Economic and Non-Economic Factors in Violence: Evidence from Organized Crime, Suicides and Climate in Mexico*

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Abstract

Changes in climate have been shown to substantially shape intergroup violence, but the mechanism remains poorly understood. We test if economic factors are the central pathway by examining killings by drug-trafficking organizations (DTOs), "normal" homicides, and suicides in Mexico. High temperatures have a large and similar impact on all three types of violence, suggesting some commonality in mechanisms. Many patterns in the data, including the limited influence of a cash transfer program in dampening the sensitivity to high temperature and a comparison with non-violent DTO crime, indicate that government monetary incentives only partially explain the observed relationship between temperature and DTO violence. We argue that previously ignored psychological and physiological factors that are affected by temperature, modeled here as a "taste for violence," likely play an important role. Our results have important implications for the understanding of violence, as well as for the impacts of climate change.

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1 Introduction

Changes in environmental conditions, particularly temperature, have been shown to shape many types of human conflict, ranging from institutional collapse to civil war, riots, and crime (Hsiang et al., 2013). While this literature has expanded rapidly in the past decade, there is limited work identifying the channels that determine this relationship. A particularly important challenge is in understanding the quantitatively large effect of temperature on intergroup violence, such as the estimated 11% increase in intergroup violence per 1σ increase in temperature reported by Burke et al. (2015). Understanding why hotter temperatures lead to substantially more group violence is important in helping us understand both the determinants of violence as well as the potential impacts of climate change on society.

A common hypothesis in economics that changes in climate affect intergroup violence mainly through their effect on income: hotter temperatures and lower rainfall are known to lower incomes, particularly in agricultural areas, and this in turn could temporarily lower the opportunity cost of participation in violence. In an early study Miguel et al. (2004) provide empirical evidence that rainfall shocks that lower economic growth also increase the likelihood of civil war in Sub-Saharan Africa. Chassang and Padró-i-Miquel (2010) explain this result by developing a bargaining model in which violence occurs when a shock to economic productivity temporarily lowers the opportunity cost to violence, but does not affect the future value of winning the contest.

This income-driven response in group-level violence, however, seems unable to explain the observed response of individual-level violence to daily or even hourly variations in temperature, as income is unlikely to change over these short periods (Card and Dahl, 2009).[1] The broader study of this sort of violence and related individual crime also has a long history in economics back to at least Becker (1968), with criminal activity in this literature understood as the result of decisions made by rational individuals who have, in the neoclassical sense, well behaved utility functions (Becker 1968, Stigler 1970, Ehrlich 1973). Violence is then primarily conceived as an action that imposes costs on others, which agents apply rationally to affect the allocation of resources when property rights are weak (Donohue and Levitt 1998, Chimeli and Soares 2011, Castillo et al. 2014).

[1] Kenrick and MacFarlane (1986), Auliciems and Bartolo (1995), Cohn and Rotton (1997), Jacob et al. (2007), Larrick and et al (2011), and Ranson (2014) also demonstrate that high frequency (hourly, daily, weekly, or monthly) variations in temperature within a location are reflected in higher rates of interpersonal violence.

Why might temperature increase individual-level violence among rational actors, and what implications if any might this have for the observed group-level response to temperature? We extend the existing literature on individual- and group-level conflict and develop an economic model of violence that includes a consumption value of violence to the aggressor, which we model as a positive or negative input into utility depending on an individual's "taste for violence."[2] If changes in temperature alter individuals' taste for violence, then we show that this parameter this might help explain patterns of both individual- and group-level violence.

We then test the model on a rich dataset in Mexico, where we simultaneously observe variation in both group-level and individual-level violence over two decades and across all 32 Mexican states. For individual level violence we observe both interpersonal violence (i.e. homicide) as well as "intrapersonal" violence (i.e. suicide) – particular types of violence that are almost certainly influenced by psychological factors. Comparing the temperature response of these outcomes to the temperature response of group-level violence thus offers a unique opportunity to understand whether these different types of violence share a common underlying mechanism.

We show that higher temperatures in a given month have a positive and significant effect on all types of observed violence in Mexico, from suicides to homicides to killings by drug-trafficking organizations (DTOs), the latter our measure of group conflict. Effects in each case are contemporaneous (with violence raising in the same months as higher temperatures), large in magnitude, and generalizable in the sense that they are not driven by any single region in Mexico. In particular, a one standard deviation increase in temperature is associated with a 23% increase in drug-related killings, a 5% increase in "normal" homicides, and a 7% increase in suicide. The fact that temperature is strongly associated with suicide rates is striking, as this form of violence appears unlikely to be driven mainly by an income mechanism and it is traditionally linked to mental illness and depression in the medical literature.

We then use a variety of approaches to look directly for evidence of an economic mech-

[2]In a similar vein, Tauchen et al. (1991), Farmer and Tiefenthaler (1997), Bowlus and Seitz (2006), and Aizer (2010) explain domestic violence as expressive behavior that provides positive utility to some men. Their partners tolerate it in return for higher transfers. Card and Dahl (2009) adopt this interpretation of family violence as motivation to consider the role for emotional cues (or "visceral factors") in precipitating violence. They use unexpected losses in football games as the trigger for emotional cues. A key contribution here is to extend this framework beyond domestic violence and to introduce these psychological factors into the rapidly growing literature on intergroup conflict.

anism that might explain these results. We find that such a mechanism can only partially explain DTO killings, and it has almost no explanatory power in the case of general homicides and suicides. For instance, the level of government social assistance through the large scale Progresa/Oportunidades program has some effect in dampening the effect of high temperatures, but it is relatively modest, and other measures of economic conditions and inequality have limited predictive power in explaining the temperature/violence relationship.

Because economic patterns appear to explain only a small part of the effect of temperature on violence, and because the timing of the DTO response to temperature so closely reflects the response of suicides and homicides, we argue that some component of the DTO response is also very likely linked to psychological factors. Prior evidence, including laboratory studies, link high temperatures to psychological responses that govern aggressive and violent behavior. Our homicide and suicide results appear fully consistent with such a psychological mechanism. Importantly, we cannot definitively demonstrate that a specific psychological mechanism is at work, rather we simply argue that such an explanation seems likely and appealing given that it is the simplest explanation capable of unifying the patterns of violence that we document.

Our paper makes several contributions. First, and most importantly, we show the limited role of economic mechanisms, and provide evidence of psychological mechanisms, behind the observed relationship between climate shocks and drug gang killings. Second, we complement the literature on climate and violence by studying a middle income country and several different types of violence in one setting. This link to the existing literature is made explicit by connecting our results to a recent meta-analysis, which summarizes studies in rich and poor countries. Third, we add two novel outcomes to the "spectrum of violence" in existing social science research on climate impacts (Figure 1): gang killings and suicides. Gangs are smaller and less organized than armed militias but larger and more organized than spontaneous groups, such as mobs, both of which have been previously linked to the climate. Suicides have been largely unexplored in relation to climate in the economics literature. Nevertheless, there is a large body of studies in other disciplines studying the effect of climate on suicides. To the best of our knowledge, those studies rely on time series variation to estimate the relationship between climate and suicides, and thus our fourth contribution is to estimate this relationship using modern panel data methods. Finally, by studying potential psychological factors linking climate and violence we contribute to the growing literature of the psychology of poverty (Mani et al. 2013, Haushofer and Fehr 2014).

The next section discusses some background and non-economic factors in violence. Section 3 offers a simple theoretical framework that builds on previous research to highlight and operationalize the role of non-economic factors. Section 4 presents our data and discusses our empirical strategy. In Sections 5, 6, and 7 we present and discuss our main set of results. Finally, Section 8 offers some conclusions.

2 Understanding Violence

2.1 Drug trafficking in Mexico

In order to understand violence in Mexico, and its escalation in recent years, we need to review the role DTOs play in the country. Sophisticated organizations trafficking illegal drugs from Mexico to the U.S. appeared in the 1990s (Grillo, 2012). Nowadays, drug trafficking organizations constitute a powerful industry that produces and distributes illegal drugs, earning between 14 and 48 billion USD annually (U.S. State Department, 2009). These organizations also carry out other criminal activities including extortion and kidnapping, especially in recent years (Rios, 2014). The exact number of DTOs operating varies by year. However, it is generally agreed that they rose from 6 in 2007 to approximately 16 in 2010 (Guerrero, 2012a). Many of these new organizations are factions of older groups, an event that tends to occur after leaders are arrested or killed, mainly because of the conflicts generated within and between organizations.[3]

The level of violence observed since 2007 in Mexico has been the focus of much media and academic attention. Following the presidential election of 2006, president Felipe Calderón declared war on the drug trafficking organizations. Shortly after this event, crackdowns spread through the country, and violence escalated to unprecedented levels (see Merino 2011, Guerrero 2011b, and Escalante 2011). Several factors have been offered as causes of this escalation: (1) Felipe Calderón's strategy against organized crime, i.e. direct crackdowns and captures of DTO leaders (Guerrero 2010, Calderón et al. 2013, Chaidez 2014, Dell 2015), (2) U.S.–Colombia efforts to reduce drug flows between both countries, a supply shock that

[3]In 2008, for example, the Sinaloa's leader was captured and, as a consequence, this organization split. Right after this event, a war between *Sinaloa* cartel and *La Famila Michoacana* began. The state of Guerrero, where both cartels operated in previous years, was the site for most of the violence associated with this fight (Guerrero 2012b and Rios 2013). Guerrero (2011a) discusses the issue of DTO fractionalisation in greater detail.

affects drug markets in Mexico (Castillo et al., 2014), and (3) exogenous movements in the international price of corn, which is the main staple crop in Mexico and whose price affects the opportunity cost of joining the drug industry (Dube et al., 2014). The relative contribution of each of these factors is, however, a matter of ongoing debate among scholars. To our knowledge, this paper is the first to link DTO violence to climate shocks.

2.2 Non-economic factors in violence

Although a causal relationship between temperature and violence has been hypothesized at least since the 19th century, and a research agenda emerged since the 1930s, there has been little discussion about the potential psychological mechanisms at work in understanding intergroup violence.[4]

To understand *why* there could be a psychological or physiological link between temperature and intergroup violence, we need to discuss how human body temperature reacts to variations in ambient temperature.[5] How exactly the temperature regulation process takes place is still not perfectly understood (e.g., Hammel 1974, Werner 1980, Cooper 2002, and Mekjavic and Eiken 2006). There is evidence, however, that neural structures are directly involved in this process (Benzinger, 1970), but only recently have researchers begun to understand how particular neural structures participate in this process (Morrison et al. 2008, Ray et al. 2011).

Serotonin, a neurotransmitter involved in body temperature regulation, has been linked to important human behaviors (National Institutes of Health, 2011). Serotonin is a monoamine neurotransmitter that is produced by relatively few neurons in the upper part of the brainstem and has a major impact on individuals' mood, emotion, and behavior (Lovheim, 2012). Importantly, both impulsive aggression and violence arise from the inability to control emotion, and are also highly comorbid with other mental disorders such as depression, suicidal behavior, and substance abuse. In addition to abnormalities in serotonin function in regions of the prefrontal cortex, studies have also found that the dysfunctional interaction between

[4]See the Appendix for a review of the literature estimating the relationship between temperature and suicide and the seasonality of suicides. For example, Baron and Bell (1976) show that individuals were more likely to behave aggressively towards others when ambient temperature was higher.

[5]This sub-section draws heavily on our companion paper Burke et al. (2014). We refer the interested reader to that paper for more details about the theory and empirical evidence regarding relationship between the temperature regulation process, serotonin, and human behavior.

serotonin and dopamine in this region is key to understanding the link between impulsive aggression and its comorbid disorders. Specifically, serotonin (5-HT) hypofunction is associated with a biochemical trait that explains predisposition to impulsive aggression and dopamine hyperfunction accentuates the serotonergic deficit (Seo et al., 2008).[6]

Overall, we know that neural structures react to maintain body temperature when ambient temperature changes. We also know that besides autonomic responses (sweating and shivering) there are particular neural structures involved in the process of regulating body temperature. Identifying specific neural structures that participate in this process is an ongoing research agenda in Physiology, but there is a growing consensus that decreased serotonergic neurotransmission in the brain may be an important neurobiological deficit that leads to aggressive behavior. Thus, it is plausible that, when ambient temperature increases, serotonin levels decrease, a response that affects mood, which could lead to impulsive aggression and even violence.

3 Theoretical Framework

The model follows the framework in Chassang and Padró-i-Miquel (2010) but incorporates a new potential mechanism affecting how high temperature can lead to violence. In the model, two sides, $i \in \mathcal{I} = \{1, 2\}$, decide whether or not to engage in costly violence and redistribution when bargaining fails. The players cannot commit to not engage in conflict for an infinite number of periods, where time is indexed by t. Each player combines l units of labor, which we normalize to $l = 1$, with productivity θ_t.

The sides can engage in two possible actions, namely being violent or peaceful, $a \in \mathcal{A} = \{V, P\}$, which they choose simultaneously. Both groups want to maximize their economic output at the end of the game. If one player attacks first, then it has a first strike advantage and captures all of the opponent's output with probability $p > 0.5$. An attack costs both the aggressor and defender a fraction $c \in (0, 1]$ of output. If both agents choose to attack simultaneously, they each win with probability 0.5. Additionally, we assume there is common knowledge of a non-rival psychological consumption value for violence, which is a function of temperature τ, i.e. $\gamma_t = \gamma_t(\tau)$ with $\frac{\partial \gamma_t(\tau)}{\partial \tau} > 0$, and $\gamma_t(\tau) \in \mathbb{R}$. If $\gamma_t(\tau) > 0$ then the player

[6]Serotonin has also been suggested to be linked to social status and aggression in many animal species, including humans, although the precise mechanisms remain unknown. In particular, lower (higher) serotonergic function is associated with reduced aggression and lower (higher) status in mammals (Edwards and Kravitz, 1997).

gains positive utility from violence. We omit the argument, τ, in setting up the model, but return to it when discussing its role in explaining violence through different channels.

We consider a dynamic model where the two groups interact in every period t. There is at most one round of fighting and the winning group reaps the benefits of its prize into the future. If there is no attack in the current period, then each agent expects a peaceful continuation value V^P, which is the discounted (δ) per capita utility of expected future consumption from the player's initial assets and which captures expectations of future values of all parameters. Similarly, if one side wins, then they have a continuation value of winning V^V which is the per capita expected utility from consumption of both their initial assets and the assets that they capture from their opponent.

We can write the condition for peace, incorporating the psychological consumption value for violence, γ_t, as:

$$\underbrace{\theta_t + \delta V^P}_{value\ of\ peace} \quad > \quad \underbrace{p(2\theta_t(1-c) + \delta V^V) + \gamma_t}_{value\ of\ violence} \tag{1}$$

In interpreting the above, a player finds it privately beneficial to choose peace if the per capita value of consuming all output with initial assets plus discounted expected utility under peace δV^P (left hand side) exceeds the expected utility of consumption from both the player's original assets and captured assets, less expenditures on the conflict, plus the expected continuation value $p\delta V^V$ and the psychological consumption value of violence (right hand side).

We then rearrange (1) so that the condition for peace becomes:

$$\theta_t(1 - 2p(1-c)) - \gamma_t \quad > \quad \delta[pV^V - V^P] \tag{2}$$

where the left side of the inequality is the marginal value of peace in the current period weighed against the discounted marginal expected utility from attacking on the right side.

In considering the mechanism, the economics literature on conflict has focused on the impact of temperature on θ_t in explaining violence. The left hand side of (2) shows that if economic conditions are sufficiently bad (i.e., θ_t is sufficiently close to zero), and ignoring psychological factors for the moment, conflict will occur. For example, a drought has a contemporaneous effect on productivity, which reduces the current opportunity cost of conflict more than it alters the continuation value of peace (note that θ_t does not feature in the right

hand side).

In the model above, we highlighted the importance of the non-rival psychological consumption value for violence, γ_t. If climatic conditions influence γ_t by increasing the utility (or decreasing the psychological cost) of acting violently, i.e., $\frac{\partial \gamma_t(\tau)}{\partial \tau} > 0$, then these changes may increase the likelihood that (2) does not hold and violence occurs.[7] That said if the sides have a general dislike of violence ($\gamma_t(\tau) < 0$), then there will be less conflict than that predicted by economic factors alone.

4 Empirical Framework

4.1 Data and descriptive statistics

We collected monthly information on reported homicides and suicides from Mexico's Bureau of Statistics (INEGI) for the period between January 1990 and December 2010.[8] This data corresponds to the universe of homicides and suicides officially reported. To avoid confounding with the Mexican Drug War, we split this time frame in a "pre-war" period between January of 1990 and December of 2006, and a "war" period between January of 2007 and December of 2010. Our empirical analysis focuses on the pre-war period when analyzing homicides and suicides, and on the war period when studying drug-related killings (henceforth DTO killings). In the pre-war period there were a total of 216,552 homicides and 54,876 suicides, with a monthly per state average (standard deviation) of 33 (43) and 8 (7) respectively.

The empirical analysis uses the total number of deaths per 100,000 inhabitants as the dependent variable, as is standard in the literature (see Hsiang et al. 2013). Figure 2 shows the time series and cross sectional variation in the three main dependent variables for each of the 32 Mexican states. Table 1 presents descriptive statistics for these variables in the

[7] An alternative is to introduce a physiological mechanism discussed in the literature on cognition. A number of studies have reported the importance of environmental factors, such as heat, on cognitive performance (Mackworth 1946, Fine and Kobrick 1978). Fine and Kobrick (1978) found that heat has significant effects on the ability of individuals to perform complex cognitive tasks involved in artillery fire and in which they were trained. In the above model, we can think of this effect as an additive error term, ϵ, whose variance increases with temperature, in which the players simply err in making their decision to fight, a decision they might not male at lower temperatures.

[8] In this section we discuss the main variables to be used in the empirical analysis. Additional data, and the corresponding descriptive statistics, can be found in the Online Appendix.

two periods of interest. We observe an average of 1.0 homicides and 0.3 suicides per 100,000 inhabitants per state-month in the pre-war period, and an average of 1.4 homicides and 0.4 suicides between years 2007 and 2010. The variation in these variables is substantial, with many states having no homicides or suicides in some months and others having as many as 6.2 homicides per 100,000 inhabitants.[9]

Monthly data on DTO killings was compiled by a committee with representatives from all ministries that are members of the National Council of Public Security in Mexico. This data is available for the period starting in December 2006 to December 2010 at the municipality level. The characteristics of each killing occurring in this period were analyzed by the committee to determine whether it corresponded to a killing that was linked to some drug trafficking organization in Mexico. There were a total of 34,550 DTO killings between 2007 and 2010, with an average (standard deviation) of 22 (51) killings per state-month. The variation in this variable is striking, with roughly 20% of state-months having zero killings and some having as many as 452.[10] Panel B in Table 1 presents descriptive statistics for this variable. DTO killings rates are roughly half the size of homicides rate during this period, and the distribution is more skewed.

It is useful to compare these figures with corresponding figures in the United States. The United Nations Office on Drugs and Crime collects information on crime killings and homicide rates in the U.S. and many other countries. Homicide rates are available for a relatively large set of countries since the year 2000 but, unfortunately, drug killings rates are only available from 2005 onwards. Calculations of suicide rates in the U.S. can be obtained from the American Foundation for Suicide Prevention. In the Appendix we compare the 2011 cross section and time series of these variables per 100,000 inhabitants between Mexico and the U.S. Not surprisingly, organized crime killings are far higher in Mexico, a difference that has been increasing since 2006. In addition, homicide rates were twice as high in Mexico before 2006 and have also been increasing. Finally, suicide rates are substantially higher in the United States than in Mexico, a difference that has remained stable over the past ten years.

[9]Monthly rate of 6.2 homicides in our dataset implies a rate of 74.4 homicides per 100,000 per year. This is an extremely high homicide rate. To put this in perspective, the most violent country in the world in 2012 (Honduras) had a rate of 90.4 homicides per 100,000 inhabitants, and the second most violent (Venezuela) had a rate of 53.7.

[10]Our results are robust to excluding states with a large upward trend in DTO killings, i.e. Baja California, Chihuahua, Durango, Guerrero, Sinaloa, and Tamaulipas. Results are also robust to including state specific trends, as discussed below.

Figure 2 shows the time series variation in our dependent variables. The upper panel shows time trends in DTO killings, and the bottom two panels show time series for all states since January of 1990 to December of 2006. Suicides do not follow a clear pattern during this time period, but homicides seem to be decreasing, something analyzed in more detail by Escalante (2011).[11]

Finally, we construct monthly temperature and precipitation for each state-month using data from Willmott and Matsuura (2014). This is a gridded dataset with monthly information for cells of size 0.5 degrees.[12] In order to transform this gridded dataset into a state-level dataset, we take the average of temperature and the sum of precipitation for all pixels inside the polygons that represent Mexican states. States during our sample period have an average temperature of 21 degrees celsius, with a standard deviation of 4.9 degrees celsius. However, after removing state, year, and month fixed effects, following our econometric specification (below), the standard variation of this variable at the state-month level is 1.8 degrees celsius.

4.2 Econometric strategy

To estimate a causal link between temperature and our dependent variables of interest, we follow Deschenes and Greenstone (2007), and the preferred method employed by Hsiang et al. (2013) (see Dell et al. 2014 for a review). Accordingly, we control for unobservable confounding factors across local populations, which could also affect conflict, and unobservable time factors, which could be correlated with climate as well as conflict. Specifically, in our preferred specification we estimate the following regression:

$$y_{smt} = \alpha + \beta \text{Temp}_{smt} + \delta \text{Precip}_{smt} + \xi_m + \lambda_t + \zeta_s + \varepsilon_{smt} \quad (3)$$

where y_{smt} is the number of DTO killings, homicides, or suicides per 100,000 inhabitants in state s, month m, and year t; α is a constant term; ξ_m and λ_t are full sets of month and year

[11] Dube and Ponce (2012) study violence in Mexico before 2006. These authors find that an expiration that relaxed the permissiveness of gun sales caused an increase of roughly 239 deaths annually in municipalities close to the relevant state borders.

[12] "Gridded weather datasets use interpolation across space and time to combine available weather station data into a balanced panel of observations on a fixed spatial scale or grid. This approach deals with the problem of missing observations at a given station or missing data because a station does/did not exist at a particular location. (...) Each "grid" approximates a weather measure for the spatial unit by interpolating the daily station data while accounting for elevation, wind direction, rain shadows, and many other factors.", (Auffhammer et al., 2013).

fixed effects; ζ_s is a full set of state fixed effects, respectively; Temp_{smt} is average temperature, measured in degrees celsius; Precip_{smt} is total precipitation, measured in thousands of millimeters; and ε_{smt} is an error term clustered at the state level.

One potential concern with equation (3) is that it does not take into account potentially different trends across states over time. There could be different trends if, for example, states implemented different policies in the past to fight violence, and those policies were successful in affecting violence. To deal with this possibility, in an alternative specification we augment regression (3) by including state linear trends.

Seasonality has also been advanced as an important factor to understand violence, particularly suicides.[13] Month fixed effects alone might not be sufficient if states have different seasonal climate patterns. In a further specification, we address differential seasonality across states by replacing month fixed effects ξ_m with a more flexible month-state fixed effect ξ_{sm}. Note that, while equation (3) imposes the same seasonality across states, this specification allows each state to have its own seasonal patterns of violence.

Finally, note that our primary interest is in β and δ, which are identified through natural exogenous fluctuations in weather conditions, conditional on location and time effects. After demonstrating that our results are robust across specifications, we employ equation (3) for most analysis.

4.3 Additional analyses

We also present estimates of the effect of leads and lags of temperature on violence. This exercise is important for a number of reasons. First, there may be temporal displacement: it may be the case that an event that would have occurred in the future anyway is triggered earlier by extreme climatic conditions. Then, the contemporaneous and lagged effects would be of similar magnitude, but opposite in sign and there would be no overall effect of climate on violence. In the case of full or partial displacement, we would then overstate the effect if the correct regression specification is not used.

It is also possible that temperature has a persistent or delayed effect on conflict. For

[13] See Marion et al. (1990), Barker et al. (1994), Hakko et al. (1997), Jessen et al. (1998), Ajdacic-Gross et al. (2007), and Casey et al. (2012). Some authors, however, do not find evidence on the importance of seasonality (e.g. Tietjen and Kripke 1994). See Ajdacic-Gross et al. (2010) for a review and evidence of heterogeneous seasonality across the world.

example, in the case of a delayed effect, a negative temperature shock during the growing season in an agricultural based economy may increase violence during the harvest season when income for the farming season is earned. We will show results testing this relationship for the case of Mexico. Finally, a different but related interpretation for an effect of weather variables in $t-1$ on violence in t is the idea of escalation. It is theoretically possible that a weather shock triggers a conflict that persists over time.

In order to test for displacement, delayed, or persistent effects of temperature on conflict, we also estimate the following regression equation:

$$y_{smt} = \alpha + \sum_{k=t-6}^{k=t+6} \beta_k \text{Temp}_{smk} + \sum_{k=t-6}^{k=t+6} \delta_k \text{Precip}_{smk} + \xi_m + \lambda_t + \zeta_s + \varepsilon_{smt} \quad (4)$$

where all variables are defined as before, and we include six monthly leads and six lags of temperature. Our interest relies in the parameters β_k and δ_k. In particular, a violation of our identification assumption would be reflected in any of the coefficients $(\beta_{t+1}, ..., \beta_{t+6})$ being statistically different from zero, i.e., future climate variation should not be correlated with past violence. Persistent effects or displacement would translate into the coefficients $(\beta_{t-6}, ..., \beta_{t-1})$ being statistically different from zero. Finding that β_t is statistically different from zero would appear most consistent with an immediate psychological/cognitive mechanism explaining the relationship between temperature and violence given that we are using within month variation.

Finally, we also present non-parametric estimates of the empirical relationship between temperature and violence using the procedure in Hsiang (2013). Non-parametric estimates take the form of "watercolor figures", which use the darkness of color saturation to display the probability that the conditional expectation function passes through a given point, out to the 95% confidence interval, using a bootstrapped distribution of estimates. To facilitate their interpretation, we present these figures after standardizing both the climate variables and the dependent variables.

5 Climate and Violence

Figure 3 presents non-parametric estimations of the relationship between our three main dependent variables and temperature using the procedure in Hsiang (2013). To facilitate the interpretation of these plots, we first partial out state, year, and month fixed effects from

both the dependent variables and temperature. Then, the x-axis is interpreted as deviations (in degrees celsius) from the average temperature in a given state-month. A one standard deviation in the temperature variable corresponds to 1.8 degrees celsius, which corresponds to moving across nearly the entire x-axis in the figure. In the y-axis, on the other hand, we measure the corresponding dependent variable as percentage deviations from its mean. The thick line corresponds to the non-parametric conditional mean, while colors depict the level of uncertainty. Lighter colors mean that the conditional mean is less likely to go through that point, while darker colors mean that it is more likely to go through it. These non-parametric relationships are clearly upward sloping for all three variables, and appear nearly linear, especially in the case of suicides.

In Table 2 we present regression results from estimating equation (3) and related specifications. To facilitate the interpretation of these coefficients, and comparison across outcomes and studies, we always present standardized effects in square brackets, i.e. the percentage change in the dependent variable with an increase of a one standard deviation in temperature within a state. The first three columns show results using DTO killings per 100,000 inhabitants as dependent variable, columns 4 to 6 use homicide rates, and columns 7 to 9 suicide rates.

There are several interesting patterns to note in this table, and these largely conform to the non-parametric patterns. First, we observe a positive and significant effect of temperature on all three types of violence, a result that is robust across all specifications. Second, the economic magnitude of these estimates varies across columns, but the general pattern indicates that the effect of temperature is larger for DTO killings, followed by suicides, and then homicides. Third, we do *not* observe any statistically significant relationships between precipitation and violence, and the economic magnitude of the precipitation coefficients is a fairly precise zero. Finally, standard errors double in the third specification where we include state specific month fixed effects. Due to this last result, and also for parsimony and comparison with the existing literature, we choose to focus the analysis on the first specification with separate state, month and year fixed effects.[14]

Comparison with existing estimates It is useful to compare these estimates with the existing literature. In Figure 4 we plot the distribution of standardized coefficients calculated from a subset of the studies used in the meta-analysis in Hsiang et al. (2013) along with our

[14]In the Appendix we also present results including temperature in the previous month as an additional right hand side variable and results are extremely similar.

results from Table 2. We construct the distributions in the second and third panels using 24 studies from Hsiang et al. (2013) that include conflict outcomes classified as intergroup and 12 studies for which conflict is classified as interpersonal.

The estimated effects for DTO killings and homicides lie within the expected distributions for intergroup and interpersonal conflict, respectively. In addition to finding smaller standardized effects for interpersonal conflict relative to intergroup conflict, Hsiang et al. (2013) also find that the former is more precisely estimated. Similarly, in the case of Mexico we find that the DTO killings are less precisely estimated relative to homicide. The authors attribute this pattern to the fact that a large number of interpersonal conflicts are observed in the data (i.e., there are many more murders than civil wars) and because of the difference in the spatial resolution of the respective data sets. What is unusual in this setting is that we have a measure for intergroup conflict that is generally used to measure interpersonal conflict (i.e. homicide versus the outbreak of civil conflict). Besides Burke et al. (2014), we are not aware of any other study using a panel data approach to estimate the effect of temperature on suicides, so we do not have a benchmark set of estimates for comparison.

Geographic estimates We also allow for geographically heterogeneous effects across states. To see this more clearly, consider an augmented version of equation (3) where β_y is allowed to vary by state for each corresponding outcome, with $y = \{\text{DTO killings, homicides, suicides}\}$. Then, we take these state-specific estimates $\beta_{s,y}$ and plot the resulting coefficients on the map of states for each of our three outcomes of interest:

$$\frac{\widehat{\beta}_{s,y}}{\widehat{\beta}_y}$$

where $\widehat{\beta}_y$ is equal to estimates in columns (1), (4), and (7) in Table 2. As can be seen in Figure 5, state-specific coefficients are fairly homogeneous across space. In fact, just 3 percent of coefficients are not positive, with most estimates in the range $\widehat{\gamma} \in (0, 2)$.

Overall, there is a positive, significant, and fairly large effect of contemporaneous temperature on DTO killings, homicides, and suicides. Our preferred estimates indicate that a one standard deviation increase in temperature is associated with an 23 percent increase in DTO killings, a 5 percent increase in homicides, and a 7 percent increase in suicides. A prevalent view among economists is that these observed effects are probably explained by an income mechanism, i.e. income reacts to changes in temperature and this is the main reason why violence increases. In the remaining sections we implement a variety of different

empirical tests to analyze to what extent the income mechanism and other economic factors can explain our results.

6 Economic Factors

6.1 Quasi-experimental variation in monetary transfers

From a policy perspective, it is crucial to understand if economic factors play a role in driving violence. If this is indeed the case, then we can design policies to mitigate the opportunity cost argument highlighted by Chassang and Padró-i-Miquel (2010). Perhaps surprisingly, there is as yet little empirical evidence on the effects public interventions on violence.[15]

We exploit the roll out of the social program Progresa between 2002 and 2010 to identify the effect of monetary transfers on violence. Progresa is a very large social program: its budget was approximately 133 million USD in 1997 (roughly 0.03% of GDP), and it has expanded to almost 5 billion USD in 2010 (roughly 0.5% of GDP). Specifically, we collected bimonthly transfers to every state during the period between January 2002 and December of 2010 from administrative sources.[16] Then, we augment our main regression equation by including the logarithm of Progresa transfers as an additional independent variable, and an interaction term between this variable and temperature. Results from this exercise are presented in Table 3.

First, transfers seem to decrease the rate of DTO killings, although the effect is relatively modest: an *increase* of 10 percent in transfers *decreases* killings by 0.1 percent. The effect is smaller in the case of homicides and suicides, not statistically significant, and changes sign in the case of suicides. Regarding the interaction term, the coefficient is also negative and marginally significant in the case of DTO killings, which suggests transfers also decrease the local sensitivity to temperature, but it is again a fairly precise estimated zero in the case of homicides and suicides.

[15]Exceptions are Fetzer (2014), who shows that the relationship between monsoon shocks and insurgent conflict is largely eliminated in India after the introduction of a public employment program (NREGA), and Bobonis et al. (2013), who show that cash transfer beneficiary women suffer less physical abuse in Mexico. Our results point in the same direction.

[16]It is important to highlight that this program targeted women with children. In that sense, our results could differ from the impact of a transfer specifically design to reduce violence, i.e., to young men or other groups most likely to engage in violence.

In additional exercises shown in the Appendix we have also incorporated an interaction term between leads and lags of PROGRESA transfers and temperature and we reach the same conclusion: transfers significantly decrease DTO killings, but only contemporaneously, these have no effect on homicides and suicides, and the interaction term is marginally significant and negative only for the case of DTO killings. Overall, it seems that even large monetary transfers to poor households in a very high-profile anti-poverty social assistance program can only slightly reduce levels of intergroup violence and have no effect in the case of interpersonal and intrapersonal violence.

6.2 Harvest and growing season effects

As agricultural income has been one of the most salient variables emphasized in the literature as a mediating factor between climate and conflict, we examine the effect of temperature during the growing and harvest seasons. More precisely, we construct an indicator variable that takes the value of one for the months of April to September, which is considered the rainy season for the majority of Mexico and includes both the canicula and pre-canicula period.[17] The harvest season indicator variable, on the other hand, takes on a value of one during the months of October to December.

We perform two different analyses. In the first one, we simply augment our main regression equation with an interaction between temperature and the indicator variable for the growing season. Note that, if growing season temperature has an effect on crops, and through crops an immediate effect on income, i.e., for agricultural laborers, we should expect the coefficient on this interaction term to be positive. However, we observe the opposite sign in Table 4 for all three outcomes. We also observe that violence is generally lower during growing season than other times of the year.

In the second exercise we analyze how violence in the harvest season reacts to temperature during the growing season. Much of the income from agricultural activities during the growing season is only realized during the harvest season. Columns 3, 6 and 9 present regression results from this exercise. To operationalize this statistical test, we collapse the data to an observation of the growing season and a harvest season and include both the temperature during the harvest and growing season. We do not observe any robust effects

[17] Canicula is a mid-summer drought period in Mexico. Both the growing and harvest season were specified following Skoufias (2012), who examines the effect of weather shocks on household welfare in Mexico.

of growing season climate on later violence.

Overall, results from sections 6.1 and 6.2 suggest that economic factors have only limited power to explain the observed effect between temperature and violence. If anything, economic factors seem to be a mechanism only when analyzing DTO killings. For DTO killings, estimated coefficients tend to have the sign suggested by prevailing theories, although they also tend to be relatively small in magnitude and often not statistically significant.

6.3 Income, unemployment, and inequality

As a further set of tests for the income mechanism, we augment equation (3) by including an interaction term between temperature and some economic variables that have been argued to have effects on violence in previous literature.

The typical pattern is that poorer places tend to be more violent than richer places (Blattman and Miguel, 2010). To test this we collected GDP data for every state and interacted the logarithm of GDP per capita in 1999 with temperature to check if poorer places react more than richer places to exogenous variations in temperature. Surprisingly, we do not find that this is the case for any of our three dependent variables. To facilitate comparison, we have standardized this and all subsequent economic variables, which also lets us interpret the magnitude of the interaction term by just examining the coefficient.

In the case of DTO killings, the coefficient has the expected sign—richer states do react somewhat less than poorer states—but the coefficient is small. For example, a one standard deviation increase in log GDP per capita, which we think of as being a fairly large increase in income, attenuates the effect of temperature on DTO killings by 12 percent ($-0.007/0.057 \approx 0.12$). In the case of homicides, we also observe a small coefficient on the interaction term; in fact, the sign is the opposite of what previous literature would have suggested. Finally, the interaction term is also the "wrong" sign in the case of suicides and indicates that *richer* places are in general *more* sensitive to changes in temperature. In this last case the interaction is statistically significant and implies that a one standard deviation increase in log GDP per capita *increases* the sensitivity of suicides to temperature by 40 percent ($0.002/0.005 = 0.4$). Although perhaps counter-intuitive, this is consistent with some statistics showing higher suicide rates in richer countries, as we show in the Appendix for the case of U.S. vs. Mexico.

Another economic variable that has been argued to be an important driver of violence is

inequality. To test for a differential effect of temperature related to inequality, we used gini coefficients constructed by Jensen and Rosas (2007) from 1999 for every state in our dataset and then interacted it with temperature. A remarkably similar pattern emerges from this exercise: temperature does somewhat affect states differently in the case of DTO killings, with the expected sign and a modest magnitude (although the effects is not statistically significant at traditional confidence levels), but the interaction is a fairly well estimated zero in the case of homicides and suicides. In the case of DTO killings, a one standard deviation in inequality increases the effect of temperature on violence by roughly 20 percent.

Another economic variable of interest in this table is unemployment. In this case we exploit the month to month variation in unemployment to identify a differential effect of temperature. Unfortunately, this variable has been only collected since 2004 at the state level, so we only include this interaction in the case of DTO killings. Again, the main effect of temperature on violence remains stable and the estimated coefficient on the interaction term with unemployment is relatively small and has the opposite sign to what was expected: a one standard deviation *decrease* in unemployment *increases* the sensitivity of DTO killings to temperature by 6 percent ($-0.003/0.051 \approx 0.06$), although the effect is once again not statistically significant.

Finally, we include an interaction term between temperature and the percentage of houses with air conditioning in 2010, the first time that this variable was systematically collected at the national level for a representative sample of houses in every state. Air conditioning may reduce exposure to external temperature. However, we do not observe that this variable helps to explain any of our variables of interest.[18]

[18]In unreported additional exercises we use monthly labor protests, available since 1990, as a proxy for the economic environment. If people protest because wages are low or unemployment is high, then this is maybe a good measure to test for the relative importance of economic factors. We do not find, however, (1) an effect of temperature on labor protests, or (2) a differential effect of temperature with variation in labor protests. We also estimated the seasonality of wages and unemployment in Mexico and check if the estimated effect of temperature on violence varies by month in a way that resembles seasonality. Again, we do not find similar patterns between the relevant coefficients and these variables.

7 Other Factors

7.1 Other DTO criminal activities

In this final section we turn to the question of why DTO killings are reacting to changes in temperature and to what extent this could have an economic mechanism as an explanation. To gain insights about potential mechanisms at work we have collected monthly data on other criminal activities carried out by drug trafficking organizations, and also yearly data about their presence from Coscia and Rios (2012). First, we analyze the response of less violent crimes that have a clear economic motivation to exogenous variation in temperature. Second, we use the DTO's presence at the municipality level to explore if our estimates are driven by the expansion of the Zetas, one of the largest and most violent organizations operating in Mexico, or the competition between DTOs.

Besides killings, drug trafficking organizations are also known for other criminal activities such as kidnappings, extortion, and car thefts. We collected administrative data on the monthly occurrence of these criminal activities, together with another variable measuring homicides, during the period between January of 2007 and December of 2010. If higher temperatures are somehow decreasing the income of these organizations, then we might observe an increase in other operations that generate revenue. One leading example could be drug production, as this is one of the main sources of income for DTOs. It could be the case that this activity is sensitive to variations in temperature and, as a response to the lower income in a given month, DTOs respond by performing other criminal activities to substitute revenues from one activity with the other. To test for this idea we estimate our main regression equation but replace DTO killings by car thefts, extortions, and kidnappings per 100,000 inhabitants. These criminal activities are motivated by more purely economic objectives, and are also intrinsically less violent than killing (although they may of course be associated with some violence).

Table 6 present the estimates of interest. We have included our main result on DTO killings for comparison in column 1, and also the analogous estimate using the measure of homicides for this later period. The first result is that this measure of homicide, collected from a different source shows the same pattern observed for the case of DTO killings. The next three columns in this table present the estimated effect of temperature on car thefts, extortions, and kidnappings, respectively. Strikingly, we do not observe any signifi-

cant relationship between temperature and these other criminal activities. In fact, estimated coefficients have a negative sign in the case extortions and kidnappings, although not significant, and the effect on car thefts is fairly small and not statistically significant. Thus it is not the case that a wide range of DTO activities increase in months with high temperatures; rather it is simply the most violent activities, killings, that increase.

The idea that drug trafficking organizations are economic agents competing for territory has been argued by many scholars (e.g., Dell 2015). To check that our estimates are not driven by the expansion of the Zetas cartel, which have been moving from the south-east region of the country towards the north-west over the last ten years, we construct variables measuring the share of a state where the Zetas and the Sinaloa cartel are present.[19] We focus on Sinaloa, as it is one of the oldest and largest DTOs, and it has been suggested that the Zetas often move disproportionally into Sinaloa's territory to take over their drug business. In addition, we also construct a variable measuring the total number of DTOs that are operating in a state (Coscia and Rios, 2012).

Table 7 presents regression results from augmenting our main specification with the shares of these groups and interaction terms with temperature. Estimated coefficients do not show any pattern that suggests our results are driven by the expansion of the Zetas. Interestingly, neither the interaction between the number of DTOs and temperature, nor the one between the share controlled by the Zetas and temperature, are statistically significant, nor does the interaction between the Zetas and Sinaloa cartel in particular appear to be playing a role. Overall, the structure of the drug industry in a state neither exacerbates nor dampens the observed effect of temperature on drug violence.

7.2 Analysis of leads and lags

We next analyze the dynamic effects of temperature on violence to get a sense of mechanisms at work. In Figure 6 we include leads and lags of temperature into our main regression equation. Then, we plot the estimated coefficients of interest the y-axis, while in the x-axis we identify the lead/lag of the estimated coefficient. More precisely, we plot coefficients from left to right where -1 is the coefficient that measures the effect of temperature in $t-1$ on our outcome of interest in t, while 1 means that the coefficient measures the effect of

[19] If we observe that an organization k is active in 100 municipalities in a state that is composed by 200 municipalities, we say that k operates in 50 percent of that state.

temperature in $t+1$ on our outcome of interest in t.

Recall that this exercise serves several different purposes, namely to test for displacement effects, and also placebo checks, as temperature three months from now should not affect violence in the current period, conditional on time and location fixed effects. Results in all panels in this figure are reassuring for the econometric identification strategy, as the estimate of a positive and significant relationship between temperature and violence is only present for the contemporaneous period.

Several other things are worth noting in this figure. First, a temperature shock does not seem to lead to any escalation of violence. One might think that a temperature shock could affect violence in the current period and over time this could triggers a war between two DTO groups because of a desire for retaliation. We find, however, no effect of temperature in the past months on current violence in the case of DTO killings and homicides.

Second, the middle panel does show weak evidence of displacement effects, as the effect of temperature in the next period has a negative and significant effect on violence in the current period. Third, the pattern is clearer in the case of suicides, which again is perhaps more likely to be driven by non-economic factors, and is remarkably similar across the three different panels.

8 Conclusion

Using state by month variation in temperature, we find significant contemporaneous effects of temperature on DTO killings, suicide, and homicides in Mexico. This is the first study to our knowledge to examine the effect of climate on suicide using panel data and to find such a similar relationship across a spectrum of violence outcomes in a single setting. The estimated effects line up well with existing estimates in the literature.

The strongest evidence testing for an income effect uses quasi-experimental variation in transfers through the Progresa/Oportunidades program and shows its limited role in explaining conflict for DTO killings and not at all for suicide or homicide. In particular, we highlight the similarity of effects on inter-group violence to the other measures in response to within month variation in temperature, which are more commonly attributed to psychological factors. We then interpret this as evidence that inter-group violence may be partially driven by psychological channels. While we cannot directly test for a physiological/psychological

channel, we have included a discussion of the role serotonin may play and believe that this is an important factor to be incorporated in the intersection of economics and psychology research in the future.

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Figure 1

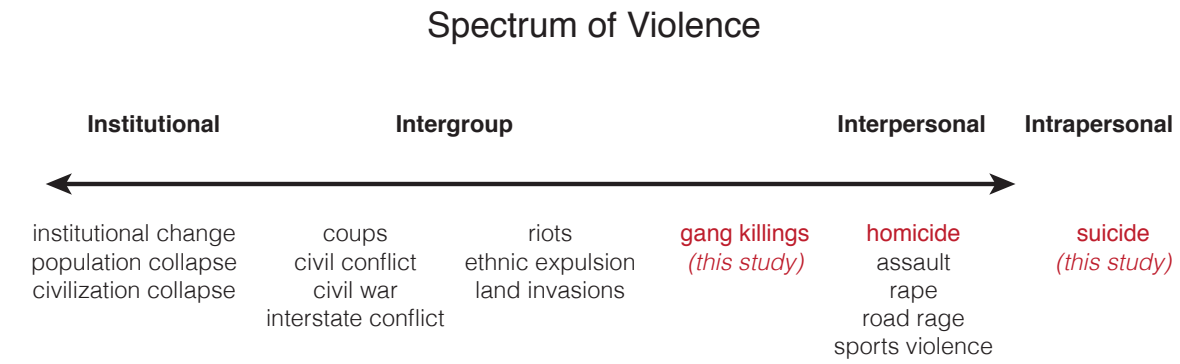
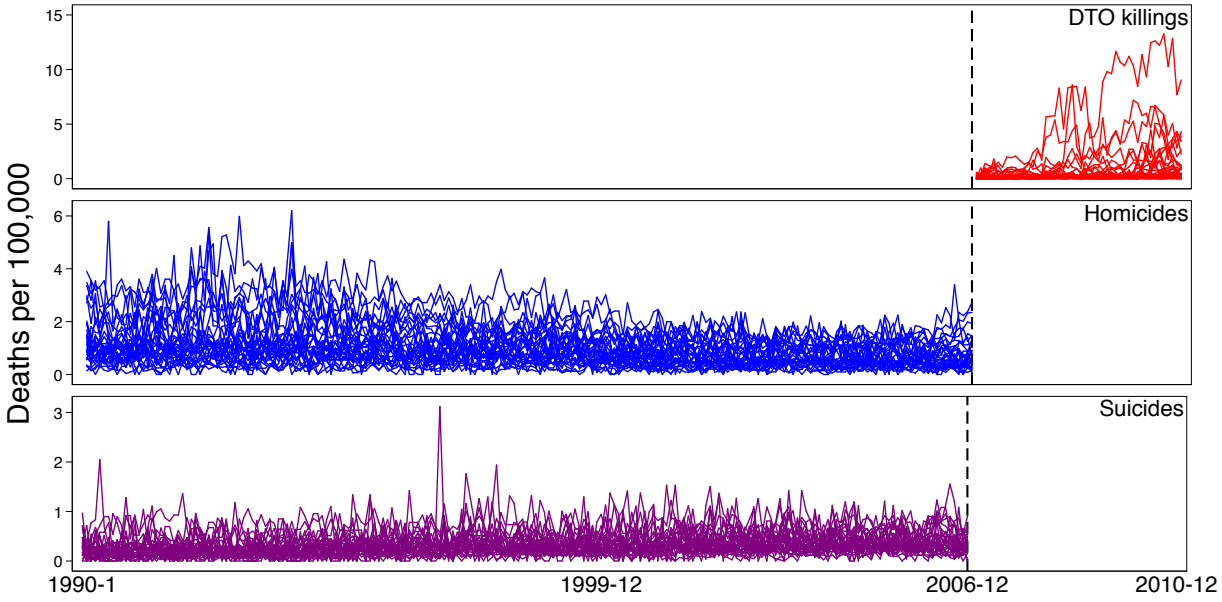
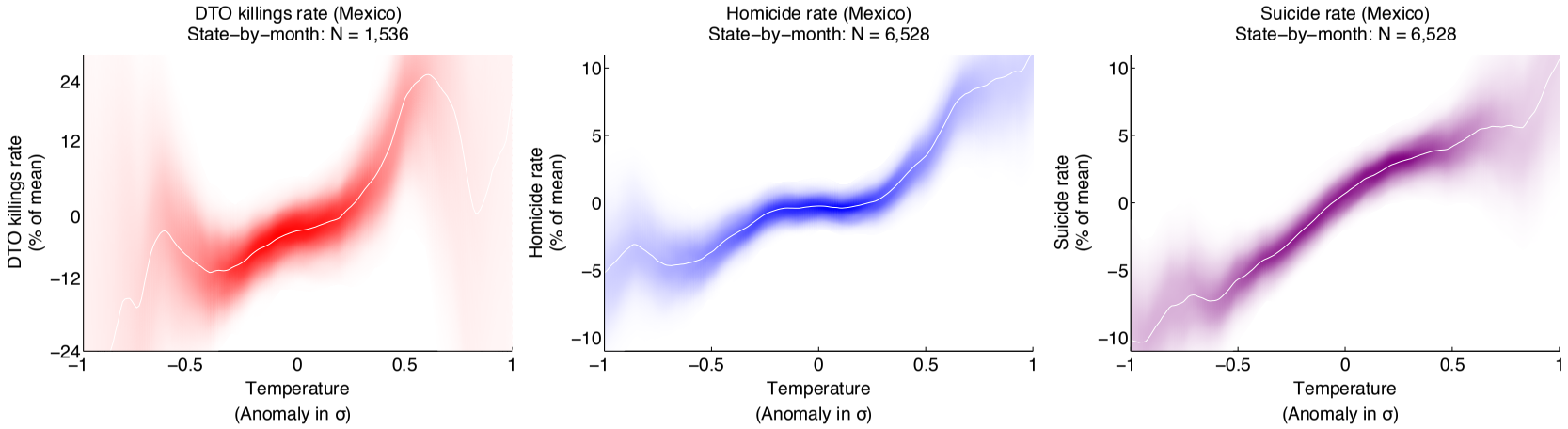


Figure 2: Time series in violence



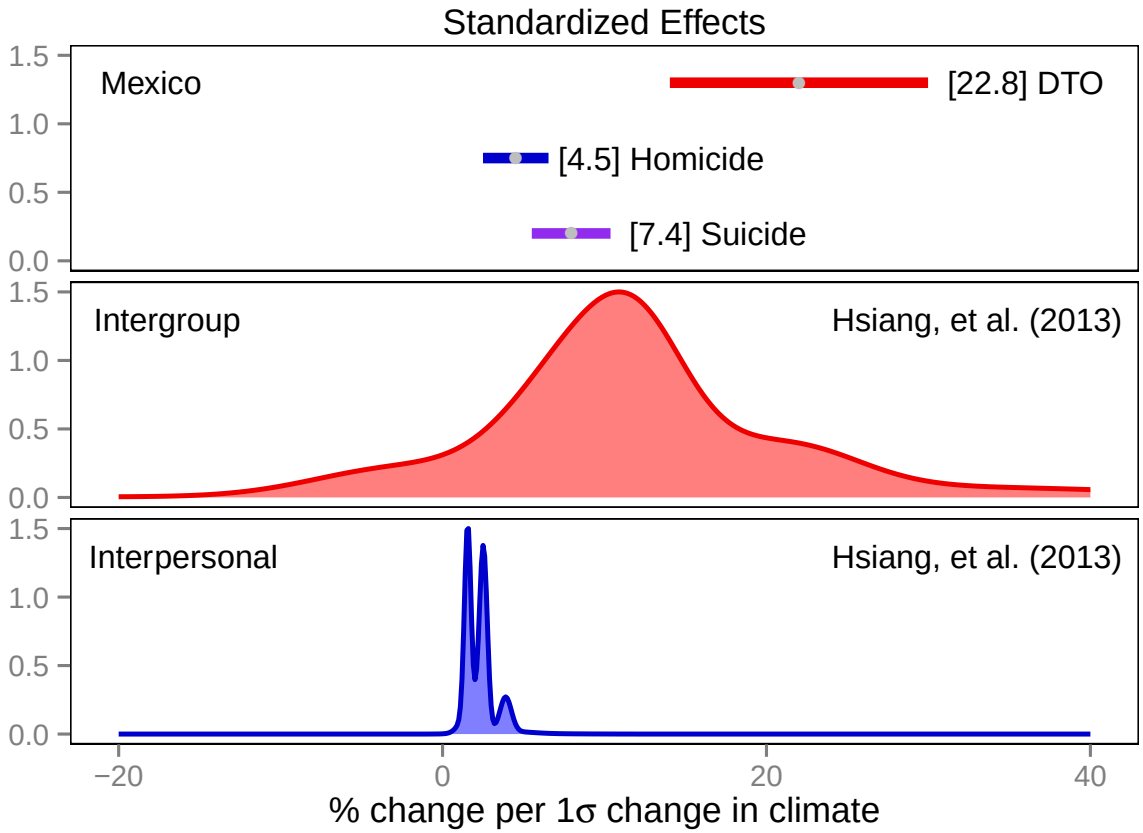
Notes: Time series for our three main outcome variables in all states in Mexico. The dash vertical black line denotes the beginning of the Mexican Drug War.

Figure 3: Non-parametric estimates



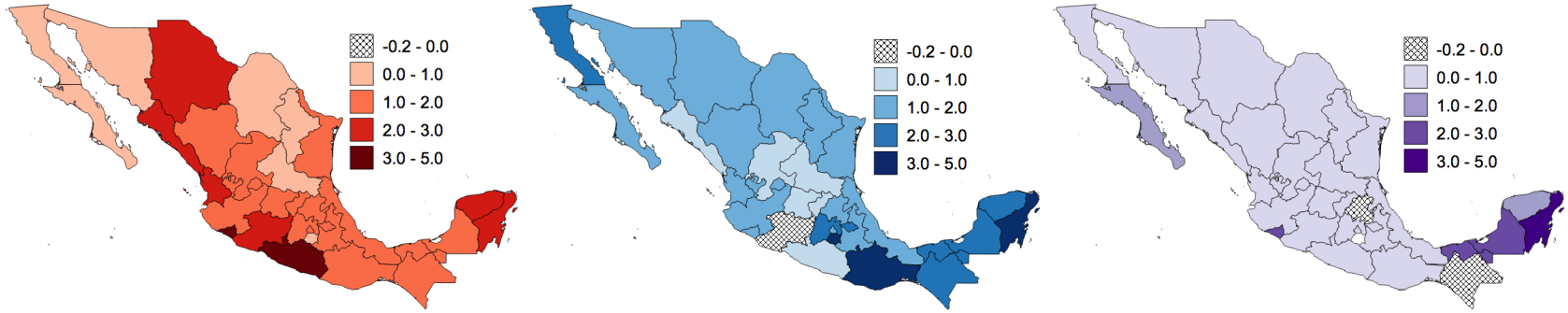
Notes: Non-parametric relations between temperature and the outcomes of interest using the procedure in Hsiang (2013). DTO stands for drug-trafficking organizations.

Figure 4: Meta-analysis



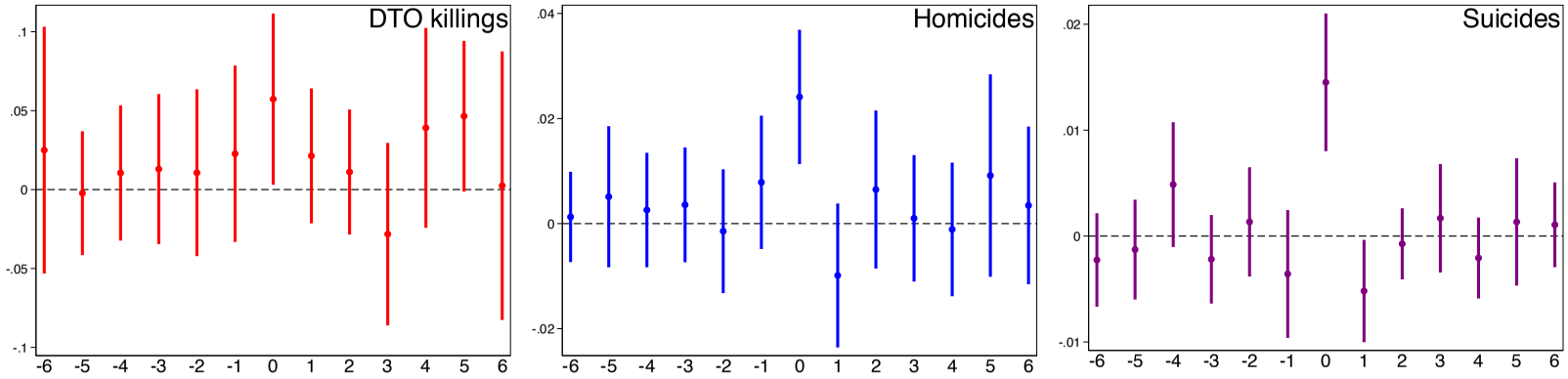
Notes: Distribution of standardized effects of climate on interpersonal (e.g. rapes) and intergroup (e.g. civil conflict) outcomes. Data for the top two panels are from Hsiang et al. (2013). Results from this paper are in the bottom panel (with the corresponding confidence interval).

Figure 5: Geographic distribution of estimates



Notes: Estimated effect of temperature on the outcome of interest for each state in Mexico. Coefficients are expressed as percentage of the average coefficient for comparison across maps. Categories in these maps correspond to intervals of the same size. Darker colors for larger coefficients. States colored in gray indicate a negative estimated coefficient.

Figure 6: Temporal distribution of estimates



Notes: This figure shows regression estimates β_{t+k} of $y_{smt} = \alpha + \xi_m + \lambda_t + \zeta_s + \sum_{k=-6}^{6} \beta_{t+k} \text{Temp}_{sm,t+k} + \sum_{k=-6}^{6} \delta_{t+k} \text{Precip}_{sm,t+k} + \varepsilon_{smt}$, where y_{smt} is DTO killings, homicides, or suicides per 100,000 people, α is a constant term, ξ_m, λ_t, and ζ_s are month, year, and state fixed effects respectively, Temp_{smt} and Precip_{smt} are temperature (in degrees celsius) and precipitation (in millimeters) respectively, and ε_{smt} is an error term.

Table 1: Descriptive statistics

	Mean	*St. Dev.*	*St. Dev within*	*Min*	*Max*
	Panel A: 1990 – 2006 ($N = 6,528$)				
DTO killings	–	–	–	–	–
Homicides	1.0	0.8	0.4	0	6.2
Suicides	0.3	0.2	0.2	0	3.1
Population	29.9	25.5	2.1	3.3	143.0
Temperature	20.9	4.9	1.8	5.0	31.1
Precipitation	65.2	86.7	55.1	0.0	1,145.5
	Panel B: 2007 – 2010 ($N = 1,536$)				
DTO killings	0.7	1.6	1.0	0	13.3
Homicides	–	–	–	–	–
Suicides	–	–	–	–	–
Population	34.4	28.9	0.5	5.8	152.0
Temperature	20.8	5.0	1.8	5.2	31.2
Precipitation	54.3	77.4	44.5	0.0	592.7

Notes: Descriptive statistics for all 32 Mexican states at the month level. See paper for data sources. **Population** is measured annually in 100 thousand. **DTO killings**, **Homicides**, and **Suicides** are measured per 100 thousand inhabitants in the state. **Temperature** is measured in degrees celsius. **Precipitation** is measured in millimeters. The summary statistic **St. Dev within** is the standard deviation of the corresponding variable after removing the state, year, and month fixed effects.

Table 2: Temperature and violence in Mexico

	Dependent variable is:								
	DTO killings			*Homicides*			*Suicides*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.050**	0.026*	0.080*	0.014***	0.013***	0.027**	0.007***	0.007***	0.009**
	(0.024)	(0.015)	(0.042)	(0.003)	(0.003)	(0.011)	(0.001)	(0.001)	(0.003)
	[22.8]	[11.7]	[36.1]	[4.5]	[4.1]	[8.4]	[7.4]	[7.2]	[8.7]
Precipitation	0.080	0.013	-0.349	-0.168	-0.123	-0.109	-0.053	-0.034	-0.040
	(0.447)	(0.387)	(0.486)	(0.122)	(0.093)	(0.135)	(0.039)	(0.038)	(0.047)
	[0.8]	[0.1]	[-3.4]	[-1.3]	[-1.0]	[-0.8]	[-1.3]	[-0.8]	[-1.0]
Mean of dep. variable	0.737			1.027			0.321		
(Within st. dev.)	(0.962)			(0.422)			(0.167)		
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Month–state F.E.	No	No	Yes	No	No	Yes	No	No	Yes
Linear trend	No	Yes	No	No	Yes	No	No	Yes	No
Observations	1,536	1,536	1,536	6,528	6,528	6,528	6,528	6,528	6,528
R^2	0.649	0.860	0.684	0.697	0.780	0.708	0.470	0.490	0.499

Notes. Estimates for all 32 states in Mexico in different periods between 1990 and 2010. **State trend** includes (1) a linear trend, and (2) a linear trend interacted with a state dummy. Standard errors clustered at the state level in parenthesis. Standardized effects in brackets. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1.

Table 3: Interaction with Progresa transfers

	Dependent variable is:								
	DTO killings			*Homicides*			*Suicides*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.052**	0.052**	0.058**	0.009**	0.009**	0.009**	0.012***	0.012***	0.012***
	(0.024)	(0.024)	(0.027)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)
Log Progresa		-0.012**	-0.012*		-0.005	-0.003		-0.000	0.000
		(0.005)	(0.007)		(0.003)	(0.003)		(0.002)	(0.003)
Log Progresa × Temperature			-0.011			0.003			0.000
			(0.007)			(0.002)			(0.003)
Mean of dep. variable	0.755			0.730			0.386		
(Within st. dev.)	(0.974)			(0.254)			(0.162)		
State, year & month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,486	1,486	1,486	1,860	1,860	1,860	1,860	1,860	1,860
R^2	0.650	0.650	0.651	0.728	0.728	0.728	0.512	0.512	0.512

Notes. Estimates for 31 states in Mexico (all except *Distrito Federal*) in different periods between 2002 and 2010. **Log PROGRESA** is the logarithm of total amount of transfers to the state (in Mexican pesos) in the corresponding month. All regressions control for **precipitation**. Standard errors clustered at the state level in parenthesis. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1.

Table 4: Interaction with growing season

	Dependent variable is:								
	DTO killings		*(Harvest Season)*	*Homicides*		*(Harvest Season)*	*Suicides*		*(Harvest Season)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.050**	0.073***	0.046	0.014***	0.016***	0.027***	0.007***	0.011***	0.013**
	(0.024)	(0.024)	(0.041)	(0.003)	(0.005)	(0.008)	(0.001)	(0.002)	(0.005)
Growing Season		-0.256			-0.113**			-0.031***	
		(0.172)			(0.024)			(0.010)	
Growing Season × Temperature		-0.047*			-0.002			-0.007***	
		(0.026)			(0.006)			(0.002)	
Temperature Growing Season			0.131			0.036			-0.006
			(0.323)			(0.047)			(0.015)
Mean of dep. variable	0.737			1.027			0.321		
(Within st. dev.)	(0.962)			(0.422)			(0.167)		
State, year & month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,536	1,536	384	6,528	6,528	1,632	6,528	6,528	1,632
R^2	0.649	0.649	0.714	0.697	0.697	0.714	0.477	0.477	0.446

Notes. **Temperature** is demeaned. Growing Season as an indicator for the months of April to September; this is considered the wet season for the majority of Mexico and includes both the canicula and pre-canicula period. Canicula is a mid-summer drought period in Mexico. The harvest season is during the months of October through December. We specified these months following Skoufias (2012) who look at the effect of weather shocks on household welfare in Mexico. The third specification therefore looks at the impact of temperature in the growing season on violence in the harvest season of the same year. All regressions control for **precipitation**. Standard errors clustered at the state level in parenthesis. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1.

Table 5: Interaction with economic variables

	Dependent variable is:									
	DTO killings				*Homicides*			*Suicides*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	0.057**	0.063*	0.051*	0.060*	0.013**	0.015**	0.016***	0.005***	0.006***	0.006***
	(0.026)	(0.031)	(0.025)	(0.031)	(0.005)	(0.006)	(0.004)	(0.002)	(0.002)	(0.002)
× **Log GDP per capita (1999)**	-0.007				0.002			0.002**		
	(0.007)				(0.003)			(0.001)		
× **Gini (1999)**		0.012				0.000			-0.001	
		(0.009)				(0.003)			(0.001)	
× **Unemployment (monthly)**			-0.003							
			(0.007)							
× **Houses with air-conditioning (2010)**				-0.007			-0.001			0.001
				(0.007)			(0.002)			(0.001)
Mean of dep. variable	0.737				1.027			0.321		
(Within st. dev.)	(0.962)				(0.422)			(0.167)		
State, year & month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,536	1,536	1,536	1,536	6,528	6,528	6,528	6,528	6,528	6,528
R-squared	0.649	0.649	0.649	0.649	0.697	0.697	0.697	0.471	0.470	0.470

Notes. **Temperature** is demeaned. **Log GDP per capita** is from 1999 at 1993 prices; source is INEGI. Air-conditioning (AC) is the saturation of residential air-conditioning, from National Household Income and Expenditure Survey 2010 (ENIGH), and is also standardized. All of the remaining interaction terms come from Jensen and Rosas (2007) and are standardized. **Unemployment** is the unemployment rate in 1999 for the economically active population. **Gini** is an income inequality index constructed by Jensen and Rosas (2007) using the Mexican national census. All regressions control for **precipitation**. Standard errors clustered at the state level in parenthesis. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1.

Table 6: Temperature and economically motivated crimes

	Dependent variable is:				
	DTO killings	*Homicides*	*Car thefts*	*Extortions*	*Kidnappings*
	(1)	(2)	(3)	(4)	(5)
Temperature	0.050**	0.050**	0.067	-0.005	-0.001
	(0.024)	(0.023)	(0.092)	(0.004)	(0.001)
	[22.8]	[13.7]	[1.7]	[-4.5]	[-3.1]
Precipitation	0.080	-0.285	-0.363	0.220	0.060
	(0.447)	(0.411)	(2.430)	(0.255)	(0.036)
	[0.8]	[-1.7]	[-0.2]	[3.9]	[6.2]
Mean of dep. variable	0.737	1.217	13.414	0.407	0.070
(Within st. dev.)	(0.962)	(0.827)	(5.600)	(0.360)	(0.088)
State, year & month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	1,536	1,535	1,535	1,535	1,534
R^2	0.649	0.714	0.886	0.603	0.392

Notes. Estimates for all 32 states in Mexico in the period 2007 – 2010. All dependent variables are rates per 100 thousand inhabitants. Source is *Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública* (SESNSP). Standard errors clustered at the state level in parenthesis. Standardized effects in brackets. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1.

Table 7: Drug trafficking organizations

	Dependent variable is DTO killings				
	(1)	(2)	(3)	(4)	(5)
Temperature	0.050**	0.049**	0.048**	0.049*	0.046*
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
× **DTOs**		0.005			
		(0.004)			
× **Sinaloa**			0.279		0.242
			(0.317)		(0.306)
× **Zetas**				0.109	0.116
				(0.086)	(0.090)
× **Sinaloa** × **Zetas**					1.371
					(2.682)
DTOs		0.071			
		(0.082)			
Sinaloa			6.627**		6.909**
			(2.890)		(2.794)
Zetas				-0.021	0.203
				(0.983)	(1.011)
Sinaloa × **Zetas**					-21.777
					(27.452)
Mean of dep. variable	0.737				
(Within st. dev.)	(0.962)				
State, year & month F.E.	Yes	Yes	Yes	Yes	Yes
R^2	0.649	0.651	0.665	0.649	0.666

Notes. See Appendix for data on drug-trafficking organizations. **DTOs** is the number of cartels that are operating in State s and year t. **Sinaloa** and **Zetas** are the *shares* of the state in which these DTOs operate. *Share* is defined as total number of municipalities where they operate over total number of municipalities in that state. All regressions control for precipitation. Standard errors clustered at the state level in parenthesis. Levels of significance are reported as ***p<0.01, **p<0.05, *p<0.1, $^{+}$p< 0.11.