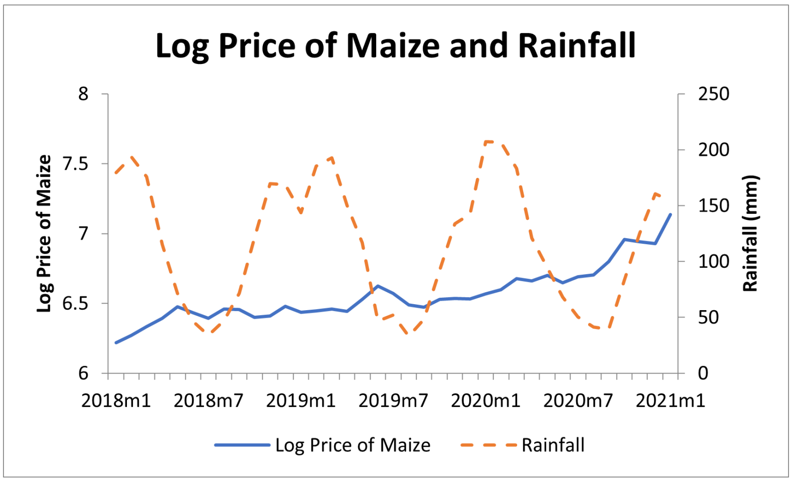
4.4 Instrumental Variable Identification Assumptions

For the IV approach to be valid and relevant, the instrumented variables must fulfil four requirements. First, the first stage needs to be relevant. Hence, the instruments must statistically significantly predict the instrumented variable. If this condition is fulfilled, the IV approach is relevant. Second, the instruments must solely affect the dependent variable through its effect on the instrumented variable. This is the exclusion restriction. Third, the IV must be randomly assigned. In other words, it must be uncorrelated to the error term to fulfil the independence assumption. If the exclusion restriction and the independence assumptions are fulfilled, the IV approach is valid. Lastly, as the treatment is continuous, the IV approach must additionally satisfy the monotonicity assumption. In detail, the IV must only affect the dependent variable in one direction and thus not cause defiers.

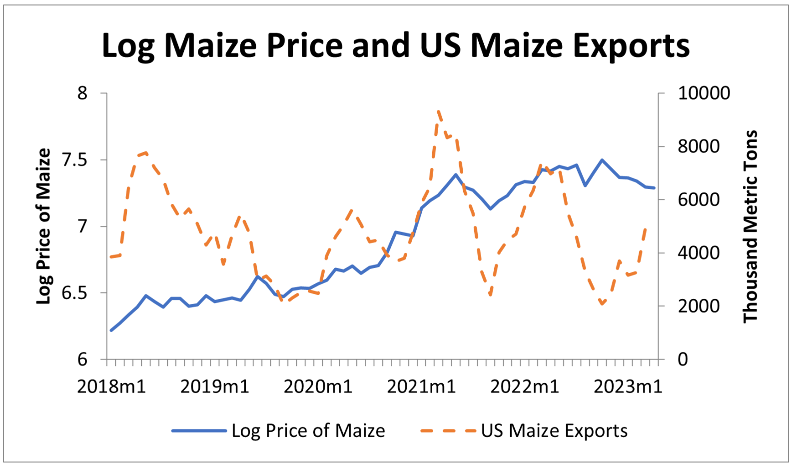
The empirical literature has shown that this specific IV approach is valid and relevant (Dube et al., 2016). Nevertheless, I additionally argue for its relevance and validity in the case of this study. The relevant instruments are illustrated in Figure 4.2. First, the relevance of the IV will be shown in the result section as it is conditional on the statistical significance of the instruments. Second, it is reasonable to assume that the exclusion restriction is satisfied. This assumption indicates that the monthly weather conditions of Brazilian municipalities, which are likely exogenous, solely affect political violence through their impact on the maize price. Furthermore, the monthly exports of US maize to the world market have a limited scope of affecting local conflict apart from their indirect effect on the maize price. Therefore, both Brazilian weather conditions and US maize exports are likely exogenous factors, satisfying the exclusion restriction. Third, the independence assumption is likely to hold as exogenous weather and US export values must be correlated with a variable in the error term that simultaneously affects conflict levels in Brazilian municipalities which is highly unlikely. Fourth, the monotonicity assumption requests that the instrument only affects the dependent variable in one direction. This holds for all the instruments being used in the first stage. Optimal weather conditions and higher US maize exports are expected to lead to a decrease in the price of maize which, in turn, should solely increase the political violence in Brazilian municipalities. Therefore, the monotonicity assumption is likely satisfied, as the instruments are expected to have a constant effect on the dependent variable in the desired direction and thereby, cause no defiers.



(a) Panel A: Log Maize Price and Temperature



(b) Panel B: Log Maize Price and Rainfall



(c) Panel C: Log Maize Price and US Maize Exports

Figure 4.2: Maize price, temperature, rainfall, and US maize exports. Each panel illustrates the monthly in-sample maize price movements in combination with an instrumental variable.

4.5 Threat to Identification

If an omitted variable is simultaneously endogenous, correlated with the dependent variable, and correlated with the instrument, it poses a threat to identification. The estimation method I use leads to the following identifying assumption. For the identification to be causal, there should be no omitted variable that simultaneously affects conflict across regions within a Brazilian municipality (1), is correlated with the maize price (2), propagates through a shock rather than a continuous trend (3), and is related to the instruments (4). The third requirement is the consequence of accounting for municipality-specific time trends. Hence, if a variable affects a municipality over time, the municipality time trends capture this trend. However, if an omitted variable simultaneously fulfils all four requirements, the identification method is threatened.

A potential threat to identification could be (shock) events that impact workers' income, which in turn affect the potential for political violence, as there is no variable controlling for the income level of a municipality. An example of such an event might be the COVID-19 pandemic. The COVID-19 pandemic was first registered on the 26th of February 2020 in Brazil and is thus, within the sample (Serdan et al., 2020). The pandemic considerably influenced various economic spheres in Brazil as the country suffered from over 37 million infections and over 700,000 deaths according to the WHO (2023). Moreover, COVID-19 negatively impacted employment, labour efficiency and social harmony in Brazil. Indeed, the pandemic could have directly influenced political violence via social unrest and indirectly impacted workers through income changes or a more hazardous working environment. This, in turn, might have had a negative impact on the maize industry, and potentially influenced the maize price. Additionally, the initial impact of COVID-19 was an unexpected shock, and thus, might not be fully captured in the municipality time trends. Moreover, the pandemic could have an impact on the instruments by affecting the US maize export behaviour through trade restrictions. To address this threat to identification, a robustness check will be conducted using monthly averages of the COVID-19 Stringency Index (Mathieu et al., 2020).

4.6 Econometric Test and Specifications

This section conducts and analyses various econometric tests to determine the correct specifications for each regression[7].

First, I compute a modified version of the Wald test to assess heteroskedasticity at the municipality level (Greene, 2000). The null hypothesis that the variance of the error terms in the regression is zero can be rejected at the 1% significance level for the level and likelihood regressions. Hence, robust standard errors are implemented to account for said heteroskedasticity.

Second, as the regression suffers from heteroskedasticity, a vital assumption of the Hausman (1978) test is violated. To continue assessing the preference between random and fixed-effects specifications, I calculate the Sargan-Hansen statistic (Schaffer & Stillman, 2010) that accounts for group-wise heteroskedasticity. The test results provide a clear indication that a fixed effects regression is preferred for the likelihood regression and a random effects approach is preferred for

[7]All the econometric test results are outlined in Appendix A.2

the level regression. Both regressions thus will be conducted in a two-fold manner, first with random effects and then compared to the fixed-effects alternative.

Third, I test for autocorrelation by using the Wooldridge test for serial correlation (Drukker, 2003; Wooldridge, 2002). The test results indicate first-order autocorrelation in the likelihood regression at the 1% significance level. In contrast, the level regressions show no signs of first-order autocorrelation. To account for the serial correlation clustered standard errors are used.

Fourth, I conduct a Levin-Lin-Chu (LLC) test (Levin, Lin & Chu, 2002) for all the variables used in the regression. My dataset fulfills the balanced panel assumption of the LLC test and hence, the LLC unit root test is viable. The lags included in the tests are decided individually based on the Akaike information criterion (AIC). Moreover, when applicable, the trend of a variable is accounted for. The test results conclude that the null hypothesis of a unit root can be rejected at the 1% significance level for all variables; thereby, indicating that the variables are likely stationary and thus, require no further transformation.

Fifth, I analyse whether the time-fixed effects have, next to their theoretical importance, statistical power. To do so, I compute the F statistics for joined significance for the time dummies using a Wald test (StataCorp, 2021). The test results show for each regression that the time dummies are statistically significant at the 1% level and are therefore included in the regressions.

Last, I compute the F-statistics of joined significance using a Wald test to determine whether the municipality-specific time trends are statistically significant. The test results show that the municipality-specific time trends are statistically significant at the 1% level. Hence, there exists an underlying trend that substantially influences the results.

5 Results and Discussion

This research paper aims to investigate the causal relationship between international maize price changes and local political violence levels and occurrence in Brazilian municipalities. The empirical literature predicts that an increase in the price of a labour-intensive commodity decreases the potential for conflict by propagating mainly the so-called opportunity cost effect. This paper analyses the labour-intensive commodity maize and the results predominantly support the opportunity cost theory.

5.1 First Stage Results

For a causal interpretation of the results, the two-stage least squares method must be relevant. Hence, the instruments in the first stage must statistically significantly predict the independent variable in the second stage. Specifically, the monthly weather conditions in Mexico must predict the monthly maize price. This can be tested by running the ordinary least squares regression for the first stage. These results can be found in Table 5.1.

While the sign of the US exports' coefficient is in line with its prediction, the weather conditions' coefficients are not. This might be the consequence of simplified assumptions regarding the relationship between the weather conditions and the price of maize. Nevertheless, the results show a strong correlation between the weather conditions and the instrumented maize price. Thus, the weather conditions statistically significantly predict the maize price and therefore, are relevant instruments for the two-stage least squares method.

Table 5.1: First Stage Estimation - Maize

$MAIZE_i \times PRICE_t$	(1) OLS
$MAIZE_i \times Temp_t$	0.006***
	(0.002)
$(MAIZE_i \times Temp_t)^2$	-0.000***
	(0.000)
$MAIZE_i \times Rain_t$	-0.000***
	(0.000)
$(MAIZE_i \times Rain_t)^2$	0.000**
	(0.000)
$MAIZE_i \times US\ Maize\ exports_t$	-0.000***
	(0.000)
Observations	12,826
Municipalities	480
R-squared	0.838

Notes: The first stage results are illustrated to indicate the relevance of the instrumented variables. The regression also includes municipality and time-fixed effects. The standard errors are robust and clustered at the municipality level and are shown in parentheses.
$^{**}p < 0.05$ $^{***}p < 0.01$

5.2 Political Violence Intensity

The following paragraphs will examine the relationship between the price of maize and its differential effect on the political violence level in Brazilian municipalities and discuss their implication with regard to the literature review. The result section will discuss and compare the results in order as presented in Table 5.2[1]. The most robust model is represented in Column (4) as it is the most sophisticated estimation method; including both the IV strategy and municipality-specific time trends. Hence, this specification will serve as a benchmark to which other results are compared.

In the benchmark specification, a statistically significant negative relationship between maize price changes and political violence in Brazilian municipalities is observed at the 1% level. This result is economically meaningful. To compute the differential effect of the maize price change, the relative maize suitability of the municipalities has to be taken into account. As the left and right-hand sides are in logs, a 1% change in the independent variable leads to a 1% $\times \beta_1$ change in the dependent variable (Erbahar, 2023). However, the differential effect of the DiD estimation method has to be taken into account. To estimate the relative impact of this price increase, a municipality at the 90th percentile and at the 10th percentile of maize suitability is considered. To analyse this differential effect, I use a one standard deviation (SD) increase in the price of maize; equivalent to 0.41 log points or 426 Brazilian Real per Metric ton[2]. A municipality at the 90th (10th) percentile of maize suitability has a maize suitability index of 3.141 (1.071). Therefore, when moving from the 10th to the 90th percentile of maize suitability, a one SD increase in maize prices results in a corresponding differential decrease in the political violence intensity of 4.24%, ceteris paribus. Given that maize price changes affect political violence through a narrow lens, these changes have considerable economic meaning. The results indicate that municipalities that are more suitable for maize cultivation are more prone to maize price changes with respect to political violence.

In comparison to the benchmark results, the IV estimation without municipality-specific time trends in Column (3), shows a statistically significant but positive relationship between price changes in maize and political violence at the 5% level. This result indicates a differential increase of 6.96% in political violence for highly maize-suitable municipalities relative to less suitable ones, following a one SD increase in maize prices, ceteris paribus.

Moreover, the OLS random and fixed-effects models, Column (1) and (2) respectively, have coefficients equalling zero and show no statistical significance. Compared to the OLS results, the IV coefficients are larger in absolute size. The OLS models do not account for the endogeneity bias. The endogeneity bias can be rationalized by the following dynamics. On the one side, high conflict levels should negatively bias the results by increasing maize prices. On the other side, high maize prices should diminish the intensity of conflict and thus, positively bias the results. Consequently, higher maize prices likely diminish conflict more than high conflict levels increase the price of maize. Therefore, the OLS bias leading to an underestimation has a larger effect

[1] The R-square of the regression is consistently below 0.002 with some specifications omitting the coefficient of determination entirely. Hence, it is omitted in each table.

[2] This approach follows the interpretation method used by Dube et al. (2016); specifically, $\Delta PRICE_t \times (MAIZE_{90th} - MAIZE_{10th}) \times \beta_1$.

Table 5.2: Second Stage Estimation - Political Violence Intensity - Maize

$PV_{i,t}$	(1) OLS-RE	(2) OLS-FE	(3) IV-2SLS	(4) IV-2SLS
$MAIZE_i \times PRICE_t$	-0.000	-0.000	0.082***	-0.050***
	(0.001)	(0.001)	(0.029)	(0.019)
$MAIZE_i$	0.001			
	(0.009)			
Municipality fixed effects	NO	YES	YES	YES
Municipality time trends	NO	NO	NO	YES
Observations	158,976	158,976	12,826	12,826
Municipalities	3,312	3,312	480	480

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level. Each regression includes time-fixed effects. Columns (3) and (4) show the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports. The first stage estimation can be found in Table 5.1. $^{***}p < 0.01$

than its bias causing an overestimation. Thus, the IV coefficients are larger in absolute size relative to the OLS coefficients.

The different outcomes between the two IV approaches spark the question of what the underlying mechanism between the two results is. Column (4) likely accounts for an underlying trend that positively biases the results in Column (3). The coefficients for the underlying trend solely have negative statistically significant coefficients. Using the omitted variable bias definition, a positive omitted variable bias with a negative coefficient necessarily implies a negative correlation between the underlying trend and the maize price (Erbahar, 2023). Thus, there must be an underlying trend in Brazilian municipalities that negatively impacts the maize price, and the conflict level, and is correlated with the IV but is neither captured by time nor municipality-fixed effects. One explanation might be that within the agricultural industry, a positive technological development facilitates maize production and thereby, increases the incentive for the industry to employ additional labour; in turn, decreasing the potential for conflict. An underlying trend in technological development would likely propagate through the opportunity cost channel in a similar manner as the maize price itself. Thereby, technological advancement might moderate the effect the maize price has on political violence. Such a technological development could influence US maize exports and the Brazilian agriculture industry simultaneously. Thereby, being a potential source of endogeneity that potentially causes the difference in the coefficient outcomes between Columns (3) and (4) of Table 5.2. While identifying the exact underlying trend that is causing this shift is economically and politically interesting, it is beyond the scope of this thesis and thus, should be analysed in future research.

The result of the benchmark specification follows the prediction of the literature review; specifically the results of Dube and Vargas (2013) and Dube et al. (2016). To reiterate, an increase in the price of maize differentially decreases the intensity of political violence in Brazilian municipalities that are relatively suitable for growing maize in comparison to less suitable ones. Therefore, the main regression result indicates that changes in the maize price indeed propagate through the opportunity cost channel discussed in the literature review. Thus, farmers have higher opportunity costs when deciding whether to join armed political conflicts when maize prices are higher. This result also underlines the findings of Bazzi and Blattman (2014) and Blair et al. (2021) who state that price increases of labour-intensive commodities reduce the risk of conflict. Moreover, my findings seem to align with studies conducted in Africa that correlate agricultural prices and income negatively with violence (Couttenier & Soubeyran, 2015; Fjelde, 2015). The micro-data evidence used in this thesis refutes recent findings that increased agricultural income is positively correlated with civil violence (Crost & Felter, 2020; Millán-Quijano & Pulgarín, 2023).

5.3 Political Violence Occurrence

The political violence likelihood results have four different specifications which yield similar results. The most robust estimation method uses a combination of the DiD and the IV approach in a Probit model. This specification serves as the causality benchmark as it accounts for potential reverse causality. However, due to the Probit specification, the causality benchmark specification does not yield results that are straightforward to interpret (Ai & Norton, 2003; Wooldridge, 2020). Hence, I will use the Probit model in Column (4) of Table 5.3 to interpret the causality and the conditional fixed-effects Logit model in Column (3) to analyse the economic magnitude of the impact.

The Probit model indicates at the 5% significance level that changes in the price of maize differentially impact the likelihood of political violence in maize-suitable municipalities relative to less suitable ones. The other likelihood specifications demonstrate similar outcomes, albeit with some variations in magnitude. In more detail, the coefficient for $MAIZE_i \times PRICE_t$ is consistently negative and statistically significant either at the 1 or 5% level. Hence, the likelihood results provide strong evidence that maize price changes indeed propagate through the opportunity cost channel. Thus, the results are in line with the majority of the current empiric literature (Dube & Vargas, 2013; Dube et al., 2016; Couttenier & Soubeyran, 2015; Bazzi & Blattman, 2014; Blair et al., 2021). Hence, it appears that the occurrence of political violence is more responsive to fluctuations in maize prices in municipalities that are relatively more suitable for maize cultivation. These results are in line with my level regression analysis and are consistent with the expectations from the literature review with regard to supporting the opportunity cost theory (Dube et al., 2016; Bazzi & Blattman, 2014; Blair et al., 2021).

The coefficients for the different specifications are economically meaningful with varying sizes. To analyse the economic impact of maize price changes, I compare the results of municipalities at the 90th percentile and the 10th percentile of maize suitability using the conditional fixed-effects Logit model. For coherence, I compute the expected odds ratio of political violence using a one standard deviation increase in the price of maize; an equivalent price change compared to the level regressions[3]. Given that a municipality is at the 90th percentile of maize price suitability and the price of maize increases by one SD, the expected odds of political violence decrease

[3]The formula follows the definition of the Logistic function to compute the log odds ratio of political violence: $ln(odds(p)) = ln(\frac{p}{1-p}) = ln(\frac{\mathbb{P}[PV_{i,t}=1]}{\mathbb{P}[PV_{i,t}=0]})$ with $p = \mathbb{P}[PV_{i,t} = 1]$. Thus, for a maize price decrease, the computation for the expected odds of political violence is $\mathbb{E}[odds(p)] = 1 - exp(\beta_1 \times MAIZE_i \times \Delta Price_t)$.

by 21.7%, ceteris paribus. In comparison, an equivalent maize price increase only leads to an expected 8% decrease in the odds of political violence for municipalities at the 10th percentile of maize suitability, ceteris paribus. These outcomes show a stark difference in municipalities that are heterogeneous in their maize cultivation suitabilities.

Table 5.3: Second Stage Estimation - Political Violence Likelihood - Maize

$PV_{i,t}$	(1) LPM OLS	(2) Random Effects Logit	(3) Fixed Effects Logit	(4) IV-2SLS Probit
$MAIZE_i \times PRICE_t$	-0.007***	-0.167***	-0.190***	-1.753**
	(0.002)	(0.057)	(0.047)	(0.808)
$MAIZE_i$		1.053***		11.373**
		(0.380)		(5.277)
$Population_t$	-0.120**	1.033***	-1.638	0.623***
	(0.053)	(0.030)	(1.184)	(0.052)
Municipality fixed effects	YES	NO	YES	NO
Observations	158,976	158,976	109,632	12,826
Municipalities	3,312	3,312	2,284	480

Notes: The standard errors are shown in parentheses and are robust and clustered at the municipality level for all regressions besides Column (3). Each regression includes time-fixed effects. Column (1) is a linear probability model. Column (2) is a random-effects logistic regression. Column (3) shows a conditional fixed-effects logistic regression. Column (4) uses the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports in a Probit model. The first stage estimation can be found in Table 5.1. $^{**}p < 0.05$ $^{***}p < 0.01$

Moreover, the population variable is statistically significant throughout most specifications. The only non-significant result is in the conditional fixed-effects Logit model that accounts for municipality-fixed effects. Although the population variable changes over time, there are only a limited number of years of observations. Consequently, much of the variation in the variable is likely accounted for by the municipality-fixed effects. Surprisingly, the LPM in Column (1) shows a negative significant coefficient even though the model includes municipality-fixed effects. Moreover, the negative sign of the coefficient implies that smaller municipalities are more likely to encounter political violence. This is counterintuitive as larger municipalities are typically expected to have a higher potential for political violence due to their larger population counts. More in line with common expectations are Columns (2) and (4) of Table 5.3. The columns indicate a statistically significant positive coefficient at the 1% level. As the IV-Probit model in Column (4) produces the most robust estimates, it is probable that larger municipalities indeed have a higher likelihood of political violence occurrence; which aligns with conventional wisdom.

Overall, the likelihood results align with the predictions of the literature review and thus, support the opportunity cost channel. In other words, the maize price increase over the sample period significantly differentially decreased the likelihood of conflict occurrence for municipalities that are relatively suitable for maize cultivation.

6 Robustness

The following sections analyse the robustness of the main regression results. This verification process uses the main section's methodology on two different labour-intensive crops, coffee and soybeans. An informal exclusion restriction test is then conducted, followed by a regression to explore whether maize price changes propagate through the opportunity cost channel by accounting for demographic heterogeneity. Finally, the potential impact of the COVID-19 pandemic on the identification process is investigated.

6.1 Coffee and Soybeans

To verify whether the result can be extrapolated to other labour-intensive agricultural commodities, I repeat the regressions for soybeans and coffee; two crops that are significant for Brazil's economy (Statista, 2023; CEPEA, 2022). I adjusted the IV first stage regressions according to the relevance of each weather condition and the availability of monthly exports of a major world supplier for each crop[1]. Moreover, I was able to use monthly US exports of soybeans to the world market. However, there was no available monthly data on any of the major global coffee suppliers. Hence, the first stage of the coffee regression does not account for common international commodity-specific price movements.

Table 6.1: Second Stage Estimation - Political Violence Occurrence - Coffee

$PV_{i,t}$	(1) LPM OLS	(2) Random Effects Logit	(3) Fixed Effects Logit	(4) IV Probit
$COF_i \times PRICE_t$	-0.001	-0.008	-0.008	-3.193***
	(0.002)	(0.037)	(0.032)	(0.963)
COF_i		0.088		7.658***
		(0.097)		(2.273)
$Population_t$	-0.099*	1.042***	-0.620	0.390*
	(0.052)	(0.030)	(1.157)	(0.203)
Municipality fixed effects	YES	NO	YES	NO
Observations	158,976	158,976	109,680	12,826
Municipalities	3,312	3,312	2,285	480

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level for all regressions besides Column (3). Each regression includes time-fixed effects. Column (1) is a linear probability model. Column (2) is a random-effects logistic regression. Column (3) shows a conditional fixed-effects logistic regression. Column (4) uses the instrumented variable approach in which the interaction between $\mathrm{COF}_i \times PRICE_t$ is instrumented by using Brazilian weather conditions in a Probit model. The first stage estimation can be found in Table A.3 Appendix A.3.2. $^*p < 0.1$ $^{***}p < 0.01$

[1]The first stage estimation for Soybeans can be found in Table A.2 in Appendix A.3.1 and for Coffee in Table A.3 in A.3.2

There is a considerable difference between the significance of the level[2] and the likelihood results. The former shows no significant coefficient for any regression method for either crop; besides the random regression OLS result for soybeans. Hence, more research is necessary to identify the causes or crop characteristics that impact the intensity of local political violence. In contrast, the likelihood regressions reveal certain statistically significant findings, although not consistent throughout all specifications.

To make the results comparable, I use the same benchmark specifications as in the main result section. Hence, the IV-Probit model will indicate the causality benchmark and the conditional fixed-effects Logit model will be used to interpret the economic magnitude of the effect.

Table 6.2: Second Stage Estimation - Political Violence Occurrence - Soybean

$PV_{i,t}$	(1) LPM OLS	(2) Random Effects Logit	(3) Fixed Effects Logit	(4) IV Probit
$SOY_i \times PRICE_t$	-0.007**	-0.155***	-0.173***	-0.199
	(0.003)	(0.060)	(0.048)	(0.257)
SOY_i		0.945**		1.373
		(0.457)		(1.890)
$Population_t$	-0.114**	1.017***	-1.180	0.643***
	(0.053)	(0.029)	(1.167)	(0.052)
Municipality fixed effects	YES	NO	YES	NO
Observations	158,976	158,976	109,680	12,826
Municipalities	3,312	3,312	2,285	480

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level for all regressions besides Column (3). Each regression includes time-fixed effects. Column (1) is a linear probability model. Column (2) is a random-effects logistic regression. Column (3) shows a conditional fixed-effects logistic regression. Column (4) uses the instrumented variable approach in which the interaction between $SOY_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US soybean exports in a Probit model. The first stage estimation can be found in Table A.2 in Appendix A.3.1.
$^{**}p < 0.05$ $^{***}p < 0.01$

While the IV-Probit model in Table 6.1 yields statistical evidence that coffee price changes impact the likelihood of political violence, the IV-Probit model in Table 6.2 does not indicate that price changes in soybeans have an impact. Therefore, the price of coffee[3] seems to impact the likelihood of conflict in Brazilian municipalities significantly. It is difficult to interpret the economic impact of the coffee price changes as the Logit regression is not statistically significant. Carefully interpreting the non-significant Logit coefficient in Column (3) of Table 6.1 indicates that a one SD increase in the price of coffee decreases expected political conflict occurrence by approximately 1.2% for a municipality at the 90th percentile and 0.05% for a municipality at the 10th percentile of coffee suitability, ceteris paribus[4]. The results indicate that next to its lack of

[2]The level results for soybean and coffee can be found in Appendix A.3.3 and A.3.5 respectively.

[3]The coffee price is weighted with 30% Robusta and 70% Arabica beans; reflecting the relative production in Brazil (Crocitti, 2012).

[4]A one SD change in the coffee price is equivalent to a 0.385 log point or a 6 Brazilian Real per kilogram change. A municipality at the 90th (10th) percentile of coffee suitability has an index score of about 3.97 (0.187).

statistical significance, its economic impact is also minimal. Hence, while the IV-Probit model indicates that coffee price changes indeed propagate through the opportunity cost channel, the economic size of the impact is small and difficult to identify.

As stated above, the Probit model in Table 6.2 suggests that soybean price changes do not propagate through the opportunity cost channel. Specifically, the interaction between soy price changes and soy suitability is not statistically significant at any common confidence level. Thus, a causal interpretation is hindered by missing statistically robust evidence. In contrast to the Probit results, the other model specifications in Table 6.2, which do not account for reverse causality issues, show statistically significant results in the expected direction. Thus, I carefully interpret the economic magnitude of the conditional fixed-effects Logit model in Column (3) without assuming a causal relationship between the variables. The Logit model indicates that a one SD increase in soy prices decreases the expected odds of political violence by approximately 21.2% for a municipality at the 90th percentile of soy suitability and 11.37% for a municipality at the 10th percentile of soy suitability[5]. These estimates are similar to the maize price results; indicating some homogeneity in the expected impact of price changes in labour-intensive agricultural commodities with respect to the likelihood of political violence occurrence.

Due to the varying results across different commodities, the theory of the opportunity cost channel cannot be generalised over labour-intensive-agricultural goods. More research is necessary to identify the fundamental factors that signify whether a commodity propagates through the opportunity cost channel.

[5]A one SD change in the soy price is equivalent to a 0.383 log point or a 872 Brazilian Real per Metric ton change. A municipality at the 90th (10th) percentile of soy suitability has an index score of about 3.60 (1.82).

6.2 Informal Instrumental Variable Exclusion Restriction

Due to the inclusion of multiple instruments, the risk increases, that one or multiple instruments violate the exclusion restriction of the instrumental variable approach. Besides theoretical approaches, there is no formal test that could certainly detect violations of the exclusion restriction. However, based on the structure of the DiD approach, there is a group in the sample that should not be affected by changes in the maize price. With regard to this research paper, the lower the maize price suitability index, the less a municipality should affected by international maize price changes. In other words, municipalities with a low maize suitability are unlikely to produce the crop. Hence, if the exclusion restrictions hold, the maize-specific instruments should have no impact on conflict levels in municipalities with low maize suitability.

Table 6.3: Informal Exclusion Restriction Test

$PV_{i,t}$	(1) Level Regression	(2) Likelihood Regression
$MAIZE_i \times Temp_t$	-0.003	-0.015
	(0.005)	(0.019)
$(MAIZE_i \times Temp_t)^2$	0.000	0.000
	(0.000)	(0.000)
$MAIZE_i \times Rain_t$	-0.000	0.000
	(0.000)	(0.000)
$(MAIZE_i \times Rain_t)^2$	0.000	-0.000
	(0.000)	(0.000)
$MAIZE_i \times US\ Maize\ exports_t$	-0.000	0.000
	(0.000)	(0.000)
$Population_t$		0.762
		(1.002)
Observations	1,769	1,769
Municipalities	72	72

Notes: The first stage results are illustrated to indicate the relevance of the instrumented variables. The regression also includes municipality and time-fixed effects. The standard errors are robust and clustered at the municipality level and are shown in parentheses.

As can be seen in Table 6.3, the instruments do not significantly impact the violence level or occurrence in municipalities at the 10% maize suitability level. As expected, municipalities that are relatively unsuitable for growing maize, are not affected by changes in the crop's price. Thus, this informal test indicates that the exclusion restriction is not violated as the instruments only impact the dependent variable through the maize price changes.

6.3 Demographic Heterogeneity

To further test the validity of the opportunity cost channel, I examine the differences between sparsely populated and well-populated municipalities. As agricultural production is predominant in sparsely populated rural areas, well-populated urban areas should experience a diminished effect of maize price changes. First, urban areas likely employ fewer agricultural workers and hence, a change in the price of an agricultural good likely influences employment to a lesser extent; therefore, leaving conflict intensity and occurrence unaffected. Second, larger municipalities likely have a more diversified economy; implying less volatile consequences following maize price changes.

Table 6.4: Demographic Heterogeneity - Political Violence Intensity

$PV_{i,t}$	(1) IV-2SLS	(2) IV-2SLS	(3) IV-2SLS	(4) IV-2SLS	(5) IV-2SLS
$MAIZE_i \times PRICE_t$	-0.861	-0.428*	-0.144	-0.115***	-0.066***
	(0.900)	(0.229)	(0.099)	(0.040)	(0.025)
Observations	314	765	2,111	5,444	9,080
Municipalities	12	29	86	213	350
Mean inhabitants	3884	5941	9915	15532	22555
Percentile population included	<10th	<25th	<50th	<75th	<90th

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level. Each regression includes time-fixed and municipality-fixed effects and municipality-specific time trends. All regression uses the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports. The first stage estimation can be found in Table 5.1. $*p < 0.1$ $***p < 0.01$

To test this hypothesis, I exclude larger municipalities based on the percentile of population in various intermediate steps. These regression results can be found in Table 6.4 and Figure 6.1 for the level regressions. The likelihood regression output of this modification can be found in Appendix A.3.5.

Interestingly, the absolute size of the coefficient increases with the exclusion of larger municipalities. The smaller the average included municipalities are, the larger the impact of maize price changes in absolute size. Due to the step-wise exclusion of more populated municipalities, the standard error of the regression increases when excluding observations. This leads to wider confidence intervals, as illustrated in Figure 6.1, which are likely the consequence of the diminishing number of observations when excluding more municipalities.

These results indicate that the maize price indeed has a stronger effect in more rural areas. However, the statistical evidence is not significant in all regressions in Table 6.4. One potential explanation for this could be that the exclusion of larger municipalities substantially decreases the observation and, consequently, the variation in the model. This, in turn, poses additional challenges for meaningful inferences.

The level regression results support the hypothesis of the opportunity cost effect. As farmers live and work predominantly in rural areas, these areas should be affected more than urban areas.

According to the theory, an increase in the price of a labour-intensive agricultural good, such as maize, should increase the wage for farmers. Consequently, the elevated wage level increases the opportunity costs for farmers to engage with illicit organizations, thereby diminishing their incentive for potentially violent behaviour. As stated previously, the absolute magnitude of maize price changes increases with the exclusion of larger municipalities. When incorporating municipalities up to the 90th percentile of population size, a one standard deviation increase in maize prices differentially decreases the intensity of political violence by 5.6% for municipalities that are relatively more suitable for maize cultivation. However, an equivalent maize price change differentially reduces the intensity of political violence by 36.3% when solely including municipalities up to the 25th percentile of population size. This stark difference indicates that smaller municipalities indeed experience a stronger effect of maize price changes. Therefore, the smaller or more rural a municipality is, the more likely that maize price changes do, in fact, propagate through the opportunity cost channel.

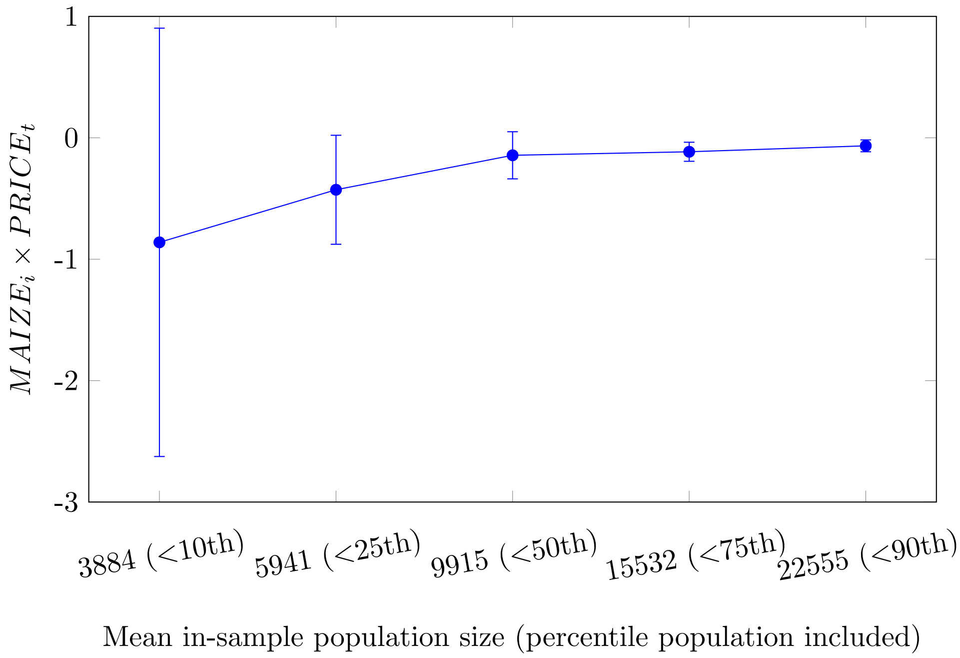


Figure 6.1: Demographic Heterogeneity - Political Violence Intensity

However, there is substantial heterogeneity in the results with respect to the level and likelihood regressions. While the former illustrates an increasing impact of a maize price change, the latter does not show coherent results. In the likelihood regressions, the null hypothesis is not rejected in all but one specification. This creates a strong caveat when interpreting these regression outcomes with regard to the political violence occurrence. The only significant result, Column (1) in Table A.6, shows a positive coefficient. This result provides limited evidence that smaller municipalities may experience an increase in the occurrence of political violence in response to an increase in the price of maize. This outcome is orthogonal compared to the benchmark result in Column (4) in Table 5.3 and to the expectations of the literature review. As stated previously, it is important to interpret this result with caution as it is the sole significant finding with respect to the likelihood regressions and might be a Type I error.

6.4 COVID-19

As discussed previously, a potential threat to the identification method could be the COVID-19 pandemic. The COVID-19 pandemic was an unexpected event that impacted social and economic spheres with sudden unprecedented changes (WHO, 2023). These influences are likely to be related to changes in social unrest and economic pressure; thereby, likely impacting political violence in Brazilian municipalities.

To analyse the impact of the COVID-19 pandemic in Brazil, I am using a monthly measure of the COVID-19 Stringency Index (Mathieu et al., 2020; Hale, Angrist, Goldszmidt & et al., 2021). This normalised index serves as a proxy for the monthly severity of the COVID-19 pandemic as it uses nine different metrics[6]. The regression only contains variation in the COVID-19 variable for the years 2020, 2021, and 2022, reflecting the period when the pandemic commenced. For these years, the COVID-19 Stringency Index provides daily data which I aggregated into monthly intervals. I illustrate the COVID-19 time series in Figure 6.2[7]. The index is a federal measurement that does not account for regional Brazilian heterogeneity in monthly COVID-19 severity. Nevertheless, it provides a general indication of the seasonal pandemic movements that likely affect Brazilian municipalities differentially. The regression results can be found in Table 6.3 for the likelihood regressions and in Appendix 3.6 for the level regressions[8].

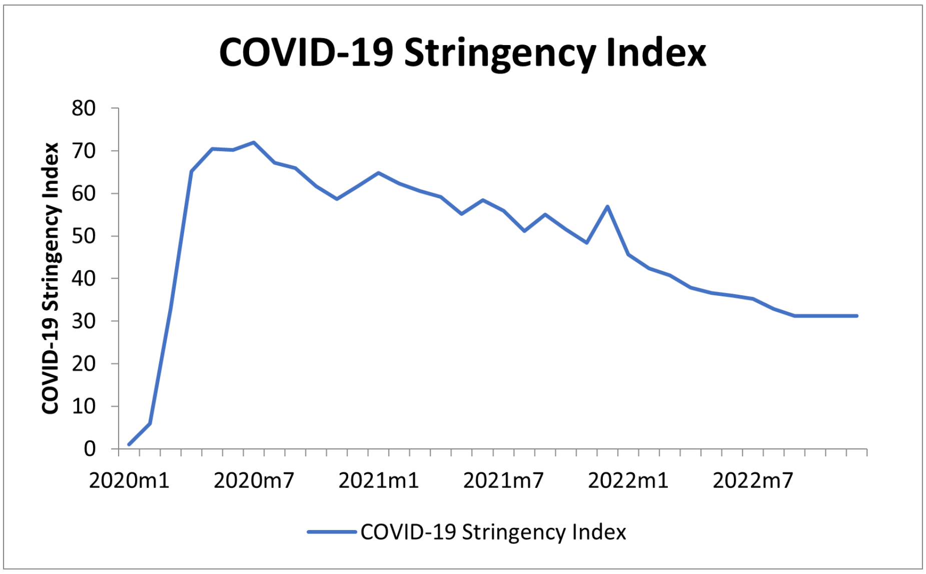


Figure 6.2: COVID-19 Stringency Index

The COVID-19 robustness check results in different outcomes regarding the likelihood and level regressions. Regarding the latter, the COVID-19 variable is non-significant for the IV and significant for the OLS regressions. Additionally, the interaction between the maize suitability and the maize price becomes statistically insignificant when introducing the COVID-19 variable

[6]These metrics include school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls (Mathieu et al., 2020; Hale et al., 2021).

[7]I conducted an LLC unit root test (Levin et al., 2002) that rejected the null hypothesis of non-stationarity for the COVID-19 Stringency Index data.

[8]Each regression, which previously included time-fixed effects, has now omitted them to facilitate the analysis of the COVID-19 variable.

in place of time-fixed effects. This could be an indication that time-fixed effects are necessary to account for more time-variant variables than the pandemic. In this case, the exclusion of time-fixed effects likely introduces an omitted variable bias because substantial unobservable variables that are consistent across municipalities are now encompassed within the error term, making them confounding factors. Consequently, the main interaction term of interest loses its statistical significance. Cautiously interpreting the statistically significant coefficient in the OLS regressions of Table A.7 indicates that the COVID-19 Stringency Index is negatively related to political violence. While the negative sign of the coefficient is surprising, it is economically not meaningful.

Moreover, the benchmark result of likelihood regressions does not find enough statistical evidence that the severity of the COVID-19 pandemic impacts the probability that political violence occurs. The benchmark result of the likelihood regression is in contrast to the other likelihood results. The Logit and LPM models indicate that the pandemic and the likelihood of political violence in Brazilian municipalities are inversely correlated. As the causality benchmark result is statistically insignificant, the following result has to be interpreted with caution. Nevertheless, the statistically significant result in Column (3) in Table 6.5 suggests that a 10-point increase in the COVID-19 Stringency Index leads to an approximate 6.76% decline in the expected odds of political violence occurrence in Brazilian municipalities, ceteris paribus. The negative and significant coefficient of $COVID-19_t$ is surprising, as it indicates that higher governmental stringency is linked with reduced political violence levels. One potential rationale could be that stricter government responses limited the mobility of individuals to an extent where organizing events that might lead to political violence became more challenging.

These results have to be interpreted with caution as the Stringency Index solely provides federal data on COVID-19 policies. More detailed data, such as monthly COVID-19 infections or deaths per municipality, is necessary to clearly identify the effect the pandemic has on the regression outcomes and specifically, political violence in Brazilian municipalities. Nevertheless, the inclusion of $COVID-19_t$ in place of time-fixed effects does impact the results and thus indicates that the pandemic potentially confounds the results, albeit this interpretation must be done with caution.

Table 6.5: COVID-19 - Maize - Political Violence Occurrence

$PV_{i,t}$	(1) LPM OLS	(2) Random Effects Logit	(3) Fixed Effects Logit	(4) IV-2SLS Probit
$MAIZE_i \times PRICE_t$	-0.012***	-0.289***	-0.312***	2.263
	(0.004)	(0.090)	(0.085)	(1.568)
$MAIZE_i$		1.925***		-15.412
		(0.634)		(10.570)
$Price_t$	0.029***	0.642***	0.739***	-4.348
	(0.009)	(0.189)	(0.192)	(3.066)
$Population_t$	-0.016	1.143***	-2.707	0.663***
	(0.133)	(0.037)	(4.118)	(0.073)
$COVID-19_t$	-0.000***	-0.003***	-0.006***	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)
Municipality fixed effects	YES	NO	YES	NO
Observations	79,488	79,488	35,736	3,725
Municipalities	3,312	3,312	1,489	426

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level for all regressions besides Column (3). Column (1) is a linear probability model. Column (2) is a random-effects logistic regression. Column (3) shows a conditional fixed-effects logistic regression. Column (4) uses the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports in a Probit model. The first stage estimation can be found in Table 5.1. $^{***}p < 0.01$

7 Conclusion

The aim of this thesis is to identify the causal relationship between maize price changes and political violence in Brazilian municipalities. To achieve this, I conducted a difference-in-difference method in combination with an instrumental variable approach to alleviate potential endogeneity concerns based on the approach by Dube and Vargas (2013) and Dube et al. (2016).

The findings of this thesis, derived from the benchmark specifications, indicate that an increase in the price of maize differentially decreases the intensity and likelihood of political violence in Brazilian municipalities that are relatively suitable for producing maize in comparison to less suitable municipalities. Thus, the results support the opportunity cost channel. In detail, as the price of maize increases, the expected wage of farmers also rises. This, in turn, elevates the opportunity cost that farmers face when considering involvement in politically motivated violent events (Dube et al., 2016). Thus, the findings of this paper align with the expectations of the literature review (Bazzi & Blattman, 2014; Blair et al., 2021; Couttenier & Soubeyran, 2015; Fjelde, 2015).

These results are especially robust for the likelihood regressions as adjustments to the model do not considerably impact the main coefficient of interest. Furthermore, the likelihood results were partially replicable when considering coffee or soybeans in place of maize. While the benchmark result for coffee indicates a causal differential effect of coffee price changes on political violence, the benchmark result for soybeans does not. Moreover, the level regression results are less robust to changes in the model specifications. In detail, the IV results show different signs given that the model specification includes municipality-specific time trends. Additionally, the level results were not reproducible when using either coffee or soybeans. Interestingly, the absolute size of the differential effect of maize price changes on the level of political violence seems to decrease the smaller the included average municipalities are. This finding further supports the opportunity cost channel, as it suggests that smaller municipalities, often more rural, tend to have economies that rely more on agriculture and are therefore more susceptible to the influence of maize price fluctuations. Furthermore, the inclusion of the COVID-19 variable in place of time-fixed effects considerably alters the results; indicating that the pandemic might be a confounding factor when omitted.

Policymakers are likely inclined to decrease the intensity and likelihood of conflict in their municipalities. As this research paper shows, municipalities that are relatively more suitable for the production of maize, suffer from a higher variance in political violence following changes in the price of maize. To lower this effect, I suggest three policy recommendations. First, policymakers could implement schemes aimed at stabilising the price of maize. The introduction of a price floor, for instance, could mitigate the negative consequence of price decreases; potentially preventing the opportunity cost of political violence from becoming excessively low. Second, expanded social safety nets might provide the necessary security for farmers to not engage in politically violent events. This way, social stability might be ensured even in times of economic hardship. Third, policymakers should aim for economic diversification, especially if their economies are excessively dependent on agriculture. This strategy would mitigate the impact of maize price fluctuations on employment and the overall economic well-being of municipalities.

This research paper has several limitations that require further research. First, while the identification method significantly decreases the scope of omitted variable bias, there might exist some confounding variables that are not included in the regressions. The monthly municipality panel structure impedes the inclusion of these confounders due to the unavailability of relevant data. Second, due to the various data sources used, there is some potential for measurement error. While it is unlikely that a measurement error in the political violence variable is correlated with any independent variable, the presence of measurement error in an independent variable cannot be ruled out. Such an error would bias the results towards zero. Third, the sign of the first-stage results is not as expected. While this does not alter the results significantly, future research should investigate the exact relationship between weather conditions and price movements. Fourth, due to the micro-level data, the results of this research cannot be generalised to other regions or countries and are thus, specific to Brazilian municipalities during the sample time. Future research should investigate how these agricultural pricing dynamics can be generalized by using micro-level data from other economic areas. Fifth, the benchmark results for maize were not reproducible for other labour-intensive agriculture commodities. Thus, more research is necessary to find the causal relationship between price changes in labour-intensive agricultural commodities and political violence. Future research should further investigate which characteristics tend to determine whether a commodity propagates through the opportunity cost channel. In addition to the mentioned research recommendations, economists should analyse how price stabilisation schemes, enhanced social security nets, and economic diversification affect political violence via changes in commodity prices.

References

ACLED. (2019a). *ACLED Codebook, 2019.* Online. Retrieved from https://www.acleddata.com

ACLED. (2019b). *Armed conflict location & event data project (acled) codebook.* Retrieved from https://acleddata.com/knowledge-base/codebook/

Ai, C. & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, *80*(1), 123-129. Retrieved from https://www.sciencedirect.com/science/article/pii/S0165176503000326 doi: 10.1016/S0165-1765(03)00032-6

Bazzi, S. & Blattman, C. (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics*, *6*(4), 1–38. doi: 10.1257/mac.6.4.1

BDMEP. (2023). *Bdmep [dataset].* https://bdmep.inmet.gov.br/.

Berman, N. & Couttenier, M. (2015). External shocks, internal shots: The geography of civil conflicts. *Review of Economics and Statistics*, *97*(4), 758–776. doi: 10.1162/REST_a_00521

Besley, T. & Persson, T. (2008). The incidence of civil war: Theory and evidence [Working Paper]. (w14585). doi: 10.3386/w14585

Blair, G., Christensen, D. & Rudkin, A. (2021). Do commodity price shocks cause armed conflict? a meta-analysis of natural experiments. *American Political Science Review*, *115*(2), 709–716. doi: 10.1017/S0003055420000957

Bodea, C. & Elbadawi, I. A. (2008). *Political violence and economic growth.* The World Bank. Retrieved from https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-4692 doi: 10.1596/1813-9450-4692

Brückner, M. & Ciccone, A. (2010). International commodity prices, growth and the outbreak of civil war in sub-saharan africa. *The Economic Journal*, *120*(544), 519–534. doi: 10.1111/j.1468-0297.2010.02353.x

CEPEA. (2022). *Brazil may be the top soybean meal exporter in the world in 2022-23.* Retrieved from https://www.cepea.esalq.usp.br/en/brazilian-agribusiness-news/brazil-may-be-the-top-soybean-meal-exporter-in-the-world-in-2022-23.aspx (Accessed on 20.09.2023)

Collier, P. & Hoeffler, A. (1998). On economic causes of civil war. *Oxford Economic Papers*, *50*(4), 563–573. doi: 10.1093/oep/50.4.563

Collier, P. & Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford Economic Papers*, *56*(4), 563–595. doi: 10.1093/oep/gpf064

Collier, P. & World Bank. (2003). *Breaking the conflict trap: Civil war and development policy.* World Bank.

Couttenier, M. & Soubeyran, R. (2015). A survey of the causes of civil conflicts: Natural factors and economic conditions. *Revue d'économie Politique*, *125*(6), 787–810. doi: 10.3917/redp.256.0787

Crocitti, J. J. (2012). *Brazil today: An encyclopedia of life in the republic* (Vol. 1; J. J. Crocitti & M. Vallance, Eds.). Bloomsbury Academic.

Crost, B. & Felter, J. H. (2020). Export crops and civil conflict. *Journal of the European Economic Association*, *18*(3), 1484–1520. doi: 10.1093/jeea/jvz025

Dal Bó, E. & Dal Bó, P. (2011). Workers, warriors, and criminals: Social conflict in general equilibrium. *Journal of the European Economic Association*, *9*(4), 646–677. doi: 10.1111/j.1542-4774.2011.01025.x

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *Stata Journal*, *3*(2), 168-177.

Dube, O., García-Ponce, O. & Thom, K. (2016). From maize to haze: Agricultural shocks and the growth of the mexican drug sector. *Journal of the European Economic Association*, *14*(5), 1181–1224. doi: 10.1111/jeea.12172

Dube, O. & Vargas, J. F. (2013). Commodity price shocks and civil conflict: Evidence from colombia. *The Review of Economic Studies*, *80*(4), 1384–1421. doi: 10.1093/restud/rdt009

Erbahar, A. (2023). *Seminar empirics of trade and development.* Retrieved from `https://canvas.eur.nl/courses/40155/files/78222205?module_item_id=954275` (Accessed on 20.09.2023)

FAO. (2023). *Gaez4 glossary.* Retrieved from `https://s3.eu-west-.amazonaws.com/data.gaezdev.aws.fao.org/documentation/GAEZ4_Glossary.pdf`

Fearon, J. D. & Laitin, D. D. (2003). Ethnicity, insurgency, and civil war. *American Political Science Review*, *97*(01), 75–90. doi: 10.1017/S0003055403000534

Fjelde, H. (2015). Farming or fighting? agricultural price shocks and civil war in africa. *World Development*, *67*, 525–534. doi: 10.1016/j.worlddev.2014.10.032

GAEZv4. (2023). *Global agro ecological zones version 4 (gaez v4) [dataset].* `http://www.fao.org/gaez/`. (Accessed May 25, 2023)

GATS. (2023). *Gats - the usda foreign agricultural service's global agricultural trade system [dataset].* `https://apps.fas.usda.gov/gats/default.aspx`.

Greene, W. H. (2000). *Modified wald statistic for groupwise heteroskedasticity in fixed effect model.* New York: Prentice-Hall.

Hale, T., Angrist, N., Goldszmidt, R. & et al. (2021). A global panel database of pandemic policies (oxford covid-19 government response tracker). *Nat Hum Behav*, *5*, 529–538. Retrieved from `https://doi.org/10.1038/s41562-021-01079-8` doi: 10.1038/s41562-021-01079-8

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *46*, 1251-1271. doi: 10.2307/1913827

Hidalgo, F. D., Naidu, S., Nichter, S. & Richardson, N. (2010). Economic determinants of land invasions. *Review of Economics and Statistics*, *92*(3), 505–523. doi: 10.1162/REST_a_00007

Levin, A., Lin, C.-F. & Chu, C.-S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, *108*, 1-24.

Mathieu, E., Ritchie, H., Rodés-Guirao, L., Appel, C., Giattino, C., Hasell, J., ... Roser, M. (2020). Coronavirus pandemic (covid-19). *Our World in Data*. (htps://ourworldindata.org/coronavirus)

Miguel, E., Satyanath, S. & Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, *112*(4), 725–753. doi: 10.1086/421174

Millán-Quijano, J. & Pulgarín, S. (2023). Oiling up the field. forced internal displacement and the expansion of palm oil in colombia. *World Development*, *162*, 106130. doi: 10.1016/j.worlddev.2022.106130

Newey, W. K. (1987). Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, *36*, 231-250.

Raleigh, C., Linke, A., Hegre, H. & Karlsen, J. (2010). Introducing acled-armed conflict location and event data. *Journal of Peace Research*, *47*(5), 651–660.

Sachs, J. & Warner, A. (1995). *Natural resource abundance and economic growth* (Working Paper No. 5398). National Bureau of Economic Research. doi: 10.3386/w5398

Schaffer, M. E. & Stillman, S. (2010). *xtoverid: Stata module to calculate tests of overidentifying restrictions after xtreg, xtivreg, xtivreg2 and xthtaylor.* Statistical Software Components. Retrieved from `http://ideas.repec.org/c/boc/bocode/s456779.html`

Serdan, T. D. A., Masi, L. N., Gorjao, R., Pithon-Curi, T. C., Curi, R. & Hirabara, S. M. (2020). Covid-19 in brazil: Historical cases, disease milestones, and estimated outbreak peak. *Travel Medicine and Infectious Disease*, *38*, 101733. doi: 10.1016/j.tmaid.2020.101733

SIDRA. (2023). *Sidra - population estimation [dataset].* `https://sidra.ibge.gov.br/tabela/6579`.

StataCorp. (2021). Stata: Release 17. statistical software [Computer software manual]. College Station, TX: StataCorp LLC. (Page 2830)

Statista. (2023). *Brazil: Coffee production volume 2023.* Retrieved from `https://www.statista.com/statistics/806275/production-coffee-volume-brazil/` (Accessed on 20.09.2023)

UCDP. (2023). *Uppsala conflict data program conflict encyclopedia.* Retrieved from `https://ucdp.uu.se` (Date of retrieval: 23/09/20)

United Nations. (2023). *A new era of conflict and violence - un75.* Retrieved from `https://www.un.org/en/un75/new-era-conflict-and-violence`

WHO. (2023). *COVID-19 Dashboard.* Retrieved from `https://covid19.who.int/`

Winne, J. D. & Peersman, G. (2021). The impact of food prices on conflict revisited. *Journal of Business & Economic Statistics*, *39*(2), 547–560. doi: 10.1080/07350015.2019.1684301

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data.* Cambridge, MA: MIT Press.

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (Seventh ed.). Cengage Learning.

A Appendix

A.1 Descriptive Statistics

Table A.1: Data Description and Sources

Variable	Description	Primary Source	Unit
Maize Suitability Index	Relative measure of maize suitability per municipality based on soil types and terrain classes averaged over different input levels, fertilizer, and water supply types	GAEZv4	Index (0 to 5)
Coffee Suitability Index	Relative measure of coffee suitability per municipality based on soil types and terrain classes averaged over different input levels, fertilizer, and water supply types	GAEZv4	Index (0 to 5)
Soybean Suitability Index	Relative measure of soybean suitability per municipality based on soil types and terrain classes averaged over different input levels, fertilizer, and water supply types	GAEZv4	Index (0 to 5)
US Maize Exports	Total amount of monthly US maize exports to the global market	GATS	1000 Metric tons
US Soybeans Exports	Total amount of monthly US soybean exports to the global market	GATS	1000 Metric tons
Maize Price	Monthly international price of maize	Indexmundi (IMF)	Natural Logarithm
Soybean Price	Monthly international price of soybean	Indexmundi (IMF)	Natural Logarithm
Coffee Price	Monthly international price of coffee	Indexmundi (IMF)	Natural Logarithm
COVID-19	Monthly COVID-19 government response indicator	OxCGRT	Index (0-100)
Total Rain	Monthly total precipitation per Brazilian municipality	INMET	Millimeter
Average Temperature	Monthly average temperature per Brazilian municipality	INMET	Celsius
Political Violence	Number of monthly political violence incidence per 10,000 inhabitants per Brazilian municipality	ACLED	Natural Logarithm
Political Violence Indicator	Indicator equalling 1 when political violence occurs in a given month in a Brazilian municipality	ACLED	Binary
Population	Number of inhabitants per year per Brazilian municipality	SIDRA IGBE	Natural Logarithm

A.2 Econometric Test Results

A.2.1 Wald Test for Heteroskedasticity

(a) Political Violence Intensity - Maize

Wald Test	Coefficient
Chi-square (3312)	1.6×10^9
P-value	0.0000

(b) Political Violence Occurrence - Maize

Wald Test	Coefficient
Chi-square (3312)	1.7×10^9
P-value	0.0000

A.2.2 Wald Test Joined Significance of Time-Fixed Effects

(a) Political Violence Level - Maize

Wald Test	Coefficient
F (47, 155616)	8.95
P-value	0.0000

(b) Political Violence Occurrence - Maize

Wald Test	Coefficient
F (47, 155616)	11.74
P-value	0.0000

A.2.3 Sargan-Hansen Statistic - Fixed vs Random Effects Model

(a) Political Violence Level - Maize

Sargan-Hansen Statistic	Coefficient
Chi-square test value	24.131
P-value	0.1953

(b) Political Violence Occurrence - Maize

Sargan-Hansen Statistic	Coefficient
Chi-square test value	32.495
P-value	0.0000

A.2.4 Wooldridge First-Order Autocorrelation Test

(a) Political Violence Intensity - Maize

First-Order Autocorrelation	Coefficient
F-Statistic (1, 3111)	0.273
P-value	0.6012

(b) Political Violence Occurrence - Maize

First-Order Autocorrelation	Coefficient
F-Statistic (1, 3111)	19.767
P-value	0.0000

A.3 Robustness Results

A.3.1 First Stage Estimation - Soybean

Table A.2: First Stage Estimation - Soybean

	(1)
$SOY_i \times PRICE_t$	OLS
$SOY_i \times Temp_t$	-0.005***
	(0.000)
$SOY_i \times Rain_t$	-0.000***
	(0.000)
$(SOY_i \times Rain_t)^2$	0.000**
	(0.000)
$SOY_i \times US\ Soy\ exports_t$	0.000***
	(0.000)
Observations	12,826
Municipalities	480
R-squared	0.946

Notes: The first stage results are illustrated to indicate the relevance of the instrumented variables. The regression also includes municipality and time-fixed effects. The standard errors are robust and clustered at the municipality level and are shown in parentheses.
$^{**}p < 0.05$ $^{***}p < 0.01$

A.3.2 First Stage Estimation - Coffee

Table A.3: First Stage Estimation - Coffee

$COF_i \times PRICE_t$	(1) OLS
$COF_i \times Temp_t$	-0.001*
	(0.001)
$COF_i \times Rain_t$	-0.000***
	(0.000)
$(COF_i \times Rain_t)^2$	0.000**
	(0.000)
Observations	12,826
Municipalities	480
R-squared	0.790

Notes: The first stage results are illustrated to indicate the relevance of the instrumented variables. The regression also includes municipality and time-fixed effects. The standard errors are robust and clustered at the municipality level and are shown in parentheses.
$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

A.3.3 Political Violence Intensity - Soybean Results

Table A.4: Second Stage Estimation - Political Violence Intensity - Soybean

$PV_{i,t}$	(1) OLS-RE	(2) OLS-FE	(3) IV-2SLS	(4) IV-2SLS
$SOY_i \times PRICE_t$	-0.000	-0.000	0.005	0.021
	(0.002)	(0.002)	(0.007)	(0.022)
SOY_i	-0.002			
	(0.013)			
Municipality fixed effects	NO	YES	YES	YES
Municipality time trends	NO	NO	NO	YES
Observations	158,976	158,976	12,826	12,826
Municipalities	3,312	3,312	480	480

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level. Each regression includes time-fixed effects. Columns (3) and (4) show the instrumented variable approach in which the interaction between $SOY_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US soy exports. The first stage estimation can be found in Table A.2 in Appendix A.3.1.

A.3.4 Political Violence Intensity - Coffee Results

Table A.5: Second Stage Estimation - Political Violence Intensity - Coffee

$PV_{i,t}$	(1) OLS-RE	(2) OLS-FE	(3) IV-2SLS	(4) IV-2SLS
$COF_i \times PRICE_t$	0.000	0.000	0.044	0.041
	(0.001)	(0.001)	(0.071)	(0.051)
COF_i	-0.000			
	(0.002)			
Municipality fixed effects	NO	YES	YES	YES
Municipality time trends	NO	NO	NO	YES
Observations	158,976	158,976	12,826	12,826
Municipalities	3,312	3,312	480	480

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level. Each regression includes time-fixed effects. Columns (3) and (4) show the instrumented variable approach in which the interaction between $\text{COF}_i \times PRICE_t$ is instrumented by using Brazilian weather conditions. The first stage estimation can be found in Table A.3 in Appendix A.3.2.

A.3.5 Demographic Heterogeneity - Political Violence Occurrence - Table

Table A.6: Demographic Heterogeneity - Political Violence Occurrence

$PV_{i,t}$	(1) IV-2SLS	(2) IV-2SLS	(3) IV-2SLS	(4) IV-2SLS	(5) IV-2SLS
$MAIZE_i \times PRICE_t$	15.224**	3.677	1.189	1.550	0.233
	(6.149)	(3.030)	(2.246)	(1.054)	(0.881)
$MAIZE_i$	-96.907**	-23.111	-7.675	-10.118	-1.568
	(39.281)	(19.531)	(14.687)	(6.880)	(5.746)
$Population_t$	-2.455***	-1.019***	-0.065	0.025	0.208**
	(0.602)	(0.283)	(0.191)	(0.137)	(0.102)
Observations	96	419	2,111	5,444	9,080
Municipalities	12	29	86	213	350
Mean inhabitants	3884	5941	9915	15532	22555
Percentile population included	<10th	<25th	<50th	<75th	<90th

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level for all regressions besides Column (3). Each regression includes time-fixed effects. All regressions use the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports using a Probit model. The first stage estimation can be found in Table 5.1.
$^{**}p < 0.05$ $^{***}p < 0.01$

A.3.6 Political Violence Intensity - COVID-19

Table A.7: COVID-19 - Political Violence Intensity - Maize

$PV_{i,t}$	(1) OLS-RE	(2) OLS-FE	(3) IV-2SLS	(4) IV-2SLS
$MAIZE_i \times PRICE_t$	-0.002	-0.002	0.002	0.018
	(0.002)	(0.002)	(0.032)	(0.038)
$MAIZE_i$	0.013			
	(0.014)			
$PRICE_t$	0.006	0.006	0.007	-0.051
	(0.005)	(0.005)	(0.065)	(0.108)
$COVID-19_t$	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Municipality fixed effects	NO	YES	YES	YES
Municipality time trends	NO	NO	NO	YES
Observations	79,488	79,488	3,725	3,725
Municipalities	3,312	3,312	426	426

Notes: The standard errors are shown in the parentheses and are robust and clustered at the municipality level. Columns (3) and (4) show the instrumented variable approach in which the interaction between $MAIZE_i \times PRICE_t$ is instrumented by using Brazilian weather conditions and US maize exports. The first stage estimation can be found in Table 5.1. $***p < 0.01$