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Murder Nature
Weather and Violent Crime in Brazil

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Abstract

This paper examines the effect of weather shocks on violent crime using disaggregated data from Brazilian municipalities over the period 1991-2015. I document that adverse weather shocks in the form of droughts lead to a significant increase in violent crime, with the effect appearing to persist beyond the growing season and over the medium run. To explain this persistence, I show that weather fluctuations are positively associated not only with agriculture yields, but also with the overall economic activity. Moreover, evidence shows the dominance of opportunity cost mechanism reflected in the fluctuations of the labor income especially for the agriculture and unskilled workers, giving credence that it is indeed the labor income that matters and not the general socio-economic conditions. Other factors such as local government budget capacity, (un)-employment, poverty, inequality, and psychological factors do not seem to explain violent crime rates.

Keywords: Weather shocks, violent crime, labor market, Brazil

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1 Introduction

According to a United Nations report, the world is expected to brace more extreme weather events with adverse effects falling disproportionately on developing countries (IPCC, 2014). With more than half of the people in developing countries residing in agro-rural communities, climate change poses a major threat to local agriculture and agriculture-generated-incomes (FAO, 2018). This could in turn trigger intense competition over scarce resources, which may eventually fold into widespread violence. Such context have spurred a growing body of literature trying to examine the consequences of extreme weather events and climate change on civil conflict and social unrest. While the bulk of this literature has focused on studying politically induced conflict such as civil wars, riots and institutional breakdowns, little work has been done to investigate non-political forms of social unrest such as criminal activities. A few recent studies have documented a positive association between crime rates and hot temperature and/or low precipitation. However, identifying the mechanism driving such association has been debatable. Some emphasize the role of income and economic motives (e.g. Blakeslee and Fishman, 2017), while others cite non-economic factors such as weather-related depression, aggressive behavior or changing habits (e.g. Ranson, 2014). Moreover, there has been little consensus on the particular effect of weather conditions on violent crime.

To contribute to this debate, this paper makes use of variation of weather conditions across Brazilian municipalities. The empirical strategy uses the within-municipality variation in weather conditions to identify their effects on violent crime (i.e. homicide rates) over the period 1991-2015.[1] In contrast to the existing literature, which have extensively employed measures of temperature and rainfall, I rely instead on Standardized Precipitation-Evapotranspiration Index (SPEI) to construct a weather indicator. The advantage of using SPEI index lies in the fact that it jointly controls for the effects of rainfall and determinants of evapotranspiration (i.e. temperature, wind speed, sunshine, soil, location), so that it can better capture exposure to water deficiencies. Besides, being a standardized measure allows for quantifying deviations from the municipality's long-run historical climate conditions, and thus, for a better modelling of weather shocks. The strategy allows for using temporal and spatial lags to take into account temporal correlations of weather shocks and spatial correlation of crime rates.

I find two primary results. First, adverse weather shocks (i.e., drought) significantly increases violent crime rates immediately and the effect persists beyond the growing season and over the medium run. These persistent effects remain after taking into account the spatial and temporal correlation of crime rates, and hold robust to a wide range of robustness tests. The estimates indicate that a one-standard deviation decrease in annual SPEI below the municipality long-run mean increases crime rates by 34% on impact and accumulatively by 70% over the medium run. This is roughly 3% and 6% of the unconditional mean of violent crime rates. Second, to explain this persistence, I show that economic factors represent the main driving force behind the observed relationship. Weather fluctuations are found to

[1] Throughout the text, I use violent crime, crime and homicide rates interchangeably.

be positively associated not only with agriculture yields, but also with the overall economic activity in a persistent way. This is because they affect non-agriculture sectors through affecting local demand. The latter effect is confirmed with evidence showing the dominance of opportunity cost mechanism reflected in the fluctuations in total earnings and wages particularly for the agriculture and unskilled labor, over (un)-employment, local government capacity, poverty, inequality and psychological factors.

As such, the analysis makes several contributions to the thin literature linking extreme weather events to crime in general and violent crime in particular. First, I show that weather shocks tend to have a persistent effect on both violent crime and economic activity, in contrast to the conventional view perceiving weather effects as transitory shocks (e.g. Brückner and Ciccone, 2011). Second, the findings provide a first local evidence of the existence of spillovers effects between agriculture and non-agriculture activities through affecting local demand. Third, it takes a broader perspective and examines a wider range of underlying economic and non- economic channels including agriculture yields, overall economic activity, labor market outcomes, socio-economic levels and public services (i.e. education and police presence). To the best my knowledge, this is the first attempt to quantify the effects of weather fluctuations on a wide range of socio-economic variables and crime determinants at a disaggregated level. Fourth, it shows that it is the labor income especially of the agriculture and unskilled workers that matters and not the general socio-economic conditions. This is because labor income determines the opportunity cost of time allocation between legal and criminal activities and affect local demand. In addition, agriculture and unskilled workers represent the hardest affected group, who are most likely to commit crime. Fifth, I document that criminal activities in neighboring municipalities can increase crime in the municipality itself reflecting a strong spatial correlation in crime rates across neighboring municipalities.

The paper builds on previous studies reporting a positive association between adverse weather conditions and crime due to economic factors (Melhum et al., 2006; Miguel, 2005; Iyer and Topalova, 2014; Blakeslee and Fishman, 2017). However, these studies have relied extensively on measures of temperature and precipitation to constitute their weather variables, which -despite their popularity- do not fully quantify the exposure to water deficiencies in an efficient way (Couttenier and Soubeyran, 2014; Harari and La Ferrara, 2018).[2] Methodologically, they do not take into account the spatial dependency of crime activities, which I show that it explains much of the municipal variation in crime rates. Without taking into account the spatial correlation of crime, the resulted estimates would suffer from an upward bias and hence, an overestimation of the effect of weather shocks on crime. Moreover, their results were mixed regarding the effect of weather on violent crimes. The latter has more to do with the difference in the studied context, for instance in countries with relatively low crime rates or using a historical period of analysis (i.e. as in case of Melhum et al. (2006) who use historical data from 19th century Germany). Equally important is that their attempts to identify the channels through which

[2]Specifically, Couttenier and Soubeyran (2014) argue that drought cannot be represented as a simple (linear) function of rainfall and temperature, because they fail to capture non-linearities such as climate history and the ability of soil to retain water.

weather shocks affected crime have been limited in scope and focused on a single income measure (e.g. agriculture output and/or wages).

Another line of studies specifically looks at temperature-crime relationship and finds that the relationship is particularly significant for violent crimes in Mexico and USA highlighting the roles of weather-inflicting aggressive behavior and/or alcohol consumption (Ranson, 2014; Baysan et al., 2018; Cohen and Gonzalez, 2018). Yet, these studies have relied on high-frequency data (e.g. daily or monthly), which could better discern the role of non-economic factors, especially given that these factors tend to be less persistent over time (Jacob et al., 2007). Therefore, employing annual data circumvents other confounding psychological or behavioral factors that could potentially intervene with economic causes. Nevertheless, because the proxy for violent crimes is homicides rates, which could be driven by either economic or non-economic motives, I address the latter motives in two ways. First, I show that homicide rates is negatively correlated with suicide rates – an indicator for deteriorating mental health. Second, I find that weather fluctuations leave no significant effect on suicide rates.

The paper more generally fits the literature on income shocks and crime. Closely related is the study by Dix-Carneiro et al. (2018) which considered the impact of Brazilian trade liberalization policy during 1991 and 1995 on homicides dynamics. They showed that micro regions exposed to larger tariff reductions experienced a temporary increase in crime in the medium-run following liberalization. In contrast to their study, I consider a more disaggregated level of data at the municipal level and a type of local shock that is recurrent. Indeed, a particular feature of weather shocks in Brazil is that they are recurrent events that unfold persisting effects that could remain for longer periods (Dell et al., 2012), while trade liberalization is a one-time event whose effects dissipates over the long run. Furthermore, their study relied on the cross-section variation of regional exposure to tariff reduction over a longer time span, whereas my empirical strategy exploits the within-municipality annual variation in weather conditions. Another distinction lies in examining the response of different labor groups, particularly the agriculture and unskilled labor, and not only the general labor market conditions. Other studies have documented a negative impact of welfare payments and conditional cash transfers on crime (Foley, 2011; Chioda et al., 2016) or a positive association between agriculture aphids and crime (Bignon et al., 2017). Commodity price shocks were examined by Corvalan and Pazzona (2019), who find that higher copper prices have reduced on property crime in the short-run in the Chilean mining-municipalities.

The paper also contributes to two other strands of literature. The first is the literature on climate and conflict (i.e. civil wars) using rainfall shocks (Miguel et al., 2004; Ciccone, 2013; Miguel and Satyanath, 2011) or global events of climate change (Burke et al., 2009; Hsiang et al., 2011) or alternative drought measures (Couttenier and Soubeyran, 2014; Harari and La Ferrara, 2018). I share with the latter two studies the use of SPEI to better model weather shocks. The second strand of studies relating weather fluctuations to revolutions, insurgency and institutional change (Jia, 2014; Dell, 2012; Brückner and Ciccone, 2011; Guardado, 2018).[3] I

[3] See Hsiang et al. (2013) for a review of the literature on climate and conflict in its different

relate to both strands by providing evidence that the income channel is main driver for the observed relationship.[4]

The remainder of the paper is organized as follows. Section 2 provides an overview of the Brazilian context and presents the conceptual framework. Section 3 discusses the data and empirical strategy. Section 4 and 5 present the baseline results and various robustness checks, respectively. Section 6 extends the analysis to identify various mechanisms. Section 7 concludes.

2 Background

2.1 Brazilian Context

Brazil is a world leading agriculture producer with exports of agriculture raw materials representing around 19% of its total exports and a total agribusiness of agriculture and food industries accounting for 35% of its exports in 2018 (WITS, 2020). Major Brazil's exports include sugarcane, coffee, corn and soybeans with the latter representing 30% of world production. Agriculture in Brazil remains largely rain-fed with agriculture-irrigated land representing around 1.6% of total agriculture land in 2006, which is very low compared to China and USA with irrigated land occupying 10.5% and 5.5% of total their agriculture land, respectively (World Bank, 2020). Moreover, Brazilian agriculture depends extensively on manpower with 35% of total workers employed in the agriculture sector according to 2010 census figures, 90% of which are informally employed.

It follows that negative weather shocks in the form of high temperature and/or low rainfall can represent a major strike to agriculture generated-revenues and earnings. This was the recently evident during the period 2014-2017, in which the country has witnessed the worst drought season in 100 years causing disruption in the production of coffee beans and sugar, and downsizing of operations.[5] There is also plenty of evidence that negative rainfall shocks adversely affects income levels, employment and agriculture production in Brazil (see, e.g., Kruger, 2007; Hidalgo et al., 2010).

Yet, drought remains a recurrent phenomenon in Brazil with episodes of dry years have been occurring since mid-1990s (CEMADEN, 2020). Based on USAID climate risk projections, Brazil is in high risk of experiencing an increase in annual mean temperature over much of the Amazon area by 2085 coupled with a decline in precipitation and prolonged drought season. This has caused extreme cycles of drought to occur more frequently.[6] Aside from its agriculture economy, Brazil occupied the 8th place worldwide in intentional homicide rate and the 1st place in absolute number of homicides, which exceeded 64,000 cases in 2017 according to the

forms plus a critique of the empirical methodologies.

[4] Other climate literature have examined the effects on agriculture profits (Deschenes and Greenstone, 2007); on health and mortality (Deschenes and Moretti, 2009; Burgess et al., 2017; Maccini and Jang, 2009); and on economic growth (Dell et al. 2012). See Dell et al. (2014) for an overview of the climate literature.

[5] See https://www.theguardian.com/world/2015/jan/23/brazil-worst-drought-history

[6] https://climateknowledgeportal.worldbank.org/country/brazil/climate-data-projections?variable=pr

United Nations Office of Drugs and Crime. The homicide rate is considerably high touching 30.8 homicides per 100,000 inhabitants compared to a world rate of only 6 homicides.

2.2 Conceptual Framework

The economic effect of weather shocks on crime rates can be gauged based on the theoretical models developed by Becker (1968) and Ehrlich (1973) regarding crime as an action taking place when the payoffs of criminal activities outweighs both the returns from legal activities and the costs of committing crime. Closely related is the Fajnzylber et al. (2002) economic framework of criminal behavior modeling it as a function of the opportunity cost of crime and the probability of apprehension and sanctions.

During drought seasons, the returns from labor-intensive agriculture activities are expected to decline –due to the slump in earnings or profits following the low agriculture yield- and thus, reducing the opportunity cost of committing crime (Dal Bo and Dal Bo, 2011). However, altering the time allocation between legal productive activities and crime, as suggested by the opportunity cost mechanism, can occur through either (1) job layoffs and declined labor demand, and hence, low earnings and freeing up time to engage in criminal activities, or (2) deteriorating labor income even in the absence of job dismissals. Moreover, non-agriculture activities are expected to be adversely affected through a decline in local demand causing a further reduction in non-agriculture labor returns and/or demand (Dell et al., 2012). In addition, the decline in labor income can exacerbate existing poverty levels and income inequalities, and hence deepening the extent of socio-economic grievances.

The costs of crime in terms of the probability of getting arrested depends on the ability of local governments to apprehend criminals and secure local property. Negative weather shocks can adversely affect local municipal revenues forcing cuts in the number of local police forces or security budgets, and in turn, increasing incentives to engage in criminal activities when the probability of escaping justice is higher (Corvalan and Pazzona, 2019; Bignon et al., 2015). An alternative channel could be through the reduction in the provision of public schooling, and may affect time allocated to illegal activities (Machin et al., 2011; Chioda et al., 2016). I refer to these channels as local governments capacity.

Aside from economic motives, the propensity to commit violent crimes can be traced back to emotional and psychological factors. Hot weather can affect human behavior by influencing stress levels or social interactions, which could eventually fold into physical aggression (Ranson, 2014). For instance, Baysan et al. (2018) find that both homicides and suicide rates respond strongly to variation in monthly temperature in Mexico. Alternatively, for the same country Cohen and Gonsalez (2014) show that higher alcohol consumption and changing in time use during hot weekends explains more weather-related crimes. A common feature of these studies is that their results are based on daily or monthly data, which explains why non-economic factors may appear to play a significant role in a narrow time window.[7]

[7]For instance, Jacob et al. (2007) show that crime rates exhibit negative serial correlation

Overall, the driving force behind the impact of weather shocks on crime rates is rendered a priori ambiguous. On one hand, the economic framework predicts that favorable (adverse) weather conditions can decrease (increase) criminal activities and this due to the increase (decline) in incomes generated from agriculture yields and its spillovers on non-agriculture sectors. The effect can occur either directly through influencing labor demand and/or income, or indirectly through municipal budget. On the other hand, suggestive evidence show that higher temperature can also increase crime due to psychological factors or changing habits. Nevertheless, because the time span employed in this study is relatively longer relying on annual variation in weather and crime rates, it is then expected to see a prevalence of income channel over non-economic factors. This is because income changes requires more time to be translated into violent crimes, while non-economic factors are more likely to be reversed over the course of the year (Jacob et al., 2007).

3 Data and Empirical Approach

3.1 Data

The unit of analysis is the Brazilian municipalities defined by their 1991 boundaries (i.e. beginning of the sample period). Given that the number of municipalities have changed over time due to subsequent mergers and splits, the fixing of municipalities' boundaries at a certain year ensures having a constant number of comparable areas that existed throughout the sample period from 1991 to 2015.[8] Because weather shocks hit harder rural areas and crime dynamics can vary between rural and urban areas, I exclude big municipalities with average population exceeding 250,000 inhabitants or average population density exceeding 125 inhabitants per square km over the sample period following convention.[9] Predominantly urban municipalities whose average share of rural population is less than 15 percent are also dropped.[10] This allows for having more homogenous sample, with modes of production and income generated activities are highly dependent on agriculture. This leaves us with a balanced dataset of 3,848 municipalities.[11]

Violent crime data.—Municipality's violent crime rate is measured by the number of homicides per 100,000 inhabitants in a given year and obtained from DATASUS (Depatamento de Informatica do Sistema Unico de Saude), a dataset published by the Ministry of Health.[12] Homicides rates serve as a good proxy for violent crime

using weekly data from US counties. That rates of violent and property crime during weeks of hot weather are offset by lower than usual crime rates in the following weeks, so that the cumulative effect becomes insignificant.

[8]See for instance Blakeslee and Fishman (2014), Dube and Vargass (2013) and Caselli and Michaels (2013) for similar methodology.

[9]Only 2 municipalities are dropped, namely: Ananindeua and São Luís.

[10]I follow Braga et al. (2016) criteria in classifying Brazilian municipalities into three categories based on the share of rural population: predominantly urban ($< 15\%$), intermediate rural (15 to 50%) and predominantly rural ($> 50\%$).

[11]The results remain generally robust when these predominantly urban municipalities are re-included as well as when the cut-off points for rural municipalities are modified (available upon request).

[12]The same measure was used by Dix-Carneiro et al. (2018), and Ishak and Meon (2019) in

rates given that lack of data on other forms of violent crimes for the same time period for all municipalities. One important advantage of using homicides rates is that they suffer less from under-reporting, which a typical feature of less violent crimes such as theft or of crimes with social stigma (i.e. rape), especially in rural underdeveloped areas (Fajnzylber et al., 2002; Gould et al., 2002). To check whether homicides is indeed a reflective of the violent crime rates, I rely on municipal level data on armed robberies and physical assault disclosed by the states of Sao Paulo and Minas Gerais from 2001 and 2013. Unfortunately, using this data is not suitable in my context because these two states are highly urbanized, with urban population representing, on average, 84% and 70% of their population, respectively. Hence, they do not constitute an appropriate setting for testing the effects of weather shocks, which should hit harder the agro local economies. Nevertheless, Table A2 in Appendix A shows a high correlation between both homicides and robberies rates, and homicides and physical assault rates. The correlation gets stronger when both measures are net of population, municipal and state year-fixed effects. Moreover, using cross-section data from 2009 National Household Survey (PNAD) on victimization rates in Brazilian states, I find a strong correlation at the state level between homicide rates and 3 types of crimes: theft and armed robbery, attempted theft and armed robbery and physical assault (Table 7 in Appendix A).[13] In both cases, the homicide rates exhibit a stronger correlation with armed robberies rates than with physical assault pointing more to the economic intentions of committing those crimes.[14]

Weather data.—I rely on Standardized Precipitation-Evapotranspiration Index (SPEI) taken from Vicente-Serrano et al. (2010) to construct the weather indicator. The SPEI dataset is a global grid divided into subnational cells of 0.5×0.5 degrees latitude and longitude (approximately 55×55 kilometers). These grid cells are then matched to the municipalities based on the latter's centroids.[15] The SPEI is available on monthly basis and expressed in units of standard deviation from the grid cell's historical average (in this case from 1901 to 2015). The annual SPEI is calculated by taking the 12-months average with higher values of this index corresponding to favorable weather conditions (i.e. extensive rainfall) and lower values indicating drought tendencies. The index was previously employed by Harari and La Ferrara (2017) and Von Uexkull et al. (2016) in studying the effect of weather shocks on civil conflicts in Africa. The advantage of using SPEI index lies in the fact that it jointly controls for the effects of rainfall and determinants of evapotranspiration (i.e. temperature, wind speed, sunshine) making it more favorable over

estimating the impact of trade shocks and oil revenues on crime rates, respectively. I follow their approach and add zero to municipality-year observations with missing data to avoid sample selection bias. Results remain also robust without making these additions (see Table B2 in Appendix B).

[13] One advantage of the victimization surveys is that they suffer less from measurement errors, a common and allows for a better measurement of actual crime rate. The PNAD survey is carried out by Brazilian national bureau of statistics (Instituto Brasileiro de Geografia e Estatística-IBGE).

[14] As shown by Dix-Carneiro et al. (2018), homicides rates also exhibit a strong correlation at the micro regional level with armed robberies. This is because violence is rendered a typical way of settling disputes in Brazil, which involves the use of firearms and might end up in the murder of one of the dispute sides.

[15] Shah and Steinberg (2017) and Iyer and Topalova (2014) for similar methodology.

conventional measures of weather shocks such temperature and precipitation.[16] To further investigates the presence of non-linear effects for weather fluctuations, Appendix C contains the results of estimating a non-parametric model with different intensity bins for SPEI to capture seasons of drought (i.e. negative weather shocks) and excessive rainfall (i.e. positive weather shocks).

Other controls.—Data on annual municipality population is obtained from intercensus population estimates provided by the Brazilian national bureau of statistics (Instituto Brasileiro de Geografia e Estatística-IBGE). Geographical variables describing the location of municipalities (e.g. longitude, latitude and area. . . etc.) are taken from Instituto de Investigación Económica Aplicada (IPEA). Other data used in measuring driving channels (e.g. agriculture yields, economic activity, labor market outcomes...etc.) and describing municipality characteristics are explained in details in Appendix A. All data are firstly obtained at the 2016 municipal administrative level, then aggregated to the municipal original 1991 boundaries. The choice of the sample period is restricted by the availability of population data from 1991 onwards, which is necessary factor to control for in all specifications. Although, population figures are also available for year 1980, which makes it possible to extend the sample period using linear interpolation. I approach this issue as conservatively as possible, maintaining the baseline period to 1991-2015, but using the alternative extended sample 1980-2015 as a robustness check (see section 5).

3.2 Empirical Approach

The empirical specification seeks to gauge the effect of weather shocks on violent crime rate. The identification strategy exploits the within-municipality variation in weather conditions taking into account the spatial distribution of violent crime rates. Formally, I estimate the following equation:

$$\begin{aligned} ViolentCrime_{ist} &= \alpha_1 SPEI_{ist} + \alpha_2 SPEI_{ist-1} + \alpha_3 SPEI_{ist-2} + \beta X_{ist} \\ &+ \rho W ViolentCrime_{ist} + \delta_i + \gamma_s \times \eta_t + \epsilon_{ist} \end{aligned} \tag{1}$$

Where $ViolentCrime_{ist}$ is the homicide rate (per 100,000 inhabitants) in municipality i in state s and year t; δ_i is municipality fixed effects; $\gamma_s \times \eta_t$ is state-year fixed effects; X_{ist} controls for population density and ϵ_{ist} is the error term. Municipality fixed effects control for the differences across municipalities that are constant over time, while state-year fixed effects control for common shocks occurring to the municipalities belonging to the same state. The weather indicator $SPEI_{ist}$ is included at times t, $t-1$, and $t-2$. Hence, the corresponding coefficients $\sum_{k=1}^{3} \alpha_k$ capture the contemporaneous and lagged effects of weather variations on violent crime rates (e.g. Mehlum et al., 2006). The inclusion of lagged terms has two advantages. First, it allows for taking into account the correlation of weather variations discerning the possibility of displacement of effects over time, and better estimating the impact of contemporaneous shocks. Second, it makes it possible to identify the persistence of effects over the course period. If the weather effects were persistent, the contempo-

[16] Refer to Harari and La Ferrara (2017) for more technical information on the construction of the index.

raneous and lagged coefficients would not sum up to zero. I control for population density to capture scale effects taking into account that dense areas are more likely to experience more violent crime.[17]

To further investigate the persistence and serial correlation of weather variations, tables A4 and A5 in Appendix A perform formal checks of the time series properties of weather shocks in Brazil. The formal tests presented in table A4 fail to reject the null hypothesis of an absence of a unit root for the time series of SPEI in levels, but rejects it for its first difference providing a first local evidence of the persistence of these shocks. Table A5 contains tests of serial correlation, which universally reject the null hypothesis of no-serial autocorrelation across years. Hence, both tests justify the inclusion of temporal lags.

Spatial dependence.—Because violent crime rates tend to spatially clustered as appeared in Figure 2, I include in equation 1 the spatial lag of violent crime rate, $WViolent\ Crime_{ist}$, where W is a spatial contiguity weight matrix that defines the potential interactions between each pair of municipalities. Two municipalities are considered to be neighbors, if they lie within a 230 km distance cutoff. The cutoff distance corresponds to the internal median distance within the federal state. A contiguous municipality is then assigned a weight of 1, while non-neighbors located beyond 230 km distance are assigned a weight of zero. Accordingly, $WViolentCrime_{ist}$ is the average homicide rate in municipality i's neighbors in state s at time t and parameter ρ reflects the strength of spatial dependence in homicide rates. Furthermore, I employ a spatial HAC correction for standard errors allowing for both cross-section spatial correlation and location-specific serial correlation within 230 km radius following the method developed by Conley (1999) and Hsiang et al. (2011).[18]

Channels.—Next, I examine the economic and non-economic channels through which weather fluctuations may affect crime and estimate two specifications of the following form:

$$\begin{aligned} Y_{ist} = \alpha_1 SPEI_{ist} + \alpha_2 SPEI_{ist-1} + \alpha_3 SPEI_{ist-2} + \beta X_{ist} + \delta_i \\ + \gamma_s \times \eta_t + \epsilon_{ist} \end{aligned} \quad (2)$$

Where Y_{ist} is one of the following outcomes: the agriculture yield per hectare, the economic activity, and the suicide rate (per 100,000 inhabitants) as a proxy for psychological disorders in municipality i in state s and year t. Agriculture yield is measured by both the real value of main crop gross output (2010 prices) and its quantity (ton/hectare). The rest of controls are similar to equation 1, except for the exclusion of spatial lag of crime rate. In this specification, standard errors

[17]Population density experiences less variation over time. Over the whole-sample period, the average change in population density has a median (mean) of 1.2 (1.9) units per square km. In addition, the variation in population density is less likely to be explained by climate variations. The R2 of a model regressing population density on SPEI, municipality fixed effects and state-year fixed effects was 0 and the joint significance of the estimated SPEI coefficients was only significant at the 10% significance level (p-value = 0.09). Results remain robust if population density enters at t-1.

[18]Results remain robust to clustering at the micro region level, which is a grouping of economically integrated contiguous municipalities with similar geographic and productive characteristics (see Table B1 in Appendix B). Changing the distance cut-off for clustering standards errors leaves the main results unchanged (see Table B3 in Appendix B).

are clustered at the micro level, the next higher administrative level, to take into account the spatial correlation in outcomes across neighboring municipalities.

For other channels, the data is only available for the years 1991, 2000 and 2010. Therefore, I employ the below specification following Michael (2011):

$$\begin{aligned} Y_{ist} = {} & \alpha_1 SPEI_{ist} + +\alpha_2 SPEI_{ist-1} + \alpha_3 SPEI_{ist-2} + \beta X_{ist} + \phi_{is} t \\ & + \gamma_s \times \eta_t + \epsilon_{ist} \end{aligned} \tag{3}$$

Where Y_{ist} is the channel of interest (i.e. earnings, unemployment, state budget...etc.) in municipality i in state s and year t and $\gamma_s \times \eta_t$ is state-year fixed effects. Given the short time dimension covering only three points of time (1991, 2000 & 2010), I excluded municipality fixed effects. Instead, I control instead for longitude, latitude, distance to federal state, distance to capital state, and dummies for capital state, rural and coast municipalities (ϕ_{is}) and allow these control to be time-varying by multiplying them with a linear time trend (t). Standard errors are clustered at the micro level.

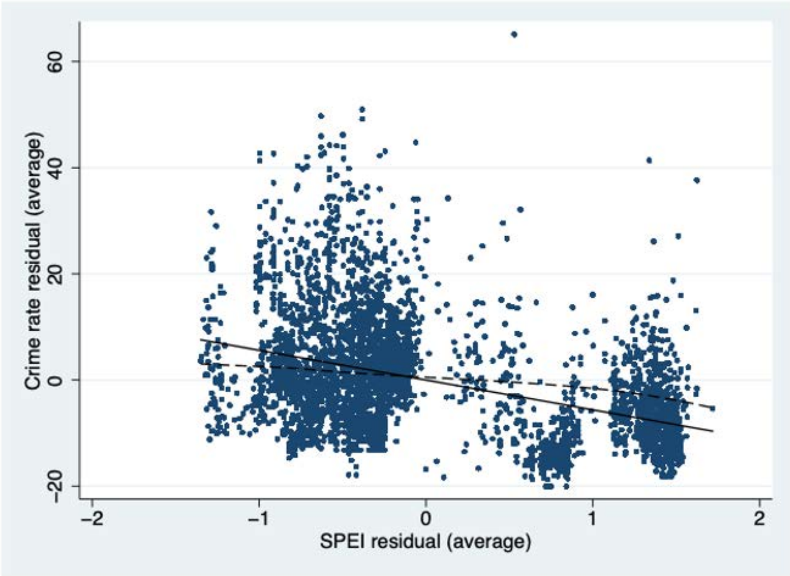
Including state-year fixed effects is essential given the Brazilian context, where part of municipality's revenues is received from the federal state (known as state funds), which in turn are received from Brazilian national government. These fixed effects capture shocks affecting federal state's revenues, so that the main effect on municipal budget revenues is only due to weather shocks. In this specification, standard errors are clustered at the micro level, the next higher administrative level, to take into account the spatial correlation in outcomes across neighboring municipalities. As the same independent variable, annual SPEI, is used consequently in multiple regressions with short time dimension, this can lead to a problem of incorrectly over-rejecting the null hypothesis in each test. To tackle that, I also report the family-wise error rate (FEWR) following methodology developed by Romano and Wolf (2005a; 2005b). The advantage of this methodology is that it uses step-wise approach to take into account the probability of committing of Type I error in the family of hypotheses.

4 Baseline Results

4.1 A First Look at the Data

The final sample consists of 3,848 municipalities over the period 1991-2015. Only 28 municipalities report no crime data over the entire sample period. Table 1 displays some descriptive statistics of the variables employed in the analysis. The annual SPEI reports an average of 0.10 reflecting a slightly favorable weather conditions relative to the grid cell's historical average.

To get a first snap shot of the relationship between weather fluctuations and violent crime rate, Figure 1 plots the whole-period average SPEI against average crime rate net of municipal and state-year fixed effects. The solid represents the linear fit and has a slope of -5.61 (with a p-value of 0.00) indicating a negative association between municipality's rate of violent crime and weather conditions. The



Notes: The graph shows the relationship between annual averaged violent crime rate and SPEI net of municipal and state-year fixed effects. The solid line represent the linear fit, while the dashed line represents the nonparametric local polynomial fit computed using an Epanechnikov kernel.

Figure 1: Violent crime rate and SPEI – Correlation

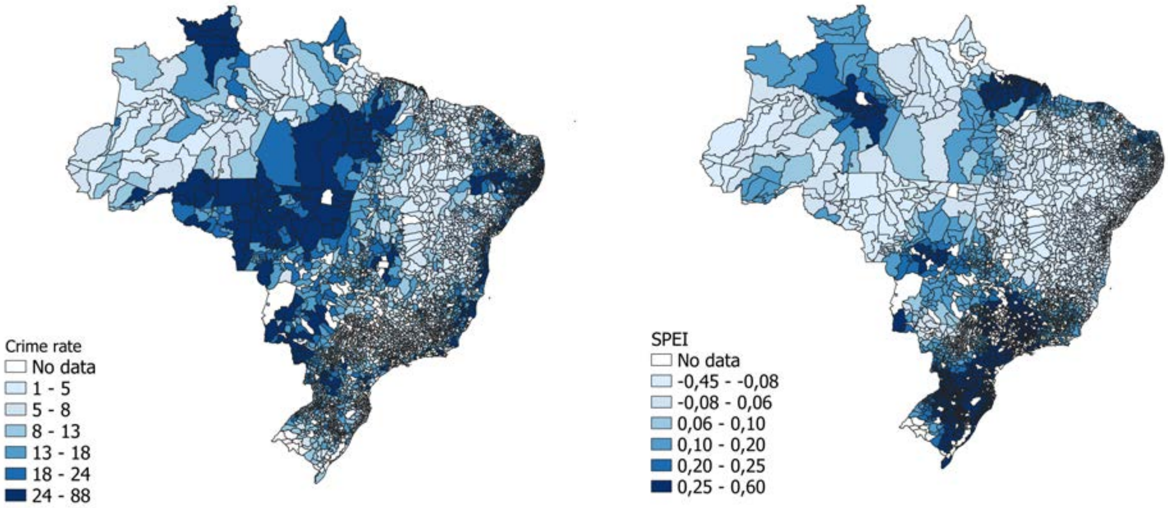
Table 1: Summary statistics

Variable	N	Mean	SD	Min	Max
Homicide rate (per 100,000)	96,200	12.12	15.59	0	268.91
SPEI (whole-year average)	96,200	0.10	0.59	-2.16	2.16
Population density	96,200	43.11	70.16	0.06	3,293.93

plot shows that most of the observations are concentrated where negative values of SPEI coincide with high violent crime rates. In other words, adverse weather conditions (i.e. drought tendencies) are correlated with high violent crime rates, while favorable weather conditions are associated with low violent crime rates. The non-parametric dashed line is close to the linear fit suggesting that the relationship is to a great extent linear, providing support for the use of SPEI levels as the main measure of weather variations. Figure 2 depicts the spatial distribution of whole-period average violent crime rate and SPEI. It shows a large degree of heterogeneity in violent crime rates and weather conditions across municipalities. Violent crime rates in the left plot seems to be spatially clustered, especially in mid-west regions and along the coast. For comparison, the average SPEI in the right plot shows coincidence with higher crime rates in municipalities with low SPEI.

4.2 Baseline Results

Table 2 reports the baseline results for estimating equation (1) using various definitions of the variables and model specifications. In all columns, the coefficient of annual SPEI is contemporaneously negative and statistically significant at 1 or 5 percent significance level. Thus, a decrease in the level of SPEI, which corresponds to lower rainfall or drought, significantly increases the violent crime rate on impact.



Notes: The graph shows the spatial distribution of whole-period average violent crime rate and SPEI

Figure 2: Violent crime rate and SPEI – Spatial distribution

In column 1, the contemporaneous annual SPEI is included along with its first and second lags. We see that a higher SPEI has a negative effect on violent crime rate at the same year and 2 years after. However, the coefficient of the second lag is lower in magnitude and significance compared to the cotemporaneous effect. In column 2 and 3, I replace annual SPEI with the average SPEI during the municipality's main crop growing season and non-growing season.[19] I do that to disentangle the effect of within-year variations in weather conditions during and outside the municipality's main agriculture season. As argued by Blakeslee and Fishman (2017), the agriculture season is the principal income source for the largest share of rural workers. Hence, a weather-driven agriculture shock could affect the earnings of farmers and workers in agricultural related activities in rural areas, and in turn affects the opportunity cost of committing crimes.

Columns 2 and 3 show that both contemporaneous SPEI is statistically significant during the growing season, but are insignificant outside the main crop's growing season. This suggests that the observed significant effects of annual SPEI on crime is driven by weather changes occurring during the growing season in line with the previous findings of Blakeslee and Fishman (2014) and Hirari and La Ferrara (2018). However, the coefficients of SPEI in column 1 is greater in magnitude and significance compared to that SPEI growing season in column 2. Column 4 runs a horse race test by simultaneously including both annual and growing season SPEI. The coefficient of the contemporaneous annual SPEI keeps its negative sign and statistical significant at the 5 percent level, while the SPEI growing season become statistically significant. If there were other unobservable factors that correlates with the effect of annual SPEI on crime aside from weather variations during the growing season, then the coefficient of SPEI during growing season should remain statistically significant. Nevertheless, the results indicate that the effects of weather conditions during the

[19]See Appendix A for more details on the construction of these two variables.

Table 2: Violent crime and weather

	Dependent varibale: Homicide rate (per 100,000)							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
SPEI, t	-0.643***			-0.767**	-0.399**	-0.498**	-0.395***	-0.313***
	(0.222)			(0.315)	(0.199)	(0.254)	(0.138)	(0.107)
SPEI, t-1	-0.210			-0.091	-0.155	-0.155	-0.002	-0.069
	(0.198)			(0.289)	(0.179)	(0.241)	(0.140)	(0.112)
SPEI, t-2	-0.467**			-0.385	-0.257	-0.244	-0.225*	-0.141
	(0.184)			(0.284)	(0.165)	(0.224)	(0.132)	(0.106)
SPEI Growing Season, t		-0.341**		0.128				
		(0.164)		(0.228)				
SPEI Growing Season, t-1		-0.160		-0.121				
		(0.145)		(0.209)				
SPEI Growing Season, t-2		-0.340**		-0.079				
		(0.142)		(0.219)				
SPEI Non-Growing Season, t			-0.094					
			(0.131)					
SPEI Non-Growing Season, t-1			0.036					
			(0.119)					
SPEI Non-Growing Season, t-2			-0.002					
			(0.115)					
W(SPEI), t						0.001		
						(0.001)		
W(SPEI), t-1						0.0001		
						(0.001)		
W(SPEI), t-2						-0.0001		
						(0.001)		
W(Violent crime)					0.002***	0.002***	0.003***	0.003***
					(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sum of coefficients (SPEI)	-1.320***			-1.241**	-0.811**	-0.897**	-0.622**	-0.523**
	(0.381)			(0.593)	(0.353)	(0.471)	(0.259)	(0.209)
Sum of coefficients (SPEI GS)		-0.842***		-0.072				
		(0.274)		(0.421)				
Sum of coefficients (SPEI Non-GS)			-0.059					
			(0.242)					
Number of observations	96,200	96,200	96,200	96,200	96,200	96,200	96,200	96,200
Number of municipalities	3,848	3,848	3,848	3,848	3,848	3,848	3,848	3,848
Adjusted R-squared	0.028	0.027	0.027	0.028	0.126	0.126	0.126	0.156
Population density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State $\times YearFE$	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	No	No	No	No	No	No	Yes	Yes
State $\times trend$	No	No	No	No	No	No	No	Yes

The dependent variable is homicide rate per 100,000 inhabitants as a proxy for total violent crime. W is a spatial binary contiguity matrix that assigns 1 to municipalities lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

growing season on violent crime rates remain thereafter throughout the year and it is not offset by variations occurring during the non-growing season suggesting a persistence in the response of crime to weather variations within a given year.[20] Furthermore, the annual SPEI embeds relatively less measurement error compared to average SPEI during the growing season, which also carry the measurement error of identifying the growing season. Assuming a classical measurement error, the coefficients of SPEI growing season will be more downward biased owing to the attenuation bias exacerbated by the inclusion of wide range of fixed effects.

Column 5 presents our main specification in equation (1) by adding the spatial lag of violent crime rate to address spatial dependence. The estimated coefficient of contemporaneous SPEI remains negative and significant, while the coefficient of

[20] The average growing season is 6.7 months, meaning that 56% of the annual weather fluctuations occur during this period, which dominates, on average, any fluctuations taking place outside it.

the spatial lag of crime is positive and significant. The latter suggests that ongoing criminal activities in neighboring municipalities can increase crime in the municipality itself reflecting a strong correlation in violent crime rates across neighboring municipalities. Compared to column 1, the coefficient of SPEI is smaller in magnitude (38% lower) indicating that neighboring crime can explain much variation in municipality's crime levels and its exclusion can overestimate the crime-weather relationship. The total explanatory power of the model has also increased with the inclusion of the spatial lag of violent crime rates.[21] To put coefficients into perspective, a one-standard deviation decrease in SPEI below the municipality's mean translates into an increase in violent crime rates by 34%, roughly representing around 3% of the unconditional mean of dependent variable.[22] The estimates are consistent with previously reported estimated effects in the climate-crime literature. For instance, Miguel (2005) estimate that a one standard deviation change in extreme rainfall (drought or floods) led to an increase in the murder of witches by over 20% in Tanzania. More generally, the estimates lie within the distributed range of estimated coefficients for the response of crime and conflict tendencies to climate changes in the meta-analysis conducted by Hsiang et al. (2013). [23]

In column 6, I introduce the spatial lags of SPEI to check whether weather fluctuations occurring in neighboring municipalities can induce spillover effects on violent crime rates in the municipality itself. The coefficients of the spatial lags enter small and statistically insignificant indicating that effects of weather fluctuations within a given municipality is strictly local and do not indirectly affect surrounding neighbors. I will further investigate the presence of spillover effects in crime and weather conditions by looking at higher administrative level data below in the robustness checks. The last two columns deal with alternative sets of fixed effects. Column 7 re-estimates column 5 without the state-year fixed effects, but adds instead year fixed effects, while column 8 additionally adds state-year specific trend. In both cases, the coefficient of SPEI remains stable in sign and significance.

To further investigates the presence of non-linear effects for weather fluctuations, Appendix C contains the results of estimating a non-parametric model with different intensity bins for SPEI to capture seasons of drought and excessive rainfall. The results show that that the effects are both quantitatively and qualitatively stronger for adverse weather shocks (i.e. drought) corresponding to negative values of SPEI. Hence, it confirms the previous finding in Figure 1 that the relationship between weather shocks and violent crime rate is linear and further justify the use of level SPEI to measure weather variations.

The bottom row of each column in Table 2 presents the cumulated effect of weather fluctuations, calculated by summing the coefficients of SPEI variable and its lags. In all specifications, the lags of annual SPEI do not sum up to zero, but

[21]The adjusted R-squared has increased from 2.6% in column 1 to 12.6% in column 5 (around a 350% jump). Note that the R-squared tend to be low because it is sensitive to the quantity of noise in crime data. Hence, the importance of weather fluctuations in explaining violent crime rates will appear to be smaller, even though the impact of weather variations is quantitatively large (Hsiang et al., 2013)

[22]Note the standard deviation of within-SPEI is 0.861.

[23]In particular in Brazil and aside from climate literature, Dix-Carneiro et al. (2018) estimate that a one standard deviation decrease in tariff led to an increase in violent crime rate run by 46%.

remain significant, indicating the persistence of weather fluctuations not only beyond the growing season, but also over the medium run confirming the formal results from unit root testing. If weather effects are reversed over its course, for instance, favorable weather conditions at one year will be followed adverse conditions in the next year, then the cumulated effect of these variations should be summed to zero or carry an opposite sign, which is not the case here. The accumulated effect of a one-standard deviation decrease in SPEI below the municipality's mean over the medium run is a surge in violent crime rates by 70%, accounting for around 6% of the unconditional mean of dependent variable.

5 Robustness Checks

IIn the previous section, I showed that unfavorable weather conditions have a persistent positive effect on violent crime rates and the effect is driven by weather fluctuations during the municipality's agriculture season. In this section, I perform a number of sensitivity checks to the baseline estimates in column 5 of 2. The results are reported in Tables 3 and 4.

Municipal characteristics.—One potential concern is that the effect of weather captures the role of unobserved time-varying municipality-specific factors. For instance, the presence of a larger share of young and illiterate could lead to more crime, while deploying more security forces can deter criminal activities (Angrist and Kugler, 2008; Gould et al., 2002; Bignon et al., 2015). To deal with this concern, I allow the effect of a number of initial municipality characteristics to change over time by including an interaction between these characteristics and a year indicator. The municipality characteristics enter at their 1991 level and include the illiteracy rate, the share of young, male, unskilled and workers in public safety jobs as well as the share of urban population. The results reported in column 1 of Table 3 show that the coefficient of SPEI remains stable in sign and significance.[24]

Weather can affect crime, if heavy rains caused roads to flood and reduced the police ability to apprehend criminals or prevent crimes from taking place. To test that, column 2 interacts weather conditions with an indicator of the presence of at least one railroad station (in service) in a municipality in year 1995 as a proxy for infrastructure (IPEA, 2019). The interaction terms enter positive suggesting that favorable weather conditions can have less impact on crime in the presence of better infrastructure that would facilitate the police movements, but they are statistically insignificant and small in magnitude especially for the contemporaneous term.

Other local shocks.—So far, the estimation of the impact of weather conditions on crime rates is applied in its reduced form holding constant other heterogeneous factors that could be spuriously correlated with weather fluctuations and crime at the municipal level. Still, one may want to check whether the presence of certain municipality's characteristics could exacerbate violent crime rates. Brazil is a world-leading exporter of oil, which casts shadows on whether the presence of oil activities

[24]In unreported results, I also checked whether weather variations affect the composition of young, unskilled and male-young-unskilled in the municipality and find no statistical significant effect.

Table 3: Violent crime and weather –Robustness checks

	Dependent varibale: Homicide rate (per 100,000)				
	(1)	(2)	(3)	(4)	(5)
	Municipal characteristics	Infra-structure	Adding oil shocks	Adding oil shocks	Dynamics
SPEI, t	-0.406**	-0.400**	-0.398**	-0.399**	-0.363**
	(0.194)	(0.203)	(0.199)	(0.199)	(0.185)
SPEI, t-1	-0.135	-0.160	-0.149	-0.151	-0.115
	(0.178)	(0.182)	(0.179)	(0.179)	(0.168)
SPEI, t-2	-0.182	-0.303*	-0.247	-0.249	-0.255*
	(0.163)	(0.168)	(0.165)	(0.165)	(0.154)
SPEI × railroad stations, t		0.024			
		(0.225)			
SPEI × railroad stations, t-1		0.008			
		(0.206)			
SPEI × railroad stations, t-2		0.318			
		(0.218)			
Oil revenues (log) (permenant)			0.571*		
			(0.303)		
Oil revenues (log) (ever)				0.253*	
				(0.152)	
Violent crime, t-1					0.149***
					(0.009)
W(Violent crime)	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.0001)	(0.0001)	(0.000)
Sum of coefficients	-0.692**	-0.863	-0.793**	-0.811**	-0.733**
	(0.350)	(0.358)	(0.353)	(0.353)	(0.312)
Number of observations	96,200	96,200	96,200	96,200	96,200
Number of municipalities	3,848	3,848	3,848	3,848	3,848
Adjusted R-squared	0.147	0.126	0.126	0.126	0.155
Population density	Yes	Yes	Yes	Yes	Yes
Controls $\times YearFE$	Yes	No	No	No	No
Municipality FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes

The dependent variable is homicide rate per 100,000 inhabitants as a proxy for total violent crime. W is a spatial binary contiguity matrix that assigns 1 to municipalities lying within 230 km distance cutoff. Controls in column 1 includes the initial levels of share of the unskilled, male, young, illiterate, urban populatiion and workers in public safety jobs. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

can contribute to proliferation of crime. Ishak and Meon (2019) provide empirical evidence that oil-abundant municipalities in Brazil suffer a proliferation of violent crime rates. To consider that, I include a number of indicators for oil abundance in Brazilian municipalities. Following Mamo et al. (2019), oil revenues for each producing municipality are calculated by multiplying international oil prices (measured in 1991 US dollars) with municipality's time-varying oil output.[25] Thus, for municipality-year observations with no reported oil output, this variable takes the value of zero. Oil revenues are then expressed in its natural log plus 1 to avoid the drop of municipalities with no oil production. In my sample, I have 102 municipalities with at least one year of reported oil production. Of these municipalities, there are 77 municipalities with active production activities taking place throughout the sample period (i.e. permanent oil producers) and 25 municipalities with interrupted production (i.e. temporarily oil producers).

The results are reported in Table 3. Column 3 adds oil revenues received only by permanent oil producing municipalities as an additional explanatory variable

[25] See Appendix A for more details on the definitions and sources of oil variables.

(i.e. revenues of temporarily oil producers are set to zero). This ensures to some extent the exogeneity of oil production to disruption incidences occurring at the municipality level that could be partly driven by pervasive criminal activities.[26] Column 4 includes all oil revenues received by all municipalities with at least one year of active oil production. Both variables captures the effect of the value of oil production (or oil revenues) at the intensive margin. The oil variables enter positive and statistically significant at the 10 percent level, whereas the coefficient of SPEI remain remarkably stable in sign, magnitude and significance. This is not surprising given that state-year fixed effects have already absorbed the heterogeneity captured by these indicators.[27] In the appendix, I alternatively consider dropping all oil municipalities with at least one year of reported oil production and results remain robust.

Dynamic Model.—Equation 1 is static and therefore does not take the inertia of violent crime rates into account, with past levels of crime rates affecting current rates. I therefore estimate a full spatially and temporally autoregressive model by adding the lagged dependent variable to the explanatory variables. Column 5 shows that the coefficient of SPEI slightly drops in size, but remains statistically significant at the 5 percent significance level. The coefficient of lagged crime rates lights is positive and statistically significant at the 10 percent significance level. Hence, the long-run effect of one-standard deviation decrease in SPEI below the mean on crime rates is 37%.

Falsification test.—In table 4, I address the concern that time-varying omitted variables could be driving the estimated relationship between crime and weather conditions. Indeed, it could be the case that the residual unobserved heterogeneity still co-moves with weather fluctuations despite the wide array of fixed effects I include. To rule that possibility out, I follow two approaches. First, on the outcome variable side, I randomly reshuffle violent crime rates across municipalities. Second, I perform a placebo test by substituting SPEI with its past values for the period from 1966 to 1990 before estimating equation 1 again. The estimated coefficients of SPEI and its lags reported in column 1 carry opposite signs and are statistically insignificant. In column 2, the coefficients of past values of SPEI behave inconsistently and exert no statistical significant effect on violent crime rates. Moreover, the sum of the estimated coefficients of shock variables is zero. In sum, as both falsification tests have resulted in insignificant results, I can safely conclude that the baseline results are not simply driven by co-movements in weather conditions and violent crime rates.

Alternative sample and unit of analysis.—I next investigate whether sample size can affect the baseline results. Column 3 of Table 4 extends the baseline sample

[26]Note the question of exogeneity of oil production in Brazil does not constitute a major issue in these estimations, since most of the oil production is produced offshore with production decisions are made by major international companies and not affected by factors occurring in a given municipality (Caselli and Michaels, 2013). Furthermore, Brazil is not a member of OPEC and hence, an oil price taker which makes international oil prices exogenous as well.

[27]In unreported results, I checked the results after dropping state-year fixed effects and including instead year fixed effects. Indeed, I find that the coefficient of oil revenues (permanent) have increased in magnitude and significance level (5% significance level), while SPEI remains negative and significant (results available upon request).

period over the years from 1980 to 2015. Recall, the baseline sample period was restricted to 1991-2015 due to lack of data on population on annual basis before this period. But, using population figures in 1980, I was able to interpolate between-years figures from 1981 to 1990. I still find the coefficient of SPEI to be negative and significant. The results of this sample should be taken with cautious since the population figures used in this sample is crudely constructed, which could introduce bias to the estimates.

Table 4: Violent crime and weather –Robustness checks

	Dependent varibale: Homicide rate (per 100,000)			
	(1)	**(2)**	**(3)**	**(4)**
	Reschuffle crime data	**SPEI (1966-1990)**	**Extended sample period (1980-2015)**	**Micro regions**
SPEI, t	0.187	0.153	-0.279**	-0.371
	(0.142)	(0.128)	(0.123)	(0.305)
SPEI, t-1	-0.111	-0.051	-0.054	-0.088
	(0.143)	(0.122)	(0.117)	(0.276)
SPEI, t-2	0.010	0.088	-0.052	-0.215
	(0.131)	(0.123)	(0.120)	(0.280)
W(Violent crime)	-0.0001	0.002***	0.002***	0.003
	(0.000)	(0.000)	(0.0001)	(0.002)
Sum of coefficients	-0.087	-0.189	-0.386*	-0.675
	(0.245)	(0.218)	(0.212)	(0.657)
Number of observations	96,200	96,200	138,060	13,675
Number of municipalities	3,848	3,848	3,848	547
Adjusted R-squared	0.000	0.126	0.132	0.277
Population density	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes

The dependent variable is homicide rate per 100,000 inhibitants as a proxy fot total violent crime. W is a spatial binary contiguity matrix that assigns 1 to municipalties lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius in columns 1-3; and within 500 km radius in column 4. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

To further explore the spillover effects of crime rates and weather fluctuations, I redefine the unit of observation to correspond to the next higher administrative level. The idea here is that by doing so we define geographic units that internalize a part of the spillover effects. The larger the administrative unit, the larger the share of spillover effects that is internalized. I therefore conduct the analysis at the micro-region level, which is a grouping of economically integrated contiguous municipalities with similar geographic and productive characteristics, then at the level of macro-regions, the next highest administrative level. Micro-regions closely parallel the notion of local economies and have been widely used as the units of analysis in the literature on effects of trade liberalization on local labor markets in Brazil (e.g. Dix-Carneiro, Soares and Ulyssea, 2018). The average micro-region in our sample comprises eight municipalities with a maximum number of 41 municipalities and an average size of 15,000 square kilometers.

Column 4 of Table 4 contains the results. We see that that SPEI ceases to have any significant effect on crime rates at the Micro-level. Recall, the findings in Table 2 signals the non-presence of spatial spillovers of SPEI on neighboring municipalities. Hence, on the aggregate, the negative direct effect of weather fluctuations on crime rates in a given municipality is offset by the non-existing neighboring effects, confirming the previous findings of the locality of the effects of weather conditions confined to the boundaries of a given municipality. Similarly, the coefficient of spatial lag of crime lost its significance, because spillover effects decrease with distance. By construction of the spatial weight matrix, the more distant the added neighbors, the less is the average neighborhood effects.

In general, throughout all the tables, the cumulated effect of weather fluctuations, calculated by summing the coefficients of SPEI variable and its lags is negative and statistically significant, except for the placebo tests. This again confirms the persistence of weather effects over the medium run.

Other robustness checks.—Further robustness checks are discussed in detail in Appendix B. These include: (i) estimating no lags model; (ii) adding more temporal lags for SPEI up to 10 lags; (iii) restrict the sample to 2000-2015 period; (iv) exploring the long-run relationship; (v) a falsification test computed by replacing the SPEI variable and its temporal lags with its one-year, two-year and three-year forward SPEI; (vi) different distance cut-offs for computing standard errors and alternative clustering at the micro level; (vi) dropping oil producing municipalities; (vii) employing fixed-effects Poisson regression; (viii) dropping SPEI outliers of more than 2 and 3 standard deviations; (ix) alternative measures for crime; (x) adding rainfall and temperature measures; and (xi) adding squared SPEI. The main results of these robustness checks can be summarized as follows. The baseline results remain robust in sign and significance with the dropping and the addition of temporal lags, but the estimates become stronger when the sample is restricted to the 2000-2015 period and when taking the long-run difference. The results of the falsification test show that the estimated coefficients of forward SPEI are jointly statistically insignificant. Increasing the distance cut-off of standard errors at 500 and 1000 km distance or clustering at the micro level have reduced the statistical significance of the weather SPEI variables echoing the results from the micro regions sample. Dropping oil municipalities and SPEI outliers as well as employing fixed-effects Poisson regression did not have an impact on contemporaneous effect of the SPEI. The same is the case with using alternative measures of crime rates (e.g. unweighted crime, dropping extreme values. . . etc.), adding squared SPEI terms or adding rainfall and temperature measures. In Appendix C, I differentiate between the effects based on the size and scope of agricultural activities in the municipality measured by the area of cultivated main crop per capita and find the effects gets larger in magnitude the bigger the cultivated area.

6 Channels

As discussed in the conceptual framework, the positive association between incomes and weather conditions is expected to play a dominant role in the final impact on crime relative to non-economic factors as predicted by opportunity cost mechanism and local governments capacity. Moreover, the baseline results put forward that the persistent effects of weather variations in violent crime rates is driven by weather fluctuations during the agriculture season, which rules out the psychological motives. Nevertheless, I analyze in this section these three potential mechanisms as previously identified in the literature to be most likely to affect violent crime.

6.1 Economic Factors

Given that variation in weather conditions are expected to affect incomes through its impact on agricultural yields, I first examine the effect of SPEI on the municipality's main crop gross output. The main crop is defined as the crop with the largest share of harvested area (measured in hectares) in the greatest number of years. Gross output is measured in both real value and quantity per hectare.

Earnings and wages are the most widely documented to have the strongest effect on crime (e.g. Gould et al., 2002; Dix-Carneiro et al., 2018; Corvalan and Pazzona, 2019). Pertaining to the agricultural context, where around 92% of agriculture workers in Brazil are on average unskilled, I explore the evolution of these two variables for both skilled and skilled workers. Unskilled workers are defined as fraction of employed individuals with completed middle school or less and are older than 18 years old. Skilled workers are therefore the fraction of employed individuals with secondary education or more. I also consider employment and unemployment ratios as additional reflectors of labor market conditions (Raphael and Winter-Ember, 2001). These set of variables reflect the opportunity cost mechanism. Other socio-economic determinants of crime include poverty and income inequality, which could be a byproduct for detreating income levels (Iyer and Topalova, 2014; Fajnzylber et al., 2002). I construct two measures for poverty. The head count ratio measuring the fraction of households whose average monthly income below poverty line, and the poverty gab, defined as the average distance of the poor household from the poverty line to capture the depth of poverty. Income inequality is measured by GINI coefficient based on household income per capita. Local governments capacity is reflected in the changes in revenues and expenses of local governments, and the degree of provision of public goods (Machin, 2011: Chioda et al., 2016). Hence, I look at the effect on per capita municipal revenues and expenses, as well as average years of schooling and public security as examples of public goods.[28]

The results reported in Tables 5 and 6 are estimated using equations 2 and 3.[29]All outcomes are expressed in logs to draw straightforward comparisons across different outcome variables. Column 1 of Table 5 presents the results of the effect of SPEI on the municipality's main crop's output value per hectare. It shows that weather conditions have a positive association with agriculture yields and the effect occurs immediately. The point estimates indicates that a one-standard deviation decrease in contemporaneous SPEI leads to a decline in agriculture yield by 20% on impact. The coefficients of the second and third lags of SPEI are also significant, but negative in sign reflecting a reverse of the effect of the weather fluctuations. In addition, the sum of SPEI coefficients suggest a less persistent effect of weather conditions on agriculture yield. This not surprising given that output fluctuations

[28]Because municipal agriculture yields, expenditure and revenues are missing for some years in some municipalities and in order to avoid selection bias, I add a zero to these missing values and include a dummy variable capturing this transformation. However, the results remain qualitatively similar without making these changes.

[29]Results remain robust if the outcomes are expressed in logs (available upon request).

Table 5: Economic factors

	(1)	(2)
	Agriculture Yield (real value/hectare)	**Night-time lights**
SPEI, t	23.271***	0.148***
	(6.591)	(0.024)
SPEI, t-1	-33.377***	0.101***
	(12.154)	(0.022)
SPEI, t-2	-58.188***	0.109***
	(14.768)	(0.022)
Sum of coefficients	-68.294**	0.358***
	(27.506)	(0.063)
Number of observations	96,200	84,304
Number of municipalities	3,848	3,848
Adjusted R-squared	0.314	0.581
Population density	Yes	Yes
Municipality FE	Yes	Yes
State × Year FE	Yes	Yes

The method of estimation is ordinary least squares with robust standard errors reported in parentheses clustered at the micro level. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

can cumulatively cancel out each other indicating level effects. Hence, a decline in agriculture yield following non-favorable weather conditions in one year, can be compensated over the next years with the improvement in weather conditions, so that the accumulative effect have a reversed sign.

To check whether weather conditions exhibit an effect on non-agriculture output, I use mean night-time lights as a proxy for overall economic activity. The measure of night-lights is provided by the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center for the period from 1992-2013. It comes on a scale of 0-63, with higher values indicating more luminosity and has been used as a proxy for GDP in recent studies (e.g. Ishak and Meon, 2020; Henderson et al., 2012; Hodler and Raschky, 2014; Michalopoulos and Papaioannou, 2014). The results are reported in column 2 showing a positive and a persistent association between weather conditions and overall economic activity captured by light density at the 1 percent significance level. A one-standard deviation decrease in SPEI below the mean reduces the overall economic activity by 13% on impact and by 31% accumulatively. This suggests that weather effects are not only confined to agriculture output, but they can extend to other sectors consistent with the findings of Dell et al. (2012) showing negative effects of temperature on industrial value added at the country level. The persistence of the effects on overall economic activity confirms the existence of spillovers between agriculture and non-agriculture sectors through affecting the local demand.

Table 6 contains the results for other outcomes. The p-values conducted from the family-wise error rate (FEWR) following methodology developed by Romano and Wolf (2005a; 2005b) is reported in squared brackets and is used to assess statistical significance. The tables also contains tests of equality between cross-model coefficients below each model. Columns 1-4 of panel A presents the results of the effect of weather conditions on the total real earnings per worker, agriculture earnings, earnings of skilled and non-skilled workers, respectively. Throughout the columns, the results show that contemporaneous SPEI is positively associated with earnings with the strongest effect, both in magnitude and significance, reported by earning

Table 6: Economic factors (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	**Earnings**	**Agr. Earnings**	**Earnings skilled**	**Earnings unskilled**	**Wages**	**Agr. Wages**	**Wages skilled**	**Wages unskilled**
SPEI, t	15.213***	34.024***	18.466	21.173***	0.033	0.102**	0.068	0.073***
	(7.514)	(10.261)	(13.879)	(6.902)	(0.039)	(0.054)	(0.079)	(0.037)
	[0.006]	[0.001]	[0.202]	[0.001]	[0.585]	[0.011]	[0.585]	[0.001]
Test of equality (p-value)		0.00	0.72	0.03		0.03	0.55	0.01
Sum of coefficients	29.290***	34.480**	28.203	30.581***	0.099*	0.076	0.119	0.118**
	(11.011)	(14.552)	(17.548)	(10.326)	(0.057)	(0.073)	(0.099)	(0.54)
Number of observations	11,544	11,544	11,544	11,544	11,544	11,544	11,544	11,544
Number of municipalities	3848	3848	3848	3848	3848	3848	3848	3848
Adjusted R-squared	0.821	0.641	0.622	0.795	0.804	0.615	0.557	0.760
Panel B		**Employment**	**Agr. employ.**	**Employ. skilled**	**Employ. unskilled**	**Unemployment**		
SPEI, t		-0.005	-0.006	-0.001	0.001	0.005		
		(0.003)	(0.005)	(0.002)	(0.002)	(0.003)		
		[0.114]	[0.491]	[0.691]	[0.691]	[0.114]		
Test of equality (p-value)			0.91	0.37	0.12	0.14		
Sum of coefficients		0.0001	-0.006	-0.002	0.002	-0.001		
		(0.005)	(0.008)	(0.003)	(0.003)	(0.005)		
Number of observations		11,544	11,544	11,544	11,544	11,544		
Number of municipalities		3848	3848	3848	3848	3848		
Adjusted R-squared		0.511	0.611	0.839	0.839	0.511		
Panel C			**Poverty gab**		**Inequality**			
SPEI, t			-0.533		0.001			
			(0.369)		(0.002)			
			[0.114]		[0.897]			
Test of equality (p-value)			0.14		0.98			
Sum of coefficients			1.467**		.006*			
			(0.670)		(0.003)			
Number of observations			11,544		11,544			
Number of municipalities			3848		3848			
Adjusted R-squared			0.858		0.276			
Panel D		**Gov. Rev. pc**		**Gov. Exp. pc**		**Schooling**		**Security personnel**
SPEI, t		12.124		0.109		0.001		0.0001
		(28.040)		(25.073)		(0.024)		(0.0001)
		[0.114]		[0.691]		[0.952]		[0.242]
Sum of coefficients		-21.667		-24.871		-0.011		0.0001
		(32.394)		(25.383)		(0.033)		(0.0001)
Number of observations		11,544		11,544		11,544		11,544
Number of municipalities		3848		3848		3848		3848
Adjusted R-squared		0.525		0.398		0.887		0.364
Population density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State *times* Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Lagged levels of SPEI are included, but not reported. Controls include longtitude, latitude, distance to capital state, distance to federal state, coast dummy, rural dummy and capital state dummy. Tests of equality is relative to log(earnings) and log(wages) in Panel A; to log(employment) in Panel B; and to log(poverty rate) in Panel C. The method of estimation is ordinary least squares with robust standard errors reported in parentheses clustered at the micro level. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

of agriculture and unskilled workers. Similarly, columns 5-8 consider the impact on total wages per worker, agriculture wages as well as wages of skilled and skilled workers, which proxy the total demand on labor. We still observe a positive significant impact of SPEI on the wages of agriculture and unskilled workers. Moreover, tests of equality reject the null hypothesis of no statistical significance difference between coefficients of agriculture earnings (wages) and coefficients of total earnings (wages). The same is the case for unskilled earnings and wages. This is consistent with the idea that the majority of agriculture workers being unskilled are the ones whose incomes are hit the hardest following unfavorable weather conditions. Indeed, in my sample 46% of employment is, on average, concentrated in the agriculture sector out of which 92% are unskilled workers.

It also coincides with the previous findings of Machin and Meghir (2004) and Gould et al. (2002) showing that property crimes respond more to declines in unskilled worker's wages. Moreover, the fact that total earnings are affected reflects the existence of spillovers between agriculture sector and other sectors in the municipality confirming the previous results on the positive association between weather conditions and other non-agriculture output. The point estimates indicate that a one-standard deviation decrease in contemporaneous SPEI below the mean leads to a decline in total earnings and wages per worker by 13.7 and 2.8%, respectively. For agriculture workers, the corresponding effect is 29.3% and 8.8%, respectively. For unskilled workers, the effect on earning and wages is 18.3 and 6.3%, respectively.[30] The corresponding estimates of the accumulative effects are statistically significant and larger in magnitude relative to the immediate impact, except for agriculture wages and earning. The latter echoes the previous findings of the reverse of the weather effects on agriculture sector, and hence the impact on agriculture wages tend to be less persistent.

Employment and unemployment rates do not appear not to respond immediately to weather fluctuations as shown in Panel B, respectively. Similarly is the case for agriculture, skilled and unskilled employment. One interpretation for this non-immediate response could be due to the inability of agriculture workers, especially the unskilled, to shift to other sectors immediately following a negative weather shock. Hence, workers could in principle bear the fluctuations in their income in exchange for not losing their jobs at least in the short run. Another possibility can be that workers shift to low earnings jobs (e.g. in the informal economy) and in this way their employment status will not change, but their earning and wages will definitely drop.

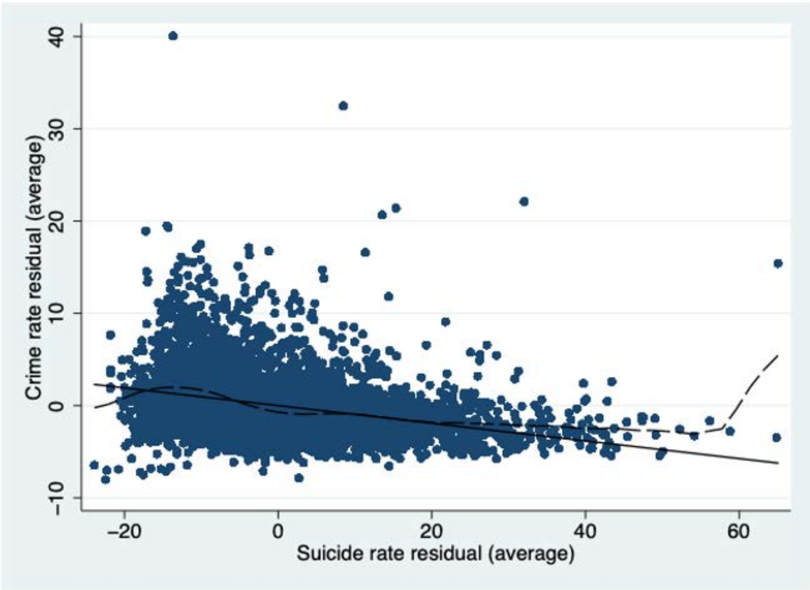
Panels C and D contain the results of the effect on other non-labor market determinants of crime. Panel C shows that the effect of SPEI is negative and insignificant on poverty gab and inequality. Panel D documents positive, but insignificant impact of weather conditions on municipal real revenues and expenses per capita. Similarly, results show no significant effect on average years of schooling or public security employment rate, despite the fact that their point estimates are positive.

6.2 Non-Economic Factors

One could possibly test psychological motives for committing crimes by looking at the effect of weather shocks on stress-induced behavior such as suicide rates (per 100,000 inhabitants). Acts of suicide is a sign for mental health deterioration due to stress or depression (Fazel et al., 2015). Committing crimes can go in line with suicidal motives, such that a mentally unstable person can kill other people

[30]Due to the lack of annual data on earnings and wages, I am unable to estimate causal effects on violent crime using weather conditions as an instrument and taking into account the overall economic conditions.

before taking his own life. If the latter were the case, one would expect to see a positive correlation between crime and suicide rates. Alternatively, if weather were the culprit for stress behavior, then one would expect an increase in suicidal rates following adverse weather conditions.



Notes: The graph shows the relationship between annual averaged violent crime and suicide rates net of municipal and state-year fixed effects. The solid line represent the linear fit, while the dashed line represents the nonparametric local polynomial fit computed using an Epanechnikov kernel.

Figure 3: Violent crime and Suicide rates – Correlation

Figure 3 depicts a negative correlation between violent crime and suicide rates, in a sharp contrast to what would be expected if psychological factors drive criminal motives. Table 7 contains the results on the effect of SPEI on suicide rates. Column 1 shows the effect of SPEI on suicide rates (per 100,000 inhabitants). Column 2 augments the specification in column 1 and add a series of initial municipal characteristics interacted with year dummies as additional control variables. The initial municipality characteristics enter at their 1991 level and include the illiteracy rate, the share of young, male, unskilled and workers in public safety jobs as well as the share of urban population. Throughout both columns, SPEI leave no statistical significant impact on suicide rates. If anything the estimated coefficients point to a positive association between favorable weather conditions and suicide rates. In short, the above results indicate the psychological motives is less likely to represent channel through which weather conditions affect crime.

In sum, weather shocks exhibits heterogeneous effects on labor markets variables. Earning and wages are more affected, especially those of agriculture and unskilled workers, compared to unemployment and employment rates in the immediate course. Poverty, inequality, municipal budgets, public services and suicide rates are less likely to respond to contemporaneous weather shocks. The results also indicate the existence of spillovers between agriculture sector and other sectors reflected in the total income generated, which goes directly to the workers pockets. Pertaining to the conceptual framework, the analysis provides evidence of the dominant role played

Table 7: Non-economic factors

	(1)	(2)
	Suicide rate	**Suicide rate**
SPEI, t	0.010	-0.028
	(0.105)	(0.106)
SPEI, t-1	0.138	0.141
	(0.101)	(0.103)
SPEI, t-2	-0.016	0.000
	(0.091)	(0.096)
Sum of coefficients	0.132	0.113
	(0.171)	(0.177)
Number of observations	96,200	96,200
Number of municipalities	3,848	3,848
Adjusted R-squared	0.003	0.030
Population density	Yes	Yes
Controls × Year FE	No	Yes
Muncipality FE	Yes	Yes
State × Year FE	Yes	Yes

The dependent variable in column 1 is suicide rates per 100,000 inhabitants. Controls include literacy. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

by economic factors over non-economic drivers of violent crime. It also shows a stronger effect of opportunity cost mechanism relative to local governments capacity and socio-economic variables in driving the impact on weather shocks on crime rates. In addition, evidence shows that the opportunity cost alters the allocation of time away from productive activities through fluctuation in labor income rather than through labor demand and job layoffs.

7 Conclusion and General Discussion

This paper examines the link between weather shocks and violent crime using disaggregated data from Brazilian municipalities over the period 1991-2015. In this context, the paper contributes to the existing body of literature on the effects of weather on crime. Previous studies have produced mixed results regarding the response of violent crime and the analysis of the driving mechanisms. In light of the little consensus on whether economic or non-economic motives drive the results, the paper takes a first attempt to discern weather effects on a broader set of economic and non-economic factors. Economic channels comprises not only agriculture output, but also all forms of economic activity, labor market response, poverty, inequality, local governments budget and public services.

Employing a measure of weather conditions that better captures exposure to water deficiencies and allowing for the spatial correlation of violent crime rates, I show that adverse weather shocks (i.e. drought) has a positive significant effect on violent crime rates with the effect persisting beyond the growing season and over the medium run. To explain this persistence, I provide evidence of the dominant role played by economic factors in driving the observed relationship. I show that unfavourable weather conditions are negatively associated not only with agriculture yields, but also with the overall economic activity. However, weather variations leave no significant effect on suicide rates. Moreover, focusing on economic factors, evidence shows the dominance of opportunity cost mechanism reflected by the fluctuations in total earnings and wages, especially for agriculture and unskilled labor, over (un)-employment, local government budget capacity and socio-economic conditions.

The results suggest that effects of weather fluctuations are not confined to agriculture sector, but extend to all economic activities, which explains the observed persistence. This comes in line with the findings of Dell et al. (2012) showing that higher temperature is negatively associated with industrial value added at the national level, in contrast to the narrow view employed by weather-crime literature. The reason is that agriculture shocks can induce a demand-side shock to other production sectors. To the best of my knowledge, this is the first local evidence produced confirming the existence of spillovers effects between agriculture and non-agriculture activities. Furthermore, results suggest that labor earnings and wages are more likely to affect crime than employment, with the effect becoming stronger in magnitude and significance for the agriculture and unskilled workers. This is an improvement over the previous studies, by looking at the effect on labor income of the hardest affected group—agriculture and unskilled labor— who are most likely to commit crime rather examining the general economic conditions. This has the implication that using weather shocks as an instrument for agriculture output (for instance in Bignon et al., 2017) will fail to satisfy the exclusion restriction as required. Additionally, it suggests that earnings are more important indicator over employment status, because the latter can remain unchanged if labor moved to low-rank jobs, but earnings and wages will definitely be affected.

A number of points are worth mentioning. First, the non-availability of annual data on employment, socio-economic conditions and public services limits the ability to analyze how these variables respond over time. However, by considering only the contemporaneous effect, it seems quite reasonable to conclude that earning and wages are the predominant drivers. Second, the insignificant response of municipal budgets and public services could be rather due to the fact that the municipal budgets and especially local police forces are allocated at the state level, so their corresponding effects can be absorbed by state-year specific effects. Third, despite the finding that non-economic factors play a negligible role in driving the results in contrast to other studies, it should be noted that using annual data can conceal a lot of the effects that might appear with the use of shorter frequencies (i.e. daily, weekly or monthly data). Yet, what I can argue that response of violent crimes to non-economic factors (i.e. aggressive behavior or changing habits) is less persistent over time and could be easily reversed on an aggregate level consistent with the findings of Jacob et al. (2007).

Nevertheless, the results are very relevant in informing policy makers of future consequences of global warming especially for agriculture-based economies. Policies aiming at mitigating the weather effects on agriculture yields and income are highly desirable. One approach to reduce income fluctuations is through introducing insurance schemes against negative shocks and provision of safety nets covering agriculture workers. This deemed an ex-post approach to mitigate negative consequences of drought seasons on earnings and consumption. However, a long-run strategy should involves the reduction of crop dependence on rainfall through installment of new irrigation systems, or adoption of drought-tolerant crops varieties (Mulwa and Visser, 2020). Another approach would be through farm diversification by adoption of a mix of crop and livestock types that can reduce the risk of exposure (Martin and Lorenzen, 2016).

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Appendix A

Variables definitions and sources

SPEI growing season is calculated by taking the average of SPEI monthly values during the municipalities' main crop growing season. The municipality's main crop is defined as the crop with the largest share of harvested area (measured in hectares) in the greatest number of years. Data on municipality's harvest area is taken from IBGE - Municipal Agricultural Production Survey (Produção Agrícola Municipal – PAM). The main crop is then matched to the start and end months of its growing season identified primary from MIRCA 2000 crop calendars (Portmann, Siebert and Döll, 2010) and secondary from FAO dataset crop calendar. Similarly, SPEI non-growing season is the average of SPEI monthly values outside the municipalities' main crop growing season.

Channels data.—Data on individual earnings, employment status, wages, poverty and inequality is computed using Brazilian Demographic Census (Censo Demográfico) for years 1991, 2000 and 2010. I also use census data to compute socio-demographic and -economic variables such as share of agriculture workers, male, young and unskilled, average years of schooling and the fraction of workers in public safety related jobs. Other socio-demographic municipal variables were already available at the Human Development Atlas in Brazil platform, namely the fraction of population living in urban areas and illiteracy rates. Geographical variables describing the location of municipalities (e.g. longitude, latitude, distance,. . . etc.) are taken from Instituto de Investigación Económica Aplicada (IPEA).

Data on municipal revenues and expenses is retrieved from Brazil's Ministry of Finance's National Treasury through Financas do Brazil (FINBRA) database. Agriculture gross output is taken from IBGE - Municipal Agricultural Production Survey (Produção Agrícola Municipal – PAM). Suicidal rates data is also obtained from DATASUS (Depatamento de Informatica do Sistema Unico de Saude). All monetary figures are expressed in real 2010 prices, with nominal figures deflated by CPI index provided by IPEA (Índice Nacional de Preços ao Consumidor - INPC). The poverty line is set by IPEA at 140 Brazilian Real (2010 prices). Table A1 contains summary statistics of these variables.

Oil output.—Data on oil production comes from Agencia Nacional de Petroleo (ANP), which provides information on oil output and oil fields locations on a monthly basis. Following Ishak and Meon (2019), I use this data to determine municipalities located over these oil fields and their production shares. International oil prices are retrieved from International Financial Statistics (IFS, 2019).

Table A1: Summary Statistics

Variable	N	Mean	SD	Min	Max
Channels					
Agriculture gross output (value/hectare)	96,200	48.44	461.90	0	62,108.90
Night-time lights	84,304	2.03	3.33	0	58.13
Suicide rate (per 100,000)	96,200	5.27	8.99	0	160.94
Real earnings	11,544	596.37	346.17	52.70	2,773.92
Real agriculture earnings	11,544	478.86	377.50	33.89	7,941.22
Real earnings skilled	11,544	923.83	507.45	58.45	7,301.28
Real earnings unskilled	11,544	491.18	290.31	51.66	2,932.40
Real wages	11,544	3.53	2.04	0.33	22.68
Real agriculture wages	11,544	2.72	2.11	0.18	41.68
Real wages skilled	11,544	5.52	3.01	0.45	54.92
Real wages unskilled	11,544	2.90	1.74	0.29	28.06
Employment rate	11,544	0.62	0.09	0.22	0.94
Agriculture employment rate	11,544	0.46	0.17	0.01	0.92
Employment rate skilled	11,544	0.23	0.12	0.00	0.68
Employment rate unskilled	11,544	0.77	0.12	0.32	1.00
Unemployment rate	11,544	0.38	0.09	0.06	0.78
Poverty depth	11,544	67.67	19.32	13.72	118.12
GINI coefficient	11,544	0.52	0.07	0.28	0.92
Municipal expenses per capita	11,546	996.27	1,074.86	0.00	58,826.74
Municipal revenues per capita	11,546	781.00	847.99	0.00	58,545.35
Average years of schooling	11,544	3.64	1.23	0.37	7.25
Share of workers in public safety jobs	11,544	0.00	0.00	0.00	0.05
Controls					
Illiteracy rate	11,544	27	15.44	1.76	84.19
Share of unskilled	11,544	0.50	0.05	0.27	0.73
Share of young (18 to 30 years old)	11,544	0.22	0.02	0.12	0.44
Share of male	11,544	0.51	0.01	0.46	0.81
Urbanization rate	11,544	0.53	0.20	0.02	1
Longtitude	11,544	-45.66	6.59	-72.90	-34.81
Latitude	11,544	-15.86	8.15	-33.52	3.88
Distance to capital state	11,544	254.78	161.97	0.00	1,476.28
Distance to federal state	11,544	1,087.74	445.86	69.24	2,867.95
Dummy for capital state	11,544	0	0.03	0	1
Dummy for coastal city	11,544	0.04	0.20	0	1

Note: The real values are based on 2010 prices.

Table A2: Correlations between homicide, robberies and physical assault rates

	Homicides rate	
	Net of municipal and state-year FE	**Net of population, municipal and state-year FE**
Robberies rate	0.411***	0.660***
Physical assault rate	0.186***	0.254***

Note: Municipal level data on armed robberies and physical assault is for the states of Sao Paulo and Minas Gerais from 2001 and 2013. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A3: Correlations between homicide and victimization rates

	Homicides rate
	Weighted by population
Attempted theft or robbery rate	0.410**
Theft or robbery rate	0.432**
Physical assault rate	0.350*

Note: State level data on the victimization rates is for the year 2009. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A4: Unit root tests

Variable	**SPEI (Panel Data Tests)**	
	Level	**Diff.**
Dickey-Fuller	n.s.	***
Breitung	n.s.	***
Levin-Lin-Chu	n.s.	***
Im-Pesaran-Shin	n.s.	***
Philipps-Perron	***	***

Note: All unit root tests contain trend. For panel data, I apply the fisher type tests for Dickey-Fuller and Philipps-Perron. I use 4 lags as indicated to be optimal by AIC criteria. Abbreviation: n.s., not significant at the 10% level. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Table A5: Serial correlation tests

Variable	**SPEI (Panel Data Tests)**		
	Lag(1)	**Lag(5)**	**Lag(10)**
Bias-corrected Born and Breitung (2016)	***	***	***
Inoue and Solon (2006)	***	***	***
Heteroskedasticity-robust Born and Breitung (2016)	***	-	-

Note: The null hypothesis is no-serail autocorrelation up to order p, determined by the choosed lag. Heteroskedasticity-robust Born and Breitung (2016) test has the null hypothesis of no first order serial correlation. Significantly different from zero at *10% significance, **5% significance level, ***1% significance level.

Appendix B

In this section I perform further robustness checks to the baseline estimates in Table 2, column 5. Table B1 contains the results for employing alternative specifications. Column 1 drops all the SPEI temporal lags, while column 2 and 3 add additional temporal lags up to 5 and 10 lags, respectively. Column 4 restrict the sample to the 2000-2015 period to overcome the confounding effects of the trade liberalization policy occurred during the early and mid-1990s, which is, as previously shown by Dix-Carneiro et al. (2018), had caused a surge in criminal activities. Column 5 investigates the long-run relationship between weather shocks and criminal activities by taking the whole-period first difference. This is done to explore whether weather effects on crime dissipates over time, for example due to better adaptation of economies via technologies, or they persist by affecting the growth dynamics of economic sectors. Columns 6 and 7 performs a placebo test by replacing SPEI by its one-year forward value, and by its one-year, two-years and three-years forward values, respectively. Throughout all the models, the estimated coefficients of contemporaneous SPEI remain the same in sign and significance, but their magnitudes become larger when the sample period is restricted and when estimating the long-run relationship. The sum of the coefficients of weathers shocks grow stronger in magnitude with the addition of temporal lags. The latter two results confirms the fact that weather shocks affect not only output levels but go beyond and affect growth determinants such as product demand, investment and/or labor productivity consistent with the findings of Dell et al. (2012). Hence, the effects are not easily reversed, but persist over time. Finally, the estimated coefficients of forward SPEI are all statistically insignificant except for the third lag in column 7 which is significant at the 10% level, but this most properly due to the drop in the sample size since the data on SPEI are only available until 2015. Nevertheless, tests of joint significance of the estimated coefficients in column 7 fail to reject the null hypothesis of no statistical significant difference between them. Column 8 clusters the standard errors at the micro level, while column 9 adds the square SPEI terms to further address non-linearities.

In the baseline results, I focused on crime rates per 100,000 inhabitants as the primary measure for criminal activities following convention. In Table B2, I inquire the robustness to alternative measures of crime and model estimations. In column 1, crime is measured as a count variable of the number of crimes occurred in a given municipality unweighted by municipality's population. To deal with outliers especially intense crime rates representing around 1% of observations, I winsorize these extreme values by replacing them with the next highest observation in column 2. This ensures that all observations are used and the effect of possibly spurious outliers is reduced. To avoid sample selection bias aroused by dropping municipalities and/or observations with no crime data, I replace these missing data with zero. However, this approach has resulted in inflating the sample with a number of zero observations. To address that, I complement the approach in column 2 and additionally winsorize the zero observations with their next lowest values in column 3. Furthermore, in column 4, all municipalities that have reported zero crime rates throughout the whole sample period are dropped. This lead to a reduction in sample size by 700 observations and an exclusion of 28 municipalities. In all cases, the explanatory variable of interest, contemporaneous SPEI, remain robust in sign and significance.

Table B3 contains additional robustness checks. Columns 1-3 use alternative distance cut-offs for computing standard errors. Column 4 drops oil-producing municipalities defined as all municipalities that has reported any oil production activity in any year. Columns 4 and 5 employ a fixed-effects Poisson regression, a well-adapted procedure to count variables and handles the zero-value observations. The downside of Poisson regressions is that they do not converge in the presence of linear trends or large number of fixed effects, which is a common feature in maximum-likelihood estimation models. For this reason, state-year fixed effects is dropped in this specification and replaced by year-fixed effects. Finally, columns 7 and 8 exclude SPEI values that 3 or 2 standard deviation higher (i.e. three-sigma and two-sigma outliers), respectively. Results show that increasing the distance cut-off of standard errors at 500 and 1000 km distance have reduced the statistical significance of the weather shocks variables since the average neighbor effect goes down with the addition of new neighbors. Dropping oil producing municipalities has no effect on the estimates. The results from Poisson regression in column 5 show that coefficient of contemporaneous SPEI stays negative and statistically significant. The second lag is also significant, but carries a positive sign in contrast. The reverse in sign could be rather due to the exclusion of state-year fixed effects, and hence, allowing the time-varying unobserved heterogeneity occurring at the state level to remain unchecked and introducing in turn biased estimates.[1] Dropping the temporal lags in column 6 do not affect the sign and significance of the contemporaneous coefficient. Finally, the estimates remain significant when excluding the three-sigma and two-sigma outliers at the 5 and 10 percent significance level, respectively.

Table B4 checks the baseline results using alternative measures of weather shocks. In column 1, I substitute the SPEI with indicators for (log) annual rainfall and average temperature. Data on rainfall and temperature are obtained from Climatic Research Unit (CRU), University of East Anglia. Both rain and temperature are included along with their one-year and two-year temporal lags. The estimated coefficient of contemporaneous rain and its temporal lags are negative, but statistically insignificant. Similarly, the coefficients of the temperature variables are also insignificant, except for its second lag. Nevertheless, a simple equality test fails to reject the null hypothesis of no statistical significant difference between the coefficients of contemporaneous temperature and its second temporal lag (p-value=0.15). In addition, the sum of coefficients of rain and temperature shocks are insignificant. The reason for such insignificant effects might be explained by the inclusion of crime spatial lags plus a wider battery of fixed effects at a finer level of data, which could absorb most of the variation in rain and temperature.[2] In contrast, SPEI controls for the joint effects of temperature, precipitation and location, as well as their historical values and thus, can withstand the inclusion of fixed effects without losing

[1]Note in the baseline estimations, we had 675 state $\times$ year fixed effects which are very demanding from data and methodological perspectives.

[2]In unreported results, dropping the state-year fixed effects causes rain and temperature estimated coefficient to gain significance.

significance. Column 2 additionally adds rain and temperature shocks with SPEI variables, and show no change in the baseline results.

Table B1: Violent crime and weather –Robustness checks

	Dependent varibale: Homicide rate (per 100,000)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	No lags	**Adding 5 lags**	**Adding 10 lags**	**Period 2000-2015**	**Long-run difference**	**Forward SPEI**	**Forward SPEI**	**Standard errors cluster at the micro level**	**Adding squared SPEI**
SPEI, t	-0.395**	-0.405**	-0.421**	-0.784***	-3.176**	-0.281	-0.029	-0.403*	-0.346*
	(0.199)	(0.200)	(0.200)	(0.267)	(1.279)	(0.202)	(0.197)	(0.220)	(0.205)
SPEI, t-1		-0.150	-0.163	-0.546**			-0.290	-0.154	-0.141
		(0.179)	(0.179)	(0.255)			(0.187)	(0.179)	(0.184)
SPEI, t-2		-0.212	-0.223	-0.427			-0.380*	-0.259	-0.244
		(0.164)	(0.165)	(0.262)			(0.195)	(0.162)	(0.166)
W(Violent crime)	0.002***	0.002***	0.002***	0.002***	0.003***	0.002***	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sum of coefficients		-1.322**	-1.871**	-1.757***				-0.816**	-0.732**
		(0.467)	(0.629)	(0.508)				(0.449)	(0.364)
Joint significance test (p-value)							0.128		
Number of observations	96,200	96,200	96,200	61,568	3,848	92,352	84,656	96,200	96,200
Number of municipalities	3848	3848	3848	3848	3,848	3,848	3848	3848	3848
Adjusted R-squared	0.126	0.126	0.126	0.096	0.168	0.115	0.093	0.175	0.1
Population density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State FE	No	No	No	No	Yes	No	No	No	No

The dependent variable is crime rate per 100,000 inhibitants. W is a spatial binary contiguity matrix that assigns 1 to muncipalties lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within the indicated cutoff radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

Table B2: Violent crime and weather –Robustness checks

	Dependent varibale: Homicide rate (per 100,000)			
	(1)	(2)	(3)	(4)
	Unweighted crime	**Winsorizing high values**	**Winsorizing high and zero values**	**Dropping municipalities with no crime**
SPEI, t	-0.202*	-0.429**	-0.427**	-0.398**
	(0.108)	(0.185)	(0.184)	(0.200)
SPEI, t-1	-0.138	-0.169	-0.168	-0.153
	(0.098)	(0.167)	(0.166)	(0.180)
SPEI, t-2	-0.124	-0.231	-0.228	-0.257
	(0.092)	(0.156)	(0.155)	(0.166)
W(Violent Crime)	0.0001***	0.003***	0.003***	0.003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sum of coefficients	-0.464**	-0.828**	-0.823**	-0.808**
	(0.233)	(0.325)	(0.324)	(0.355)
Number of observations	96,200	96,200	96,200	95,500
Number of municipalities	3,848	3,848	3,848	3,820
Adjusted R-squared	0.167	0.131	0.131	0.126
Population density	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

The dependent variable in column 1 is number of crimes; in columns 2-5 is crime rate per 100,000 inhibitants. W is a spatial binary contiguity matrix that assigns 1 to muncipalties lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

Table B3: Violent crime and weather –Robustness checks

	Dependent varibale: Homicide rate (per 100,000)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Distance Cutoff (150)	**Distance Cutoff (500)**	**Distance Cutoff (1000)**	**Drop oil producing muncipalties**	**Poisson**	**Poisson**	**Outliers > 3 SD**	**Outliers > 2 SD**
SPEI, t	-0.399**	-0.399*	-0.399	-0.403**	-0.028***	-0.028***	-0.391**	-0.373*
	(0.188)	(0.220)	(0.243)	(0.200)	(0.007)	(0.007)	(0.200)	(0.209)
SPEI, t-1	-0.155	-0.155	-0.155	-0.094	0.015**		-0.157	-0.092
	(0.170)	(0.194)	(0.213)	(0.178)	(0.007)		(0.179)	(0.183)
SPEI, t-2	-0.257	-0.257	-0.257	-0.205	0.006		-0.254	-0.184
	(0.158)	(0.180)	(0.199)	(0.164)	(0.007)		(0.165)	(0.168)
W(Violent crime)	0.002***	0.002***	0.002***	0.002***	0.0001***	0.0001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum of SPEI coefficients	-0.811**	-0.811**	-0.811**	-0.701**	-0.007		-0.802**	-0.649*
	(0.339)	(0.374)	(0.397)	(0.351)	(0.015)		(0.353)	(0.367)
Number of observations	96,200	96,200	96,200	93,650	95,500	95,500	96,176	90,946
Number of municipalities	3,848	3,848	3,848	3848	3,820	3,820	3848	3848
Adjusted R-squared	0.126	0.126	0.126	0.117			0.126	0.123
Log-likelihood ratio					-621,664.12	-621,700.54		
Population density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is crime rate per 100,000 inhibitants. W is a spatial binary continguity matrix that assigns 1 to muncipalties lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

Table B4: Violent crime and weather –Alternative weather shocks

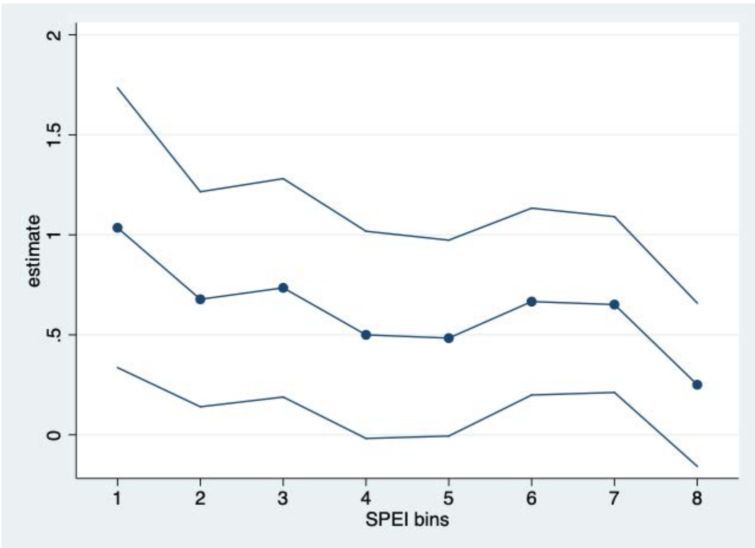
	(1)	(2)
	Homicide rate	**Homicide rate**
	Alternative weather indicators	**Alternative weather indicators +SPEI**
Rain (log), t	-0.251	0.974
	(0.697)	(0.876)
Rain (log), t-1	0.128	0.931
	(0.671)	(0.850)
Rain (log), t-2	-0.695	0.092
	(0.677)	(0.876)
Temperature, t	0.044	-0.103
	(0.771)	(0.774)
Temperature, t-1	-0.740	-0.688
	(0.775)	(0.773)
Temperature, t-2	-1.481*	-1.407*
	(0.765)	(0.771)
SPEI, t		-0.571**
		(0.252)
SPEI, t-1		-0.295
		(0.229)
SPEI, t-2		-0.294
		(0.213)
W(Violent crime)	0.002***	0.002***
	(0.000)	(0.000)
Sum of coefficients (SPEI)		-1.161**
		(0.487)
Sum of coefficients (Rain)	-0.819	-1.997
	(1.338)	(1.823)
Sum of coefficients (Temp)	-2.178	-2.197
	(1.362)	(1.362)
Number of observations	96,200	96,200
Number of municipalities	3,848	3,848
Adjusted R-squared	0.128	0.128
Population density	Yes	Yes
Municipality FE	Yes	Yes
State × Year FE	Yes	Yes

The dependent variable is crime rate per 100,000 inhabitants. W is a spatial binary contiguity matrix that assigns 1 to municipalities lying within 230 km distance cutoff. The method of estimation is ordinary least squares with Conley (1999) standard errors reported in parentheses, allowing for spatial correlation within 230 km radius. Significantly different from zero at *10% significance, **5% significance, ***1% significance.

Appendix C

C.1 Non-Linear Effects of Weather Shocks

So far, it was assumed that the response of violent crime rates to weather fluctuations is linear. I relax this assumption and estimate instead an extended non-parametric model with different bins for SPEI based on the decile values of SPEI. Each bin is an indicator for the values belonging to the first eight deciles. The omitted category corresponds to the nineth decile (i.e. highest levels of SPEI). Figure C1 plots the estimated response of crime rates to each of the eight SPEI bins along with 90% confidence interval. The estimated coefficients are relatively larger in magnitude and stronger in significance for the first three bins (i.e. values below -0.05 units) indicating the effect of SPEI on violent crime rates is greater for the negative SPEI values corresponding to drought seasons relative to the higher positive SPEI values. The magnitudes of the effects are quite large as well, for instance, one-standard deviation decrease in SPEI below -0.05 units (relative to a range of 0.86 and more) will increase crime by 58%-86%, which is more than double the effect of the baseline estimates (34%).



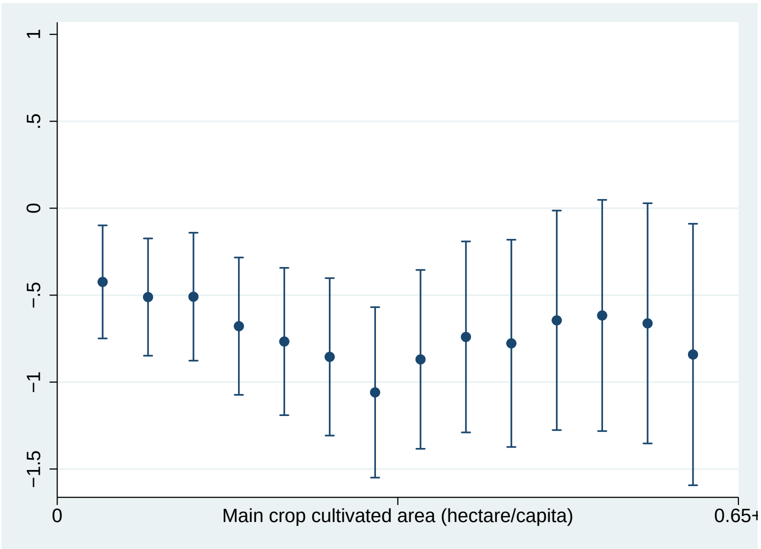
Notes: This Figure reports coefficient estimates for the deciles of the SPEI (bin 9 –highest values- is the reference) along with the 90% of confidence interval. Bins 1-3 contains the negative values of SPEI.

Figure C1: Non-linear effects of SPEI

C.2 Rural vs. urban areas

Following the conceptual framework, the effects of weather are expected to hit harder the rural areas where the agriculture sector is the primary economic activity and the main source of income. Similarly, the spillovers to other non-agriculture sectors are expected to be stronger. Results already show that the earnings of agriculture and unskilled workers are the most affected by weather shocks underlying the dominance of income mechanism. Another strategy to investigate this mechanism is to reestimate the effect of weather fluctuations on violent crime rates on sub-samples split by municipality rural characteristics, in which agriculture sector is regarded as the primary economic activity (Siqueira and Osorio, 2001).[3] To capture that, I use the cultivated area of main crop per capita (hectare/capita) to measure the scope of agriculture activities. The larger the size of the cultivated area, the more workers are needed to harvest the main crop, hence more households are dependent on agriculture income.

Figure C2 plots the estimated coefficients for each sub-sample split based on cultivated land per capita in 1991 along with the 90% of confidence interval. The x-axis defines the cutoff points splitting the sample ranging from 0 area to over 0.65 units, so that municipalities are excluded with respect to increasing values of this share. The results show more clearly that municipalities with a relatively larger share of cultivated land experience more crime rates following weather shocks. The point estimates depict an increase in absolute magnitude of the effect with the rise in the cultivated area until 0.40 cutoff. Afterwards, they decline in magnitude and become imprecisely estimated beyond the 0.55 cutoff due to the significant decline in sample size (i.e. the sample size drops by around 57



Notes: This Figure reports coefficient estimates for each sub-sample split based on main crop's cultivated area per capita (hectare/capita) in 1991 along with the 90% of confidence interval. The municipalities are sequentially excluded based on the increasing share of agriculture workers. The x-axis defines the cutoff points splitting the sample ranging from almost 0 cultivated area to over 0.65 hectare per capita.

Figure C2: Split by main crop's cultivated area per capita

[3]See L.G. Scorzafave et al. (2015) for more information on the different criteria for defining rural Brazil.

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