In the Heat of the Moment: Economic and Non-Economic Drivers of the Weather-Crime Relationship

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Abstract

Though the relationship between weather and crime is well established, the precise mechanisms underlying this relationship remain imperfectly understood. Using daily data on the universe of crimes that we collected from 600 police stations in the Indian state of Karnataka between 2011-2016, and daily weather data from a dense network of monitoring stations, we disentangle the economic and non-economic mechanisms underlying the weather-crime relationship. We analyze a wide variety of crime types, and find that violent crimes respond to both daily and seasonal variation in temperatures and rainfall, whereas property crimes only respond to seasonal variation. This is consistent with the existence of both (same-day) psychologically driven and (seasonal) agricultural-income driven impacts of weather on crime. The results provide novel evidence for the economic theory of crime, but also for the importance of non-economic drivers of violent crime, including violence against women and ethnically marginalized groups, and even inter-group conflict. Economic development, in the form of a larger non-agricultural labor force and higher female labor force participation, does not attenuate the non-economic impacts of weather on violent crime or on violence against women.

Key words: Climate Impacts, Crime, Psychology, Conflict, Gender.

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1 Introduction

One of the most alarming threats presented by climate change is the possibility that it will lead to substantial increases in crime, which may in turn generate a host of negative social and economic effects. A large body of research has consistently demonstrated the impact of climatic variability on a variety of interpersonal and intergroup conflicts (see Hsiang et al., 2013 for a review). However, the mechanisms driving these associations remain imperfectly understood. In developing countries, researchers have generally invoked economic models emphasizing the opportunity cost of criminality (Becker, 1968), driven by the effects of weather variation on agricultural output (Blakeslee and Fishman, 2017). Research from developed countries, conducted primarily by psychologists, has pointed to alternative channels by which weather variation may influence conflict—for example, through the effects of temperature on social interactions and aggression levels (Anderson et al., 2000). Determining the contribution of such non-economic mechanisms to the weather-conflict relationship in developing countries, however, has proven difficult.

In this paper, we make substantial progress in disentangling the economic and non-economic drivers of the climate-conflict relationship in developing countries. Our contribution is made possible through the use of a novel crime data set which we collected from roughly 600 police stations in the Indian state of Karnataka. This data set includes the universe of criminal incidents reported at each police station, including each incident's exact date and type, for the six years spanning 2011-2016. We combined this with data from a recently installed, remarkably dense network of digital weather stations providing daily temperature and rainfall data. Such data sets are seldom available outside of advanced economies, and allow us to analyze the weather-crime relationship at the lowest level of spatio-temporal aggregation ever undertaken in a developing country.

Karnataka is a particularly suitable place for studying the climate-crime relationship in developing countries. With a population of more than 60 million people, Karnataka is roughly the size of France or Italy, and is larger than most developing countries. Like other developing countries, much of the labor force is employed in the agricultural sector, making incomes highly dependent on seasonal weather variation. In addition, as with many other developing countries, temperatures are generally quite high—with the median daily temperature being $31°C$—which generates psychological and economic stressors far more extreme than those occurring in advanced economies.

The remarkable spatio-temporal resolution of our data and the wide variety of crimes covered allow us to examine variations in the weather-crime relationship along two dimensions: (1) the temporal frequency at which the impact occurs; and (2) the nature of the crime involved. Simple theoretical considerations suggest that psychologically driven impacts should be stronger for violent crimes "of passion," and should respond to daily weather variation. Economically driven impacts, on the other hand, are likely to influence both violent and property crimes, due to the effect of income variation on the opportunity cost of crime (Becker, 1968). In addition, income-mediated impacts will be more closely associated with seasonal weather variation, due to the dependence of agricultural incomes on cumulative rainfall and temperatures (Guiteras, 2009; Auffhammer et al., 2012; Fishman, 2016; Blakeslee and Fishman, 2017).

Our analysis reveals precisely such patterns, giving strong evidence for the importance of non-economic channels in mediating the weather-crime relationship. We find that elevated daily temperature leads to a concurrent increase in daily violent crime but not in property crimes. Importantly, we also find that elevated daily rainfall leads to a decline in daily crime, a novel result in the climate-conflict literature, which has generally focused on the economic effects of rainfall. Finally, we find that both violent and property crimes go up with seasonal weather variation that reduces agricultural output, and that this relationship holds even when accounting for daily weather impacts.

These findings call into question the attribution of inter-annual associations between temperature and violent crime in developing countries solely to agricultural income shocks (Sekhri and Storeygard, 2014; Blakeslee and Fishman, 2017), as well as the use of seasonal rainfall to instrument for income shocks (Sarsons, 2015). On the other hand, they validate the emphasis on agricultural income shocks in the case of property crimes (Blakeslee and Fishman, 2017). To more directly test for the existence of economically driven impacts, we estimate specifications simultaneously controlling for daily and seasonal climatic variability. Both types of variability are found to impact crime rates. Seasonal weather variation affects both property and violent crimes, whereas daily variation only affects violent crime, further reinforcing our hypotheses. Accounting for the effect of daily weather variation attenuates the estimated effect of seasonal weather on violent crime by approximately 25%–40%, though seasonal effects continue to be important, and of slightly larger magnitude than daily effects. The economic interpretation of the seasonal weather-crime relationship is further bolstered by the finding that seasonal effects occur only in areas with relatively high agricultural employment. In contrast, the daily weather-crime relationship is unaffected by the size of the agricultural labor force, consistent with a non-economic channel.

Our analysis pays special attention to forms of violence more common in developing countries, including those against socially vulnerable groups such as women and ethno-religious minorities. Such crimes are particularly salient in India, where violence against women and low castes groups (Scheduled Caste/Schedule Tribes, or SC/STs), as well as Hindu-Muslim conflict, are common. Previous analyses have generally assumed economic channels to be driving the effect of weather on gender-based violence (Miguel, 2005; Sekhri and Storeygard, 2014; Aizer, 2010; Pronyk et al., 2006), Hindu-Muslim conflict (Mitra and Ray, 2014; Iyer and Topalova, 2014; Bohlken and Sergenti, 2010), and violence against marginalized castes (Sharma, 2015). We complement this research by demonstrating the importance of non-economic channels as well. Specifically, we show that higher daily temperatures lead to an increase in violence against women and socially marginalized groups, and that higher rainfall leads to a decline. Importantly, these daily effects occur for Hindu-Muslim conflict as well, and indeed are of larger magnitude than for other violent crimes, indicating an important role for non-economic channels even with intergroup conflict.

Existing evidence from developing countries, which focuses on inter-annual variation in weather and crime, makes it difficult to predict whether economic development is likely to reduce the future impacts of elevated temperatures on crime. If the mechanism operated primarily through agricultural incomes, one might expect structural transformation to attenuate the relationship between temperature and crime in coming decades. In a similar vein, changes in the economic status of women and minorities might also reduce their vulnerability to weather-induced aggression through economically driven social empowerment. Our findings on the non-economic factors at play in the weather-crime relationship casts doubt on such a prospect. This pessimism is supported by the absence of any mediating effect of the size of the agricultural labor force on the *daily* weather effects, despite a substantial decline in the effects of *seasonal* weather. This suggests that, while structural transformation may attenuate economically driven impacts of climate change on crime, it will not help to mitigate the non-economic impacts. Similarly, an analysis of crime against women disaggregated across regions with high and low female employment, a measure of women economic empowerment, shows, if anything, a small *increase* in the temperature-crime relationship in areas with higher female labor force participation.

This paper is one of the first to bridge the previously disjoint economic and psychological investigations of the climate-conflict relationship. It also provides some of the first evidence on the form and the magnitude of the psychological impact of weather conditions on criminal behavior in developing countries. Evidence from developed countries (e.g., Ranson, 2014) is unlikely to be sufficiently informative for developing countries, where populations are typically exposed to much higher temperatures, are less able to shield themselves from extreme weather, and are subject to different types of social interactions, institutions and crime types. Because climate change will have the largest impacts on these populations, results from developing countries are therefore particularly important for estimates of the global impacts of climate change.

In this regard, three recent papers, all based on municipality-level data from Mexico, make important related contributions. Cohen and Gonzalez (2018) differentiate between a number of non-economic influences of daily temperatures on a variety of crime types. Garg et al. (2018) distinguish between seasonal and daily influences of elevated temperatures on homicide rates, a primary type of violent crime. They interpret them as economic and non-economic, respectively, and find them to be of similar magnitude. Baysan et al. (2018) use monthly data to find evidence for strong non-economic impacts of temperatures on conflict between drug trafficking organizations. They find clear similarities between the patterns of the impacts on this form of inter-group violence and those on "non-economic" crimes such as homicides and suicides. Our analysis integrates strengths of all of these approaches, since our data allows us to simultaneously investigate the weather-crime relationship at a range of temporal frequencies (as in Garg et al., 2018 and Baysan et al., 2018) as well as for a comprehensive range of crime types (as in Cohen and Gonzalez, 2018), allowing us to sharpen the attribution to psychological channels. The consistency of the key findings–such as the evidence for non-economic influences on similar types of crime and the linear response to temperature–lend them with a remarkable degree of external validity, given the dramatically different context in which these and our own study take place. While we find no evidence that the impact of weather on violent crime is lower in locations where the labor force is less agricultural or male-dominated, both Garg et al. (2018) and Baysan et al. (2018) utilize discontinuities in the roll out of a large social support program to investigate the effects of increased incomes on the impacts of weather in a more causally interpretable manner. However, whereas Garg et al. (2018) find it to reduce these impacts in the case of homicides, Baysan et al. (2018) find no evidence of a substantial effect.

Our paper also speaks to the broader literature on the causes and consequences of crime.[1] Much of this research seeks to understand the determinants of crime within an economic framework, including: the link between crime and unemployment (Raphael and Winter-Ebmer, 2001; Lin, 2008; Fougère et al., 2009; Gronqvist, 2013), crime and income (Gould et al., 2002; Machin and Meghir, 2004; Chalfin and Raphael, 2011), and crime and education (Lochner and Moretti, 2004; Machin et al., 2011); as well as the effect of incarceration length on labor market outcomes (Raphael, 2010; Kling, 2006). Other papers have focused on policy interventions for reducing crime, which often appeal to non-economic factors for their efficacy. Among these are: reshaping attitudes (Dhar et al., 2018), cognitive behavioral therapy (Blattman et al., 2017), and decriminalization (Adda et al., 2014). The vast majority of this research has focused on developed countries, with developing countries having received relatively little attention (Hsiang et al., 2013). This paper, therefore, represents an important addition to the emerging literature on crime in developing countries, where many of the factors generally associated with crime—e.g., high levels of poverty and inequality, low education, and low state capacity—are found in more extreme form than in advanced

[1] Extensive reviews (see e.g., Draca and Machin, 2015; Levitt and Miles, 2006) using bibliometric evidence show a rise of these studies in the recent time.

economies.

The remainder of the paper is structured as follows. In Section 2 we describe the data and provide some background on the study area. In Section 3 we develop our empirical strategy. In Section 4 we report results on the effect of daily weather variability on a wide variety of crime types. In Section 5 we report similar results for crimes of particular interest in a developing-country setting, namely those committed against women and marginalized groups, as well as intergroup conflict between Muslims and Hindus. In Section 6 we turn to a discussion of the potential mechanisms. To help distinguish the relative contribution of economic and psychological channels, our analysis separates the impacts of annual and daily variation in weather on various crime types. In Section 7 we explore heterogeneities in the climate-crime relationship using precinct-level economic and social data, and find evidence that economic development mitigates the economic, but not the psychological, impacts of climatic variability. Section 8 concludes.

2 Data

This section documents the various sources and content of data utilized in this study. A major innovation of our paper is the original crime data we collected from nearly 600 police stations in Karnataka, which gives the day and type of every crime reported in the state from 2011–2016. We devote the next subsection to lay out the details of our crime data. The following two subsections describe the climate data, as well as the economic and demographic censuses which were also used in this study.

Crime Data

The principal innovation in our paper is the use of *daily* crime data. We contacted each of the 584 rural police stations in the state of Karnataka to collect all reported daily crimes. These police stations are the lowest units of the police department, and are the unit of analysis used in this paper. Above the police stations are the 230 circle offices, which in turn report to 91 sub-divisional police offices, which are under 31 division (i.e., district) police offices. The area covered by an individual police station, which we henceforth call a "precinct," contains an average of 70,000 individuals.

For each crime recorded, we collect information by the first incidence reporting (FIR) number, which gives the date on which the crime was first reported to officials. Each reported crime must be classified according to the pre-specified "crime group," which is simply the broad *type* of crime, as well as a sub-classification called the "crime head."[2] For example,

[2] The records also indicate the identity of the victim, the accused, and the complainant. However, for

a crime might be broadly classified as murder, with the "crime head" specifying that it was for the purpose of financial gain. In Table 1 we present summary statistics on sum of the most important types of crimes, disaggregated by season.

Climate Data

Daily weather data is collected from an unusually dense network of weather stations installed throughout the state by the Karnataka State Natural Disaster Monitoring Center (KSNDMC). Daily weather is observed at the *hobli* level, an administrative unit just above the village and below the sub-district. Among the variables collected are rainfall, minimum and maximum temperature. This data therefore provides us with a level of temporal and spatial resolution unprecedented for a developing country, and comparable to what would be available for a developed country.

Figures 1.1 and 1.2 show the time series of daily rainfall and temperature across the six years of the study period. Daily rainfall is highest during the monsoon season, which begins in late-May and early-June and continues through September. Rainfall, then falls through the post-monsoon months, though some parts of the state experience a second monsoon during October and November. The months of December through April experience very little rain. Temperatures are highest during the months of March through May, which is considered the summer, then begin to fall with the onset of the monsoon, becoming relatively temperate during the winter months.

Additional Data

In addition to the weather and crime data, we also make use of data from the demographic and economic censuses. The demographic census is decennial, with the most recent one being conducted in 2011, the first year of our study period. From this data set we collect village-level information on labor force composition, literacy rates, and population density. Because our analysis is at the precinct level, these variables are aggregated up based on the precinct within which each village lies.

We also use the economic census, which gives cross-sectional firm-level information on a variety of firm characteristics, including: firm size, industry code, gender and caste of owner, and gender of employees, among others. The most recent economic census was conducted in 2013, two years into our study period; while the previous census was conducted in 2005. From the economic census 2013, we use information on female firm ownership, as well as the number of firms employing large numbers of women. As before, these variables are reported at the village level, which we then aggregate to the level of the precinct.

anonymity purposes, this data was not collected.

Table 1 gives summary statistics for the most important variables. For the weather and crime variables, we disaggregate the statistics by season. Weather variables are given as the daily means, with the standard deviation shown in parentheses. Crime variables are given as monthly means. For socioeconomic variables from the economic and demographic censuses, we show the precinct-level mean, with the standard deviation given in parentheses.

Figure 2 shows the time series of crime incidents (per 100,000 people) for the most common types of property and violent crimes. These are described in greater detail in the subsequent analysis. As is apparent, crime shows a strong seasonal pattern, with crimes rising during the hot months, and falling sharply in the cold season. In Figure 3 we show the time series for violent and property crimes separately. Though the patterns are somewhat similar, violent crimes peak slightly earlier in the year than do property crimes, and show a more consistent seasonal cyclicality.

3 Empirical Strategy

In this section, we first present our methodology and then present the non-parametric estimates which guide our choice of methodology.

3.1 Baseline Specification

We begin by estimating the impact of weather fluctuations on crime rates at a daily resolution. The unit of observation is a precinct on a particular date during the period of the study (2011-2016). The mean daily precinct-level crime incidence (per 100,000 people) is plotted in Figure 2. Because the number of incidents is a count variable, we employ a Poisson count model in our primary specification as follows:

$$Y_{P,D} = \exp(\tau(T_{P,D}) + \rho(R_{P,D}) + f_P(D) + \pi_P + \epsilon_P), \tag{1}$$

where $Y_{P,D}$ is the number of crime incidents in precinct P on date D. Here, $\tau(T)$ and $\rho(R)$ are functions of the daily maximum temperature T and rainfall R. When rainfall is included in the estimation, we limit the sample to the monsoon season, which lasts from June to October, because little rainfall occurs outside of this season (see Figure 1.1). The function $f_P(D)$ captures time trends that are potentially precinct-specific, and π_P are precinct fixed effects. We cluster standard errors at the precinct level, in order to account for serial correlation over time. The identifying assumption is that conditional on flexible time controls (including seasonal cycles), fluctuations in daily levels of temperature and rainfall within a location (precinct) are exogenous.

Since 97.4% of the observations exhibit $Y \in 0, 1$, as a robustness test we estimate a linear probability models (LPM), with the outcome variable defined as a binary indicator for the occurrence of any crime. We also estimate ordinary least squares regression using the count of crime incidents as the outcome variable. The resulting estimates are presented in Figure A2.

In our benchmark specifications, we control for global month and year fixed effects $f_P(D) = \alpha_y + \beta_m$. Here, we have decomposed each date as $D = d, m, y$, where $1 \leq d \leq 31$ is the date, $1 \leq m \leq 12$ is the month and $2011 \leq y \leq 2016$ is the year of observation. We also test robustness to models that include month-year fixed effects $f_P(D) = \alpha_y \times \beta_m$ as well as models that control for precinct-specific seasonal cycles $\delta_{P,m}$, and even models that include precinct-month-year fixed effects.

3.2 Non-Parametric Specification

We begin by estimating a non-parametric form of the relationship between daily temperature, rainfall and crime rates. In this specification, we divide the range of observed daily temperatures (rainfall) into ten $2°C$ (2 mm) bins (denoted by j), and specify

$$\tau(T_{P,D}) = \sum_{j=1}^{10} \tau_j I_j^T(T) \tag{2}$$

$$\rho(R_{P,D}) = \sum_{j=1}^{10} \rho_j I_j^R(R), \tag{3}$$

where I_j^T and I_j^R are binary indicators of whether the values of temperature and rainfall, respectively, on the day of observation, fell in bin j. The coefficients τ_j and ρ_j are the objects of estimation.

Non-parametric specifications of weather shocks such as specification 2 have become commonplace in the climate impacts literature since they were introduced by Deschenes and Greenstone (2007). Normally, such specifications are used even though outcomes are observed at an aggregate (monthly or annual) level, and are motivated by the idea that aggregate outcomes are simply summed aggregates of daily impacts. Here, in contrast, we are able to observe each day's own impact separately and directly.

Figure 4 presents a plot of the estimated coefficients τ_j and ρ_j from specification 2 with global month-year fixed effects. Figure 4.1 plots the temperature coefficients, using the 29–32$°C$ as the reference category. Figure 4.2 plots the rainfall coefficients, using the 4–6mm bin as the reference category. The relationship between temperature and crime is remarkably monotonic, with even extreme daily temperatures continuing to display a strong and increasing impact on crime rates. The relationship between rainfall and crime is negative, with higher levels of rainfall associated with a decline in crime. The rainfall-crime relationship is noisier than that of the temperature-crime relationship, though it is still statistically significant. Both sets of estimates suggest a roughly linear association.

The coefficients for temperature suggest that for each $1°C$ decline below the reference bin, there is an approximately 1 percent decrease in the probability of the occurrence of an additional crime until the 23–25$°C$ temperature bin, at which point further declines in temperature cease to have an effect. For temperatures above the reference bin, there is an approximately 0.4 percent increase in the probability of an additional crime for each $1°C$ temperature increase. The effect of temperature spikes at the highest temperatures, with temperature above $42°C$ being associated with a 14 percent increase in the probability of a an additional crime relative to the reference temperature. For rainfall, precipitation of less than 2mms is associated with a 5 percent increase in the probability of an additional crime relative to the reference bin of 4–6mms. Elevated rainfall is associated with a countervailing decline in the incidence of crime, with rainfall above 10mms being associated, on average, with a 5 percent decline in the probability of an additional crime relative to the reference bin.

In Appendix Figure A1 we report estimates derived from Poisson specifications that include alternative fixed effects, including global year-month-week and year-month-day fixed effects. In Figure A2 we report estimates from OLS and LPM specifications. The OLS specification takes as the outcome a count variable while the LPM specification takes as the outcome a dummy variable indicating the incidence of any crime on a given day. For both the OLS and LPM specifications we report estimates of models that include the same set of global time fixed effects, as above, as well as estimates from specifications that include precinct-year and precinct-month fixed effects, which capture precinct-specific seasonal cycles and flexible annual trends. All of these specifications yield virtually identical results. The remarkable robustness of our results to these alternative modeling approaches allays any potential concerns about the use of our benchmark specification. We therefore focus on specification 1—a Poisson count model with precinct, year, and month fixed effects—for the remainder of the paper.

We also study the relation between crime and climate using the above non-parametric approach for two broad categories of crimes which are usually employed in the past literature. These broad categories of crime are *property* and *violent* crimes, which are the two main types usually employed in the existing literature (see the data section for the categorization of crime types). In figures 5 and 6, we report estimates of the impacts of temperature and rainfall on property and violent crimes separately. The results indicate a stark contrast between the two types of crime. Violent crimes display a strong and monotonic response to elevated temperatures, whereas property crimes display a *decrease* at higher temperatures, which is strongest as temperatures rise above $38°C$. Similarly, the negative relationship between rainfall and crime is largely driven by violent crimes, with no evidence for a relationship between rainfall and property crime.

4 Results

The non-parametric estimates suggest a linear association between crime and both temperature and rainfall. We therefore estimate models in which temperature and rainfall are specified as having linear effects on the outcomes of interest i.e., with the functions $\tau(T)$ and $\rho(R)$ specified to be linear in temperature (in $^{\circ}C$) and rainfall (in mm), respectively.

4.1 Baseline Results

Table 2 reports the resulting estimates for all crimes, and separately for property crimes and violent crimes. In Columns (1), (3), and (5) we use the entire sample, while in Columns (2), (4), and (6) we limit the sample to the monsoon season, June–October, since little rainfall occurs outside of this period. The estimates suggest that an increase of one degree Celsius in daily maximum temperature is associated with a 0.6 percent increase in the expected crime count on a given day. This effect is entirely driven by violent crimes, for which we estimate a 0.8 percent increase in probability of an additional crime with each $1^{\circ}C$ temperature increase; while property crime, if anything, slightly declines in response to higher temperatures, though not during the monsoon season. Rainfall displays similar effects, causing a decline in the probability of an additional crime of 0.3%. This effect is substantially larger for violent crimes (0.4%) than for property crimes (0.1%), and is measured with greater precision.

One might be concerned that the results reflect the effect of weather variation on the timing of crime *reports*, but not on the actual incidence of crime. This would be particularly true of rainfall, which may cause a delay in the reporting of crime due to the difficulty of traveling. A related concern is that the effects of weather variation on crime may simply shift the *timing* of crime, with high temperatures for example accelerating the incidence of crimes that would have otherwise occurred at a later date. To explore these possibilities, in Appendix Table A3 we report the effects of lagged daily weather on daily crime. In columns (1)–(4) we use the full sample while columns (5)–(8) are restricted to the monsoon season. Temperature on the day preceding the criminal incident displays a significant effect that is similar in magnitude to that of same-day temperature; while in the monsoon season temperature variation also affects crime with a two-day lag. Rainfall has no lagged effect on crime, though in results not shown we find that extremely high levels of rainfall do reduce crime up to a two-day lag.

These results indicate that changes in crime due to same-day weather variation do not simply shift the timing of crimes that would have occurred anyway. The similarity of the one-day lag to the same day temperature changes suggests that elevated temperatures continue to increase crimes even after they have passed, which may indicate that tensions arising on a hot day can instigate conflicts that carry over to the following day. It is also possible that some of the lagged effects are due to delays in the reporting of crimes, or that they are due to the high correlation in daily weather. In any case, the occurrence of lagged reporting or correlated weather will only bias the results towards zero, but don't fundamentally undermine the association of crime and weather presented in our baseline results.

4.2 Seasonal Heterogeneity

In Table A1 we estimate the effect of daily weather variation separately in each of the three seasons: summer (March–May), monsoon (June–October), and winter (November–February). The effect of elevated temperature on violent crime is positive and significant in all three seasons, although it is somewhat smaller in magnitude during the winter season, when hotter days are relatively rare. For this reason, we exclude the winter season from our baseline specifications in the remainder of the paper. All our results are robust to the inclusion of the winter months, though the coefficient falls slightly in magnitude.

4.3 Impacts on Individual Crime Types

In Table 3 we show the results for a variety of individual crimes. Column (1) gives the temperature coefficient when using the hot seasons, while Columns (2) and (3) give the temperature and rainfall coefficient when limiting the sample to the monsoon months. For property crimes, there is virtually no relationship between daily crime and weather, save for small declines in theft and cheating at higher temperatures. In stark contrast, virtually every violent crime shows the same patterns as was found for aggregated violent crime: high temperatures are associated with increased probabilities of all five violent crimes, and range from a 0.9 to a 1.3 percent increase in the probability of crime count with each additional $1°C$ increase in temperature. In addition, arson, auto accidents, gambling, and various forms of unnatural death (death due to drowning, electrocution, burning, and other accidental deaths) also increased with higher temperature.

We also see a similar pattern with respect to rainfall, where all violent crimes show a statistically significant decline at higher levels of rainfall. In addition, several property crimes also decline with rainfall, though the effects are smaller and less uniform than those for violent crime. We also see that gambling declines with higher levels of rainfall, while unnatural deaths increase with higher rainfall.

5 Crimes Against Vulnerable Populations

In addition to more typical types of crimes such as murder, theft, and assault, developing countries tend to have a high incidence of identity-based crimes, such as those driven by gender, religion, and ethnicity. Such crimes are more common in developing economies due to their higher levels of ethno-linguistic fractionalization, and the rapidly changing social status of women and various marginalized groups. With respect to India, some of the more important fault lines include gender divisions, Hindu-Muslim conflict, and cleavages based on caste. Due to the importance of these crimes in India, and in developing countries more generally, we next give a more detailed analysis of their relationship to daily weather shocks, which may differ in important ways from more traditional property and violent crimes. We describe our results below.

5.1 Crimes against women

In Table 4 we explore the effects of daily weather variation on crimes against women. The crimes against women included in our sample are dowry-related murder and domestic abuse, non-dowry-related domestic abuse, public harassment, and rape. It is important to note that the vast majority of rapes reported in our data set are committed by family members or other people known to the victim. There are statistically significant increases in the expected count of harassment and rape with elevated temperatures, which increase by 1.0 and 0.9% with each $1°C$ increase in temperature. Dowry-related crimes are unaffected by daily temperature, which is consistent with the null results for other types of property crime. In contrast, non-dowry domestic abuse increases with temperature (though only during the monsoon season), which suggests it is driven by the same psychological channels as found for other types of violent crime.

Rainfall has a negative relationship with harassment, consistent with the hypothesis that rainfall affects crime primarily through its effects on social interactions, as high rainfall would reduce public interactions between men and women. We also see a decrease in domestic abuse with higher levels of rain, which is also consistent with the social interaction channel, as the corollary to a reduction in social interactions is that family members spend greater time in their homes, decreasing the exposure of women to domestic violence. A similar channel explains the decrease in rape with higher levels of rainfall, as rape primarily occurs within the home. An additional factor potentially contributing to the decline in domestic abuse and rape are the psychological effects of rainfall, as high daily rainfall, though having no immediate economic effect, may reduce stress by signaling to farmers higher expected yields. Such mechanisms are akin to that in (Card and Dahl, 2011), where domestic abuse in America is negatively related to the success of the favored sports team.

As increasing numbers of Indian women join the labor force, one might expect this transformation to empower women socially and change societal norms, potentially reducing violence against women. On the other hand, one might also be concerned that it may lead to a social backlash, or expose women to greater threat of violence due to their increased presence in public spaces. To investigate the question empirically, we focus on the relationship between violence against women and female employment and entrepreneurship. For the purpose of studying the role of female labor force participation, we use data from the economic census on the number of firms employing 15 or more women. Within the Indian context, firms of this size are considered to be large, and their emergence in rural areas has been a major catalyst for female formal-sector employment. We calculate the median number of firms which employ more than 15 women, and create an indicator variable that takes a value of 1 for precincts above this value. For female entrepreneurship, we use information from the Economic Census on the percentage of firms owned by women. Because female firm ownership is skewed to the right, with most precincts having very low rates of female firm ownership, we divide the sample into areas where the rate of female firm ownership is above or below 25 percent, corresponding to the 85th percentile of female firm ownership.

Appendix Figure A4 shows the time series incidence of harassment, dowry-crime, and rape disaggregated by the female labor force participation measure described above. Both harassment and dowry crimes are substantially higher where there is greater female labor force participation. However, the incidence of rape is no different across the two samples. The corresponding regression coefficients are given in Columns (1), (4), and (7) of Table 5, where we regress the three types of gender crime on dummy variables for female labor force participation and female entrepreneurship. As can be seen, there is an approximately 30 percent increase in the probability of an additional crime occurrence for both dowry-related violence and harassment in areas with higher female labor force participation. There is also a 20 percent reduction in the probability of an additional incidence of harassment in areas with higher female entrepreneurship.

Looking at the mediating effect of labor force participation and entrepreneurship, we find that the relationship between rainfall and harassment is somewhat attenuated where there are more female-owned firms, and that the relationship between harassment and temperature is somewhat larger where there is more female employment, though the latter is measured imprecisely.

Though the coefficients cannot be interpreted as causal, the level effects are striking. It appears that the entry of larger numbers of women into the workplace exposes them to greater harassment. In addition, the increase in dowry crime with greater female employment may indicate that in-laws seek to appropriate the higher female incomes generated by this employment. Countering these disturbing effects are the substantial decline in the harassment of women where a larger share of firms are owned by women, though it is unclear what the direction of causality is here.

5.2 Crimes Against SC/STs and Muslims

As discussed in Burke et al. (2015), the weather variation associated with increases in interpersonal crime is similar to that for intergroup conflict, including civil war. Our data allows us to contribute to this literature using the incidence of Hindu-Muslim violence, as well as violence against SC/STs. We therefore use our baseline specification to estimate the effect of daily weather variation on intergroup conflict. The results are given in Table 6. Elevated temperatures are associated with large increases both in Hindu-Muslim violence and attacks on SC/STs. The magnitude of the increase in Hindu-Muslim violence is striking, and is nearly twice that for violent crimes more generally. There is also a negative relationship between rainfall and Hindu-Muslim violence, the magnitude of which is four times larger than that for violent crimes.

These results represent an important contribution to our understanding of the drivers of inter-group conflict. While some research has shown that elevated temperatures are associated with an increase in Hindu-Muslim riots, the mechanism is generally regarded as being economic (Bohlken and Sergenti, 2010). Indeed, the preponderance of the literature on Hindu-Muslim violence stresses the strategic and economic factors that underlie this phenomenon (Mitra and Ray, 2014).[3] The findings shown here indicate that inter-group conflict can be triggered by psychological factors in much the same way as interpersonal violent crime. In addition, daily rainfall has a negative association with Hindu-Muslim conflict, which moreover is dramatically larger in absolute magnitude than that for any other crime. We are unaware of other research showing such an effect of daily rainfall on inter-group violence, though this finding is reminiscent of research from the US showing the negative effect of rainfall on Tea Party rallies (Madestam et al., 2013).

6 Mechanisms

In the previous section, we reported compelling evidence of a causally identified, short-term (daily) impact of weather fluctuations on the incidence of crime. In this section, we discuss some of the potential mechanisms that may be driving this association. We begin by presenting what we believe to be the most plausible mechanisms: a psychological mechanism in the case of temperatures, and a reduction in social interactions in the case of rainfall. We

[3] Mitra and Ray (2014) present a model in which ethnic conflict is strongly influenced by changes in the economic circumstances of groups. These authors show that long-run changes in incomes are associated with changes in the incidence of Hindu-Muslim riots.

then discuss alternative mechanisms based on economic and other channels, and provide evidence against such interpretations.

6.1 Psychological Impacts of Elevated Temperatures

The patterns with respect to daily temperature variation and daily crime are strongly suggestive of a psychological mechanism being at play. First of all, because the increase in crime occurs on the same day as the elevated temperature, it is unlikely that the increase in crime is occurring due to the economic effects of temperature. Though research has shown that elevated daily temperatures do in fact cause a reduction in non-agricultural output, these effects are likely driven by reductions in worker efficiency due to ergonomic factors (Hsiang, 2010), which would also likely *reduce* crime, and in any case will only lead to significant losses of income over time. Further evidence against an economic channel comes from the fact that the effect of temperature on crime occurs entirely for violent crimes (Figure 5), with property crimes in fact showing a small decrease with extremely high temperatures.

While the relationship between temperature and crime is likely driven by elevated aggression, there may also be some general erosion of cognitive functioning at work. For example, several papers have shown that test scores decline in hot weather (Garg et al., 2016; Park, 2016). This would help to explain the increase of some crimes having no clear relationship with elevated aggression, such as unnatural deaths, gambling, and arson (Table 3). With respect to auto accidents, it is possible that both mechanisms are at play, with heat-induced aggression leading to an increase in accidents due to "road rage," while diminished cognitive functioning leads to a general deterioration in driving ability.

6.2 Social interactions

The patterns with respect to rainfall are more complicated, and can plausibly be explained through the effect of rainfall on social interactions, with low rainfall allowing more social interactions, and high rainfall fewer. Previous researchers have posited that rainfall may affect conflict through its effect on transportation conditions, with higher rainfall reducing the likelihood of actors coming into contact with one another (Miguel et al., 2004). Our results show that crime, at least, does indeed decline with higher levels of daily rainfall, providing some of the first evidence for the impact of rainfall on conflict through non-economic channels. This finding should sound another note of caution for identification strategies using rainfall as an instrument for income (Sarsons, 2015).

One might be concerned that the effects of daily rainfall are driven not by changes in the incidence of crime, but rather in the reporting of crime, as individuals may delay the reporting of crime on days where rainfall levels are high. While in principle crime reports should record the day on which the crime occurred, and not on which it was reported, there may be some level of reporting error. We take three measures to account for this possibility. First, we test for whether the crimes affected by rainfall are those for which social interactions are particularly important. Second, we look for evidence that there has indeed been a change in social interactions. Finally, we test for lagged crime effects: if rainfall affects crime only through reporting, then the following day should show an off-setting change in crime rates.

All three methods validate the explanation for the effect of rainfall on crime as being due to logistical factors. First, we see that the increase in crime with low rainfall occurs largely for violent crimes, which depend more on social interactions.[4] Second, we find that there is a no change in the number of auto accidents when rainfall levels are high. Because driving is more dangerous on rainy days (Qiu and Nixon, 2008; Konstantopoulos et al., 2010), the fact that there is no increase in auto accidents suggests that there are fewer cars on the road. Finally, we find no evidence that the relationship between rainfall and crime has a different sign for lagged rainfall (Table A3), indicating that deferred reporting is unlikely to account for the results, and that crime has not been simply displaced in time.

An important point worth noting is that the increase in crime with elevated temperatures and deficient rainfall are strongest for violent crimes, with property crimes if anything declining with elevated temperatures, and increasing far less with deficient rainfall. Given the relatively similar effects of annual weather shocks on property and violent crimes found throughout the literature, this would suggest that the annual crime-weather relationship is driven largely by the economic effects of seasonal weather variation for property crimes, but that violent crimes are driven as well by the psychological and social effects associated with daily weather variation. This is consistent with the greater importance of economic factors generally assumed to prevail in the commission of property crimes. Below, we explore this hypothesis in greater detail through regressions that include both daily and seasonal weather variables.

6.3 Economic Channels

6.3.1 Short Term Economic Channels

One potential concern is that daily weather shocks may have immediate economic effects that are driving the weather-crime relationship. For example, if labor demand declines on days with lower levels of rainfall or higher temperatures, and if households are sufficiently dependent on daily wages, then economic channels might be present even with the daily weather-crime relationship.

[4]Most valuable assets in India are stored within the home, so that property crime does not require the congregation of large groups.

To test this, in Table A2 we separately estimate the baseline specification for each day of the week separately, as well as for public holidays, both secular and religious. We see that the weather-crime relationship is no smaller on non-working days than on working days, and indeed that temperature-crime relationship is considerably larger on Sundays and holidays than it is on working days. This is strong evidence against there being an economic channel mediating the daily weather-crime relationship, and if anything suggests that being engaged in work reduces the ability or proclivity of resorting to violence. The higher temperature effect on weekends and holidays may be due to larger social gatherings and/or more alcohol consumption, which could amplify the temperature effect.

6.3.2 Seasonal Economic Channels

Our analysis is concerned principally with demonstrating the daily effects of weather on crime, which we argue operates primarily through non-economic channels. This raises the question of the extent to which the well-documented relationship between *annual* weather variation and crime is driven by the aggregation of these daily effects, or whether there are additional economic channels that have an independent effect on crime.

Figure 3 provides suggestive evidence for the mechanisms driving the effects of daily and seasonal weather on crime. Specifically, violent crime moves in close tandem with temperatures, peaking in May when temperatures are highest, and falling during the cooler winter months. Property crime displays a slightly different seasonality, peaking towards the latter months of the monsoon season (late-August), then declining through the winter. Significantly, the patterns for property crime closely match those for rainfall and the planting season, while those for violent crime closely match those for temperature (Figure 1). Additional evidence comes from the daily crime regressions (Table 2), where we find that daily temperature and rainfall have no effect on property crime, despite the well-known effects of annual weather variation on property crime, suggesting that property crimes are driven primarily by economic factors associated with weather variation at the seasonal and annual levels. Violent crimes, in contrast, show large effects from daily weather variation, indicating that at least part of the annual effects are driven by these non-economic factors.

To make further progress on this, we estimate a specification which includes seasonal and daily weather variables in a single regression. The seasonal variables are specified as the mean daily rainfall and temperature during the monsoon months (June–October). This variable takes a single value for all observations within a given year. The results are given in Table 7. In columns (1), (4), and (7) the regression is estimated at the police station-year level, with total crime during the monsoon season regressed on mean temperature and rainfall during the monsoon season. In the remaining columns the regression is estimated at the precinct-day level, with the sample restricted to the months of the monsoon season. For the latter, the seasonal weather variables take a single value for all observations in a given year.

When conducting the analysis at the police station-year level, we find that the expected count of crime increases by approximately 1.7 percent with each $1°C$ increase in the mean monsoon-season temperature, and that the effect is relatively similar for property and violent crimes. Rainfall also exerts a large effect on crime, with each 1 mm increase in the mean daily rainfall associated with a 1.4 percent decline in the count of crime, which is somewhat larger for property crimes than violent crimes. When daily weather variables are included, the effects of seasonal weather variation are relatively similar for property crime, but become smaller for violent crime.

Three findings stand out. First, property crime is only affected by seasonal weather variation, consistent with the Becker (1968) model emphasizing the economic incentives to commit crime. Second, violent crime is affected by both daily and seasonal weather variation, indicating that both economic and psychological channels mediate the weather-crime relationship for violent crime. Finally, the seasonal effects of weather are quite similar for both property and violent crimes. However, a substantial share of the relationship between weather and violent crime is actually driven by daily variation, as evidenced by the fall in the seasonal weather coefficients when the daily variables are included. This may explain why most research finds rainfall and temperature shocks to have such similar effects on crime, despite the far smaller effect of the latter on agricultural output (Blakeslee and Fishman, 2017).

We also estimate the respective roles of economic and non-economic channels in mediating the effect of weather variation on intergroup conflict and violence against women. The results are given in Appendix Table A5. One of the most striking results is the large effect of seasonal rainfall variation on Hindu-Muslim conflict, which is in fact substantially larger than the daily effects. This suggests that economic factors play a larger role than non-economic factors in driving the effect of weather on intergroup conflict, and gives support to the literature emphasizing the economic sources of intergroup conflict (Mitra and Ray, 2014). Seasonal weather variation also plays a disproportionate role in the incidence of rape. Finally, we also find a positive effect of seasonal rainfall on dowry violence, which may be indicate that a “looting” mechanism is at play, which would also be consistent with the higher levels of dowry violence observed in areas with higher female labor force participation.

In addition, we estimate the effect of seasonal (monsoon) weather variation on crime during the months after the monsoon, which is here defined as November through March of the following year. Seasonal weather variation has no effect on violent crime during the post-monsoon period, but continues to exercise an effect on property crime. The effect of temperature is substantially larger than that of rainfall, perhaps due to the effect of elevated temperature in killing livestock and destroying other productive assets. The persistence of the temperature effect during post-monsoon period may also be a factor in the disproportionately large effect of seasonal temperature on crime relative to its much smaller effect on agricultural output.

The seasonal distribution of crime and the weather-crime relationship may also help to shed light on the causal channels mediating the rainfall-crime relationship. Specifically, it is unclear whether the increase in crime with low seasonal rainfall and high seasonal temperature occurs due to the decline in incomes for (small holder) farmers, or whether it is income losses for (landless) agricultural laborers driving this relationship. While landowners only realize their agricultural incomes in the fall when the harvest season arrives, agricultural laborers also receive agricultural income during the monsoon months when they are employed in planting the crops. The fact that property crimes increase during the monsoon season—as shown in the regression results of Table 7 and the seasonal crime distributions in Figure 3.1—therefore suggests that it is agricultural laborers who commit property crimes, and that the resort to property crime commences relatively soon after the negative shock to labor demand with deficient rainfall.

7 Will Economic Development Dampen the Impact of Climatic Variability on Crime?

An important question is whether higher levels of economic development may help to mitigate the effect of weather variation on crime. There is some reason to suspect that such may be the case. For example, Miguel and Satyanath (2011) show that the rainfall-economic growth (and civil war) relationship in Sub-Saharan Africa is not present after 1999, which the authors attribute in part to growth in the non-agricultural sectors, while Burgess et al. (2013) show that the heat-child mortality relationship exists only for rural areas, with no effect in urban areas.

We first estimate the role of various socioeconomic characteristics in mediating the effect of daily weather variation on daily crime. We focus on the share of the workforce engaged in agriculture, the population density, and the literacy rate. The results are given in Table A4. The outcome variable is the incidence of violent crime, as these were the categories for which daily weather variation had the largest effect.

Both areas with large non-agricultural labor forces and areas with high population density are associated with larger effects of temperature on violent crime, though only the latter is also found during the monsoon season. Literacy rates also mediate the effect of temperature, though only in the monsoon season, where high literacy areas experience a far smaller increase in crime when temperatures are high.

Because we have argued that the economic channels mediating the weather-crime relationship are operational primarily for seasonal weather variation, we next focus on the role of economic development in mediating the effects of both daily and seasonal weather variation on crime. For this, we focus on the size of the agricultural labor force. In Figure 9, we show the time series of property and violent crimes disaggregated into areas with non-agricultural labor force shares above and below the median (23%). Areas with a larger non-agricultural workforce had a slightly higher incidence of violent crime, and a substantially larger incidence of property crime. This cross-sectional comparison suggests that the increasing opportunity cost to crime with rising incomes may be swamped by the increasing returns to crime due to the greater amount of appropriable wealth, as in Demombynes and Özler (2005).[5] Interestingly, despite the level shift according to the size of the non-agricultural labor force, the seasonal patterns of crime are strikingly consistent across the two samples, suggesting that the level of development may have only a small effect in mitigating the effects of daily and seasonal weather variation.

In Table 8 we interact the non-agricultural labor force variable with both the daily and seasonal weather variables. The effect of daily weather variation on crime is relatively similar in precincts where the agricultural workforce is below and above the median. The effect of seasonal weather variation on crime, however, occurs entirely in precincts with large agricultural labor forces. Each $1°C$ increase in mean daily temperature is associated with a 2.4 percent increase in crime in areas with large agricultural labor forces, but has no effect where the agricultural labor force is below the median. A similar pattern holds for rainfall, with each additional mm of mean daily rainfall being associated with a 3.4 percent decline in crime count in precincts with large agricultural labor forces, but no effect where the agricultural labor force is below the median. The differences for both the temperature and rainfall coefficients across low- and high-agricultural workforce precincts is statistically significant at the 1 percent level.

8 Conclusion

Understanding the mechanisms underlying the associations between climatic variability and various types of conflict and crime remains a persistent gap in the literature. In this paper, we use large-scale data of high temporal and spatial resolution to make progress on this question.

Our results highlight the importance of non-economic channels in the weather-crime

[5] Demombynes and Özler (2005) find that property crime is more prevalent in areas where the poor are in closer proximity to wealthier households (i.e., the "looting" mechanism).

relationship, as demonstrated by a remarkably robust association between daily weather fluctuations (both temperature and precipitation) and the occurrence of a wide variety of crime types. These results hold not only for "classic" violent crimes such as murder, but also for forms of aggression—such as intergroup conflict and violence against women—that had previously been studied primarily through an economic lens. Simultaneously, the results found in this paper lend strong support to the hypothesis that an agricultural income mechanism plays an important role in the weather-crime relationship, as was conjectured, but not proven, in a number of previous studies. In that, they provide novel evidence for the economic theory of crime.

These findings indicate that research on the climate-conflict relationship must take greater account of the role that psychological and logistical effects of weather have on the incidence of conflict, even where conflicts originate primarily in social cleavages. While researchers have generally recognized the potential role of these alternative mechanisms, ours is one of the first studies to quantify the relative contributions of economic and non-economic channels. For rainfall in particular, our results demonstrate a surprisingly large contribution of non-economic factors, consistent with the results found in Sarsons (2015).

The results presented here are also important to assessments of the potential future impacts of climate change in developing countries. In contrast to climatic variation which operates through its effect on economic output, effects mediated by psychological channels are less likely to be susceptible to amelioration by either economic development or economic adaptation to climate change. We find no evidence to suggest that areas with higher levels of economic development or female labor market participation experience smaller crime responses to climatic variability.

One significant aspect of our study is that it takes place in a region with persistently high temperatures. Residents of Karnataka experience seasonal temperatures that range between 30–35°C throughout most of the year. Yet even individuals who are accustomed to such perennially high temperatures continue to display a strong tendency for violence when a single day's temperature makes a comparable, unexpected rise. This may indicate that physiological acclimatization has limited potential to reduce the future impacts of climate change.

However, even if the potential of economic or physiological adaptations to reduce the impacts of climatic variability on crime is limited, there is some evidence that carefully tailored policy interventions addressing the non-economic drivers of crime may prove more effective. Among these are: reshaping attitudes (Dhar et al., 2018), cognitive behavioral therapy (Blattman et al., 2017), and decriminalization (Adda et al., 2014). Identifying and evaluating such interventions is an important subject for future studies.

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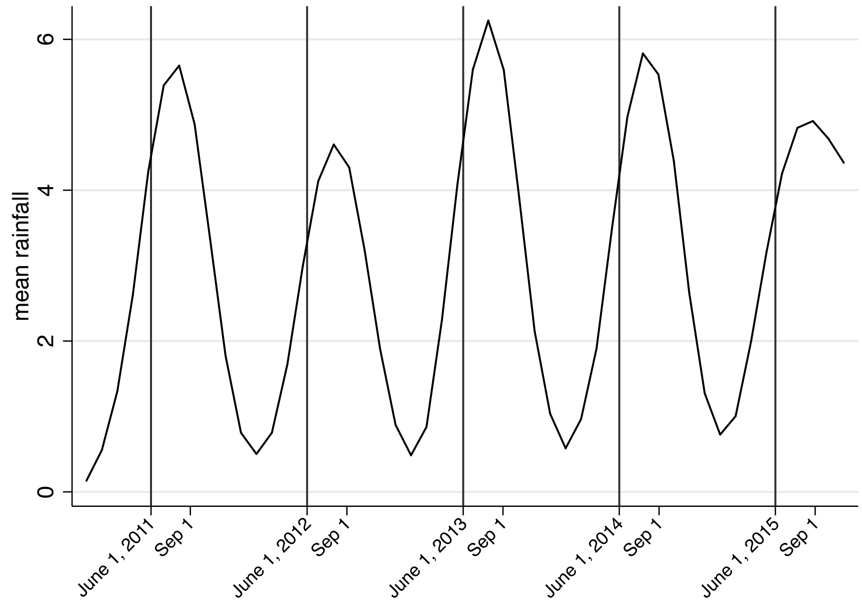
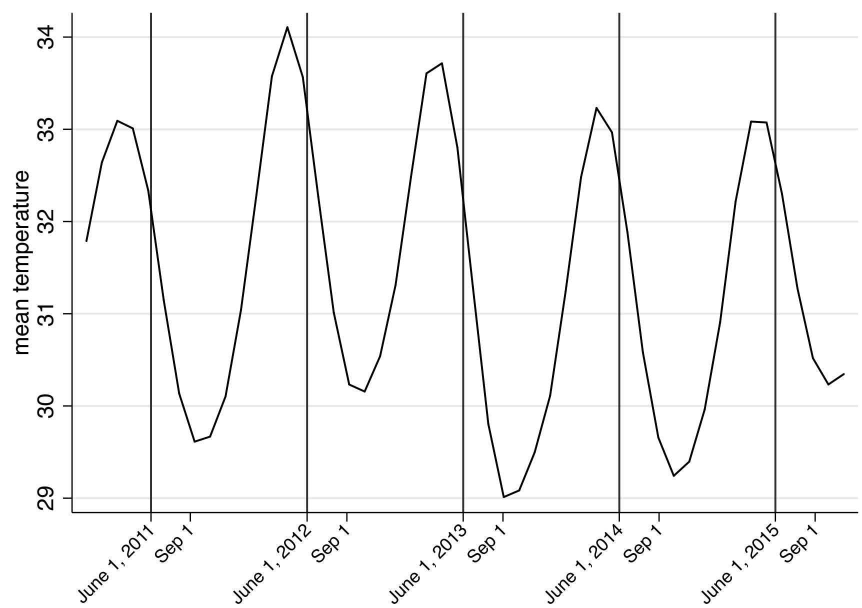
Figure 1: Daily Weather



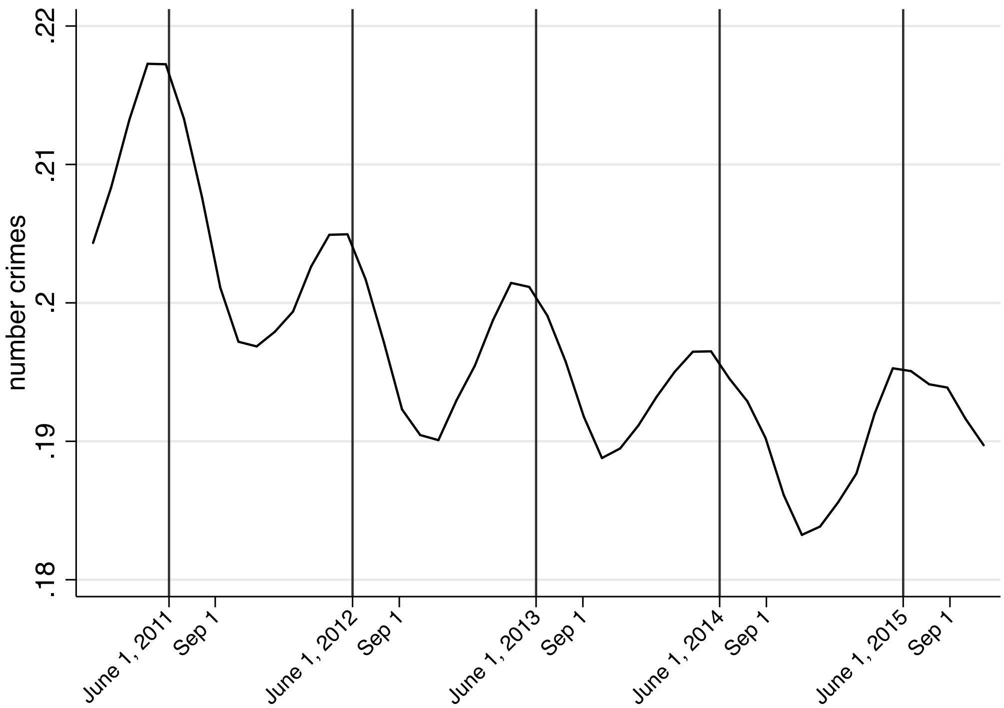
1.1: Mean Daily Rainfall



1.2: Mean Daily (Max) Temperature

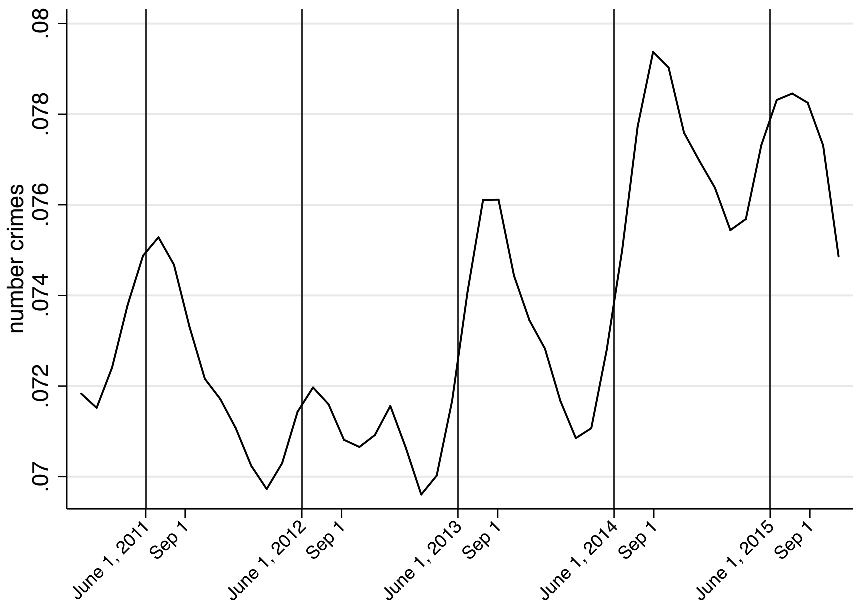
Notes: Figure 1 shows the mean daily weather for the study period. Figure 1.1 shows the mean daily rainfall in millimeters. Figure 1.2 shows the mean maximum temperature in degrees celsius.

Figure 2: Statewide Daily Crime

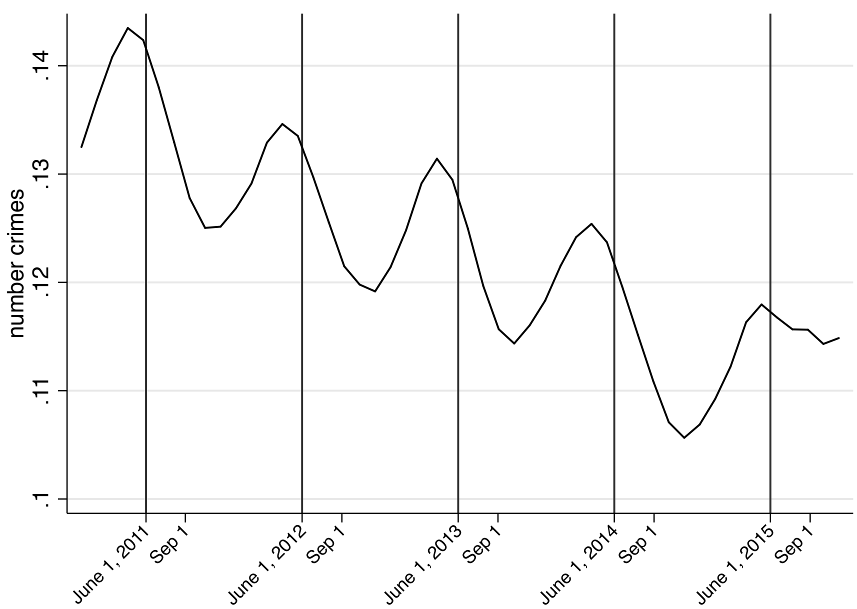


Notes: Figure 2 shows the statewide average daily incidence of crime for the study period. Crimes include all registered property and violent crimes.

Figure 3: Daily Crime



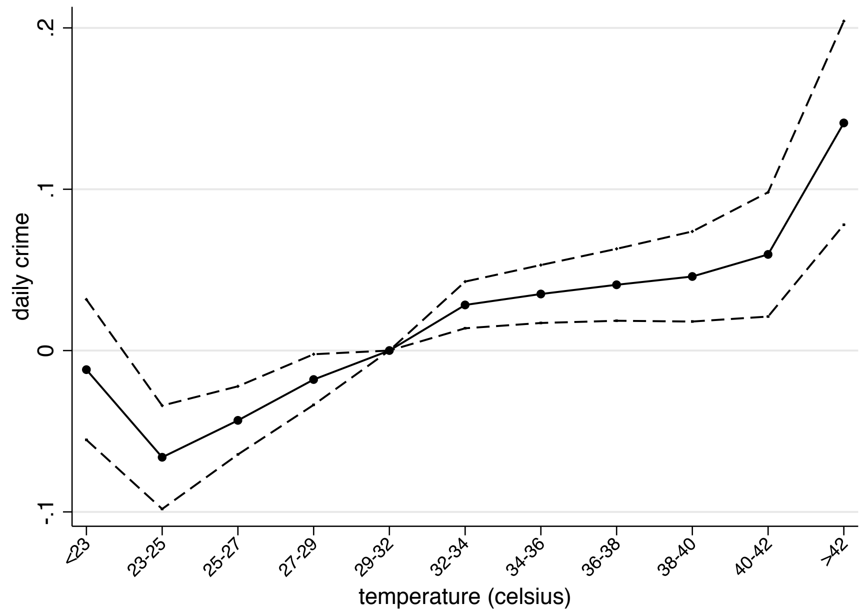
3.1: Property Crime



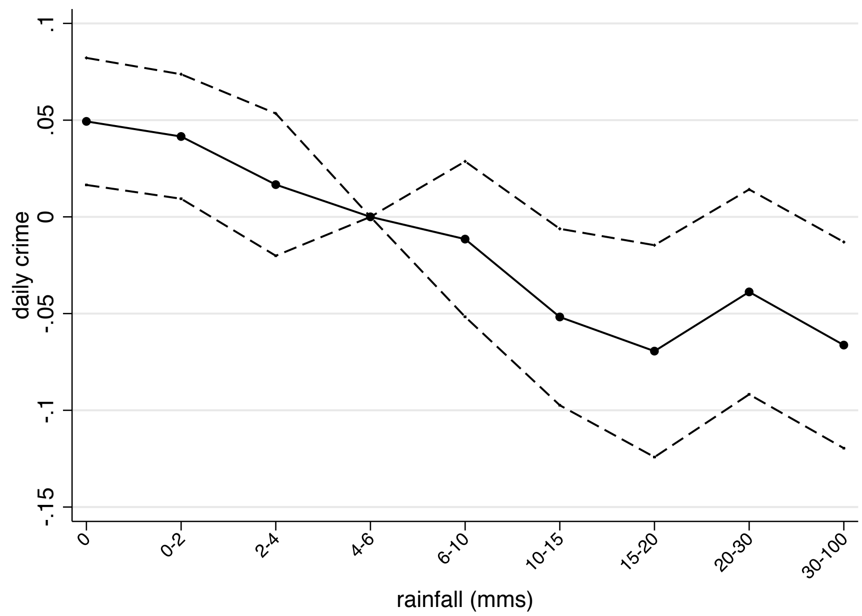
3.2: Violent Crime

Notes: Figure 3 shows the statewide average daily incidence of crime for the study period. Figure 3.1 shows property crimes while Figure 3.2 shows violent crime.

Figure 4: Daily Weather and Crime



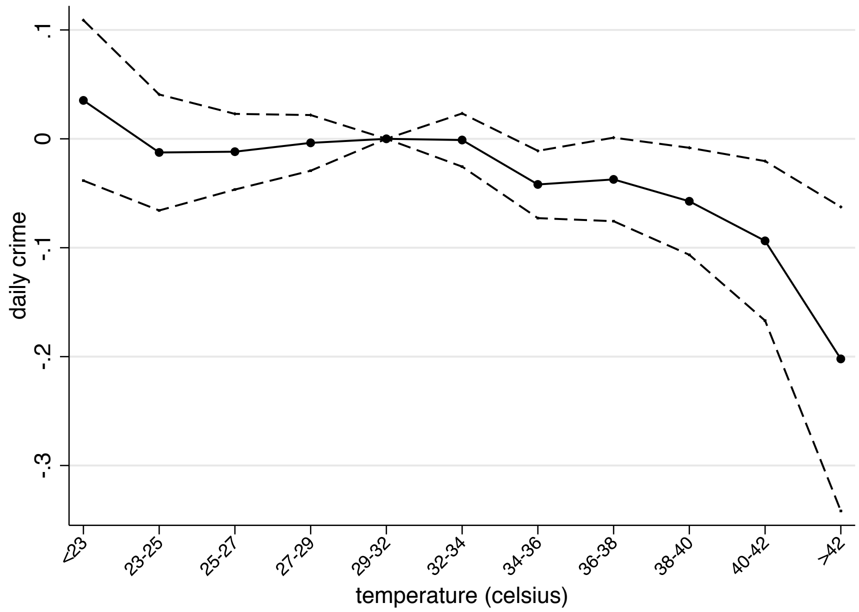
4.1: Temperature and Crime



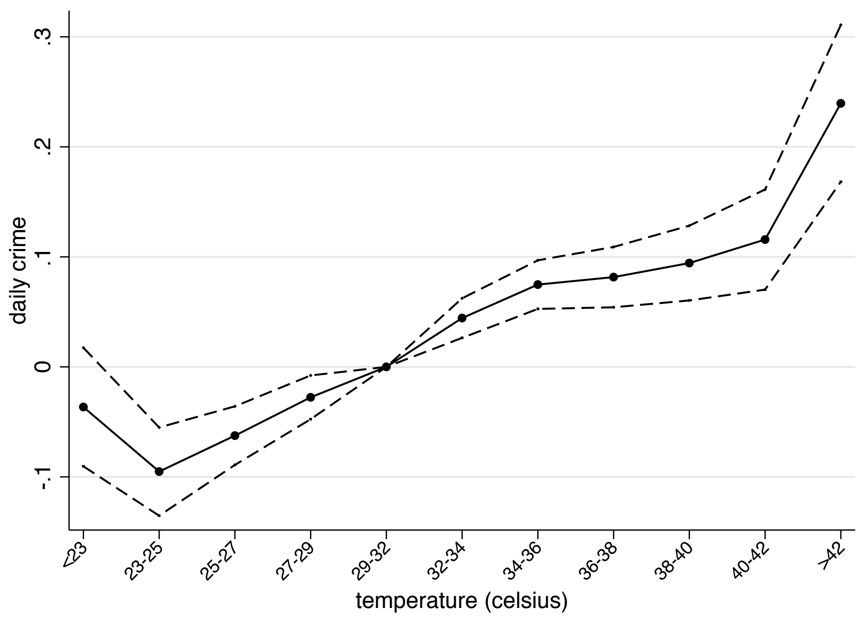
4.2: Rainfall and Crime

Notes: Figure 4 plots the estimated impacts of daily temperature on crime incidence, as per specification 2. Figure 4.1 plots temperature bin, with temperature of 27–30 degrees Celsius as the reference category, and Figure 4.2 shows rainfall bin coefficients, with daily rainfall of 4–6 millimeters as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 5: Daily Temperature and Crime



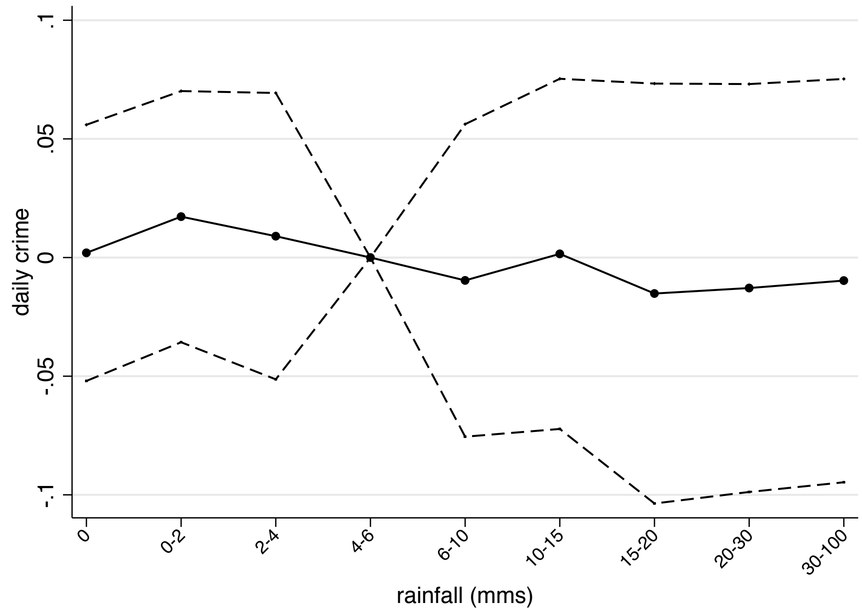
5.1: Property Crime



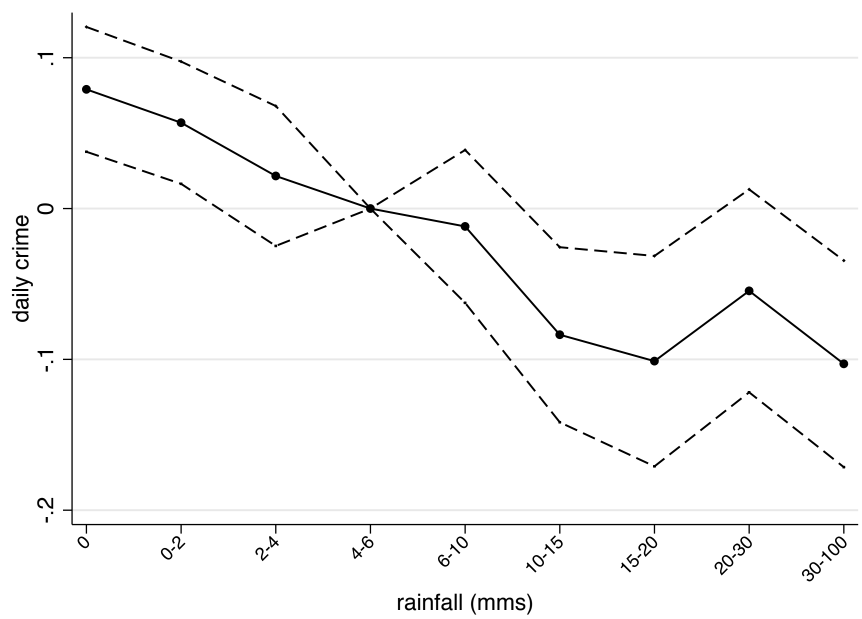
5.2: Violent Crime

Notes: Figure 5 plots the estimated impacts of daily temperature on property (Figure 5.1) and violent (Figure 5.2) crime separately, as per specification 2, with temperatures of 27–30 degrees Celsius as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 6: Daily Rainfall and Crime



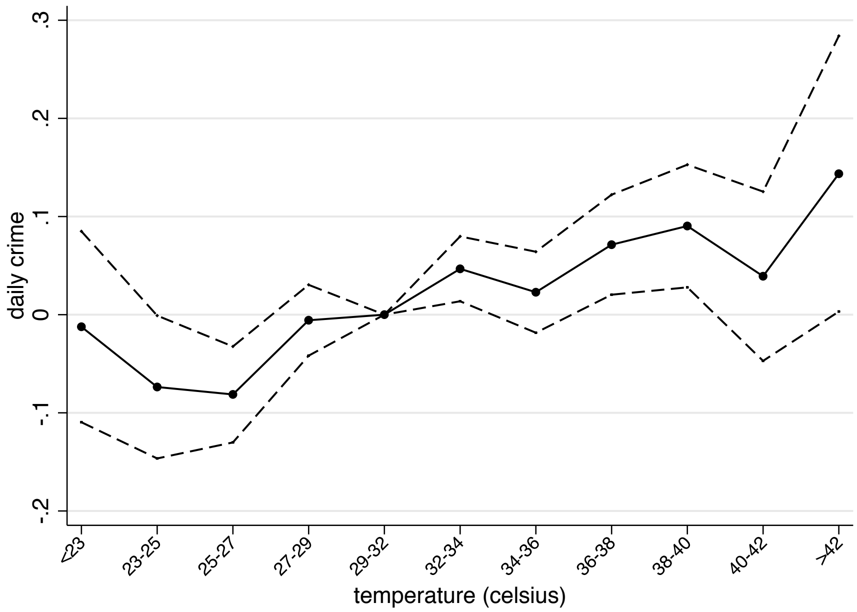
6.1: Property Crime



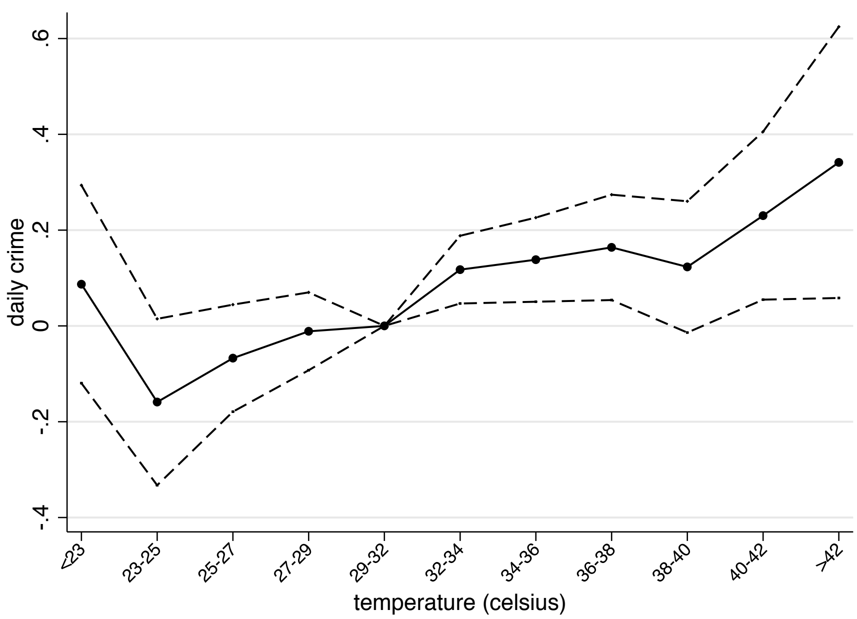
6.2: Violent Crime

Notes: Figure 6 plots the estimated impacts of daily temperature on property (Figure 6.1) and violent (Figure 6.2) crime separately, as per specification 2, with temperatures of 27–30 degrees Celsius as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 7: Daily Temperature and Crime



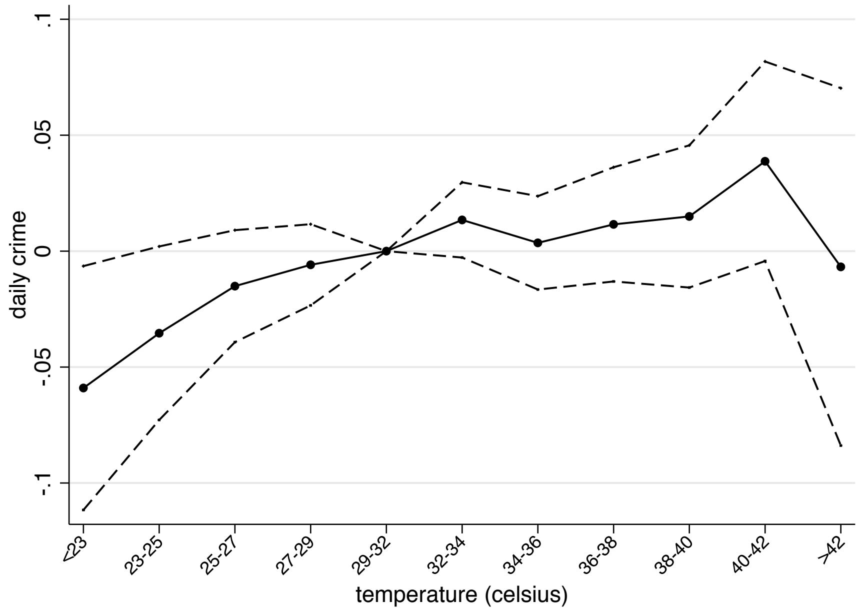
7.1: Gender-related Crime



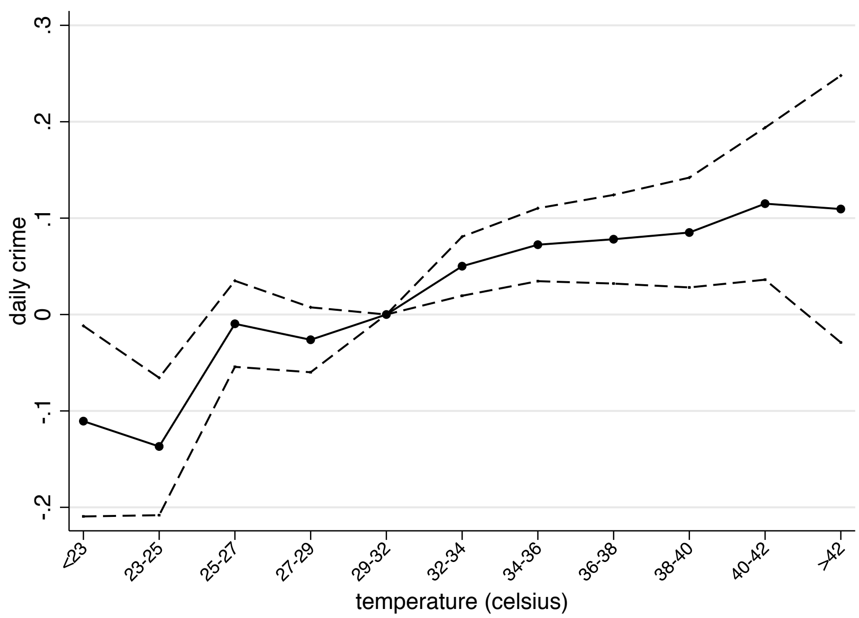
7.2: Intergroup Crime

Notes: Figure 7 plots the estimated impacts of daily temperature on crimes against women (Figure 7.1) and inter-group violence (Figure 7.2) crime separately, as per specification 2, with temperatures of 27–30 degrees Celsius as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 8: Daily Temperature and Crime



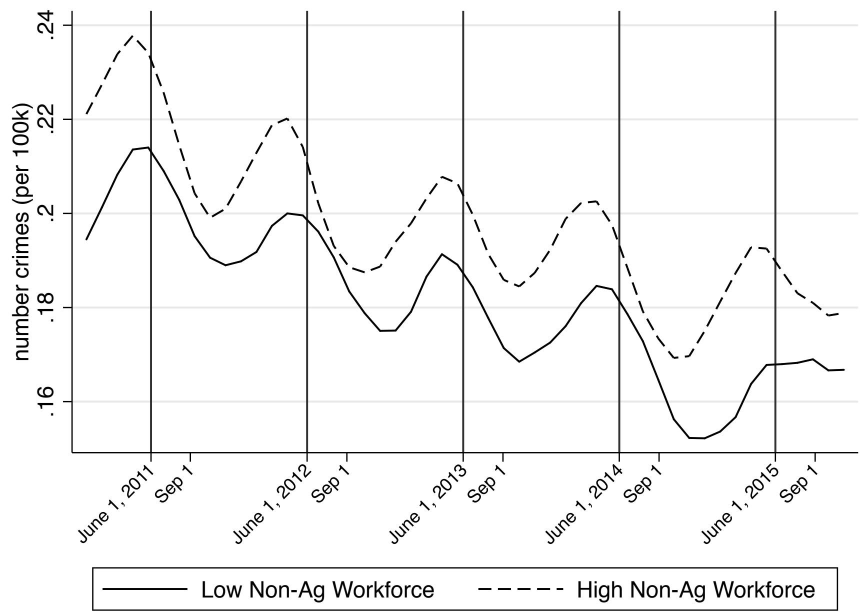
8.1: Auto Accidents



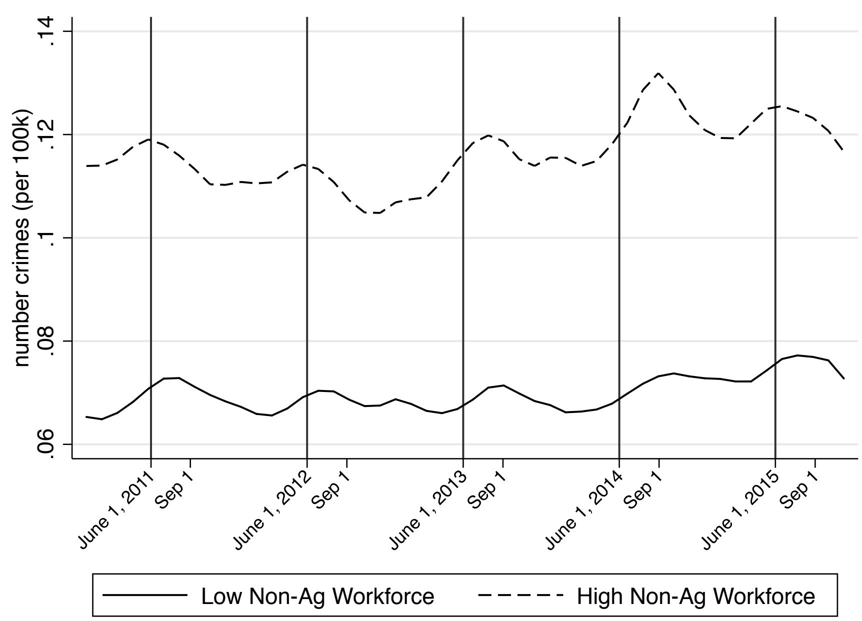
8.2: Unnatural Deaths

Notes: Figure 8 plots the estimated impacts of daily temperature on the number of auto-accidents (Figure 8.1) and unnatural deaths (Figure 8.2) crime separately, as per specification 2, with temperatures of 27–30 degrees Celsius as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 9: Crime and Development



9.1: Violent Crime



9.2: Property Crime

Notes: Figure 9 plots the time series of the mean frequency of daily property and violent crimes over the study period. The dashed (solid) line is for police precincts with above (below) median share of non-agricultural labor in the total labor force.

Table 1: Summary Stats

Variable	All (1)	Season: Summer (2)	Season: Monsoon (3)	Season: Winter (4)	Variable	(5)
Weather, Daily Mean					**Socio-Demographic**	
Rainfall (mms)	2.73	0.93	6.22	2.35	Population (10,000)	7.18
	(4.56)	(1.12)	(7.49)	(2.31)		(3.48)
Max Temperature (C)	31.29	33.49	29.79	29.67	Pct Workers Non-Ag	0.33
	(3.41)	(3.43)	(2.75)	(2.03)		(0.24)
Crime, Monthly Mean					Pct Ag Workers Laborers	0.45
Banditry	0.20	0.23	0.21	0.17		(0.15)
	(0.58)	(0.60)	(0.62)	(0.51)	Pct Illiterate	0.31
Theft	5.43	5.62	5.60	5.10		(0.08)
	(7.51)	(7.71)	(7.64)	(7.17)	Pct Population SC	0.21
Robbery	0.78	0.82	0.81	0.72		(0.12)
	(1.68)	(1.69)	(1.81)	(1.49)	Pct Population ST	0.09
Kidnapping	0.83	0.90	0.85	0.74		(0.09)
	(1.37)	(1.47)	(1.39)	(1.26)	Population density	2.52
Riots	4.65	5.30	4.70	4.12		(1.46)
	(4.58)	(5.12)	(4.55)	(4.12)	Sex Ratio	1.02
Murder	1.02	1.13	1.02	0.95		(0.05)
	(1.29)	(1.35)	(1.30)	(1.22)	Light Density	9.04
Assault	12.77	14.90	12.45	11.59		(5.96)
	(10.85)	(12.55)	(10.38)	(9.79)		
SC/ST	1.18	1.24	1.20	1.10		
	(1.51)	(1.57)	(1.52)	(1.44)		
Hindu-Muslim	0.18	0.16	0.15	0.22		
	(0.79)	(0.64)	(0.48)	(1.14)		
Rape	0.52	0.56	0.51	0.50		
	(0.87)	(0.93)	(0.88)	(0.79)		
Dowry	1.03	1.13	1.06	0.94		
	(1.65)	(1.80)	(1.64)	(1.55)		
Cruelty	1.98	2.22	1.98	1.80		
	(3.22)	(3.46)	(3.28)	(2.93)		
Harassment	2.78	3.03	2.84	2.54		
	(3.12)	(3.40)	(3.13)	(2.86)		

Note: This Table reports precinct-level summary statistics for key climatic, crime, and socio-demographic variables used in the analysis. Climatic and crime data are reported on a seasonal basis.

Table 2: Daily Weather and Crime

	All Crime		Property crime		Violent Crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.006***	0.006***	-0.004**	0.001	0.008***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Rainfall		-0.003***		-0.001*		-0.004***
		(0.000)		(0.001)		(0.001)
N	910367	373418	910367	373418	910367	373418
Full Sample	yes		yes		yes	
Monsoon Season		yes		yes		yes

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are separately reported for all crimes (Columns 1 and 2), property crime (Columns 3 and 4) and violent crimes (Columns 5 and 6). Columns (1), (3), and (5) report estimates from a model that only includes temperature and includes all days in the sample; and Columns (2), (4), and (6) also control for rainfall and therefore include only days falling in the monsoon months (June–October). All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1.

Table 3: Disaggregated Crimes

	Hot Seasons	Monsoon Season	
	Temperature	Temperature	Rainfall
	(1)	(2)	(3)
Property			
Burglary	-0.007**	-0.007	0.000
	(0.004)	(0.005)	(0.001)
Banditry	0.002	0.003	-0.013*
	(0.011)	(0.014)	(0.006)
Theft	-0.001	0.005*	-0.002*
	(0.003)	(0.003)	(0.001)
Robbery	0.003	0.005	0.001
	(0.007)	(0.007)	(0.003)
Cheating	-0.005	-0.005	-0.003*
	(0.004)	(0.006)	(0.002)
Kidnapping	0.003	0.005	0.001
	(0.006)	(0.006)	(0.003)
Violent			
Riots	0.009***	0.009***	-0.004***
	(0.002)	(0.002)	(0.001)
Murder	0.007*	0.006	-0.006**
	(0.004)	(0.005)	(0.003)
Attempted Murder	0.011***	0.009***	-0.006**
	(0.002)	(0.003)	(0.002)
Assault	0.008***	0.007***	-0.003***
	(0.001)	(0.001)	(0.001)
Fight	0.013***	0.008	-0.013**
	(0.005)	(0.008)	(0.006)
Other			
Auto Accident	0.002**	0.002*	0.000
	(0.001)	(0.001)	(0.000)
Arson	0.014**	0.008	0.006
	(0.006)	(0.011)	(0.005)
Gambling	0.007***	0.002	-0.002*
	(0.001)	(0.002)	(0.001)
Unnatural Death	0.005***	0.006***	0.002**
	(0.002)	(0.002)	(0.001)
Negligence	-0.010	-0.014	-0.003
	(0.015)	(0.021)	(0.006)

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are reported for specific crime types, as indicated in the leftmost column. Column (1) reports estimates from a regression that controls for temperatures alone and is estimated for all days during the hot parts of the year (March-October). Columns (2)–(4) report estimates from a model that controls for both temperature and rainfall and is therefore estimated using days in the monsoon months (June–October) only. All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1.

Table 4: Crime Against Women

	All	Dowry-Related Murder	Dowry-Related Abuse	Non-Dowry Abuse	Rape	Harassment
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Hot Seasons						
temperature	0.007***	-0.005	0.001	0.000	0.009**	0.010***
	(0.001)	(0.016)	(0.011)	(0.004)	(0.004)	(0.002)
N	618342	350016	294170	605574	538965	614912
Panel B: Monsoon Season						
temperature	0.007***	-0.000	-0.008	0.007**	0.010**	0.008***
	(0.002)	(0.019)	(0.020)	(0.004)	(0.005)	(0.003)
rainfall	-0.004***	-0.004	-0.005	-0.006***	-0.005*	-0.003**
	(0.001)	(0.006)	(0.006)	(0.002)	(0.003)	(0.001)
N	372687	161448	133318	355820	281575	364702

Note: This table gives the estimated coefficients from a linear specification of model 1 for crimes against women. Estimates are reported separately for dowry related murder (Column 2) and abuse (Column 3), non-dowry related abuse (Column 4), rape (Column 5) and harassment (Column 6). Panel A reports a temperature-only model and includes all days in "hot" months (March-October); Panel B reports a model with both temperature and rainfall controls and therefore only includes days in the monsoon months (June–October). All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1.

Table 5: Crime Against Women and Female Economic Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Harassment									
Temperature		0.011***	0.009***		0.008***	0.004		0.010***	0.005
		(0.002)	(0.003)		(0.002)	(0.004)		(0.002)	(0.004)
Rainfall			-0.004**			-0.005**			-0.005***
			(0.002)			(0.002)			(0.002)
Temp X Fem Ownership		-0.007	-0.009					-0.006	-0.007
		(0.005)	(0.013)					(0.005)	(0.014)
Temp X Fem Employment					0.005	0.008		0.004	0.008
					(0.003)	(0.005)		(0.003)	(0.005)
Rain X Fem Ownership			0.006*						0.006
			(0.003)						(0.004)
Rain X Fem Employment						0.004			0.004
						(0.003)			(0.003)
Female Ownership	-0.204**						-0.242***		
	(0.092)						(0.091)		
Female Employment				0.301***			0.316***		
				(0.074)			(0.074)		
N	1165500	613855	364105	1167600	614996	364786	1165500	613855	364105
Panel B: Rape									
Temperature		0.011***	0.010**		0.005	-0.004		0.007	-0.002
		(0.004)	(0.004)		(0.006)	(0.013)		(0.006)	(0.013)
Rainfall			-0.006			-0.008*			-0.008*
			(0.004)			(0.004)			(0.005)
Temp X Fem Ownership		-0.019	-0.023					-0.018	-0.016
		(0.016)	(0.033)					(0.016)	(0.034)
Temp X Fem Employment					0.008	0.019		0.007	0.017
					(0.007)	(0.013)		(0.007)	(0.013)
Rain X Fem Ownership			0.001						-0.000
			(0.008)						(0.008)
Rain X Fem Employment						0.006			0.005
						(0.007)			(0.007)
Female Ownership	-0.003						-0.018		
	(0.099)						(0.100)		
Female Employment				0.081			0.082		
				(0.080)			(0.081)		
N	1165500	539036	281647	1167600	539036	281647	1165500	539036	281647
Panel C: Dowry									
Temperature		-0.000	0.001		-0.000	0.004		0.002	0.005
		(0.006)	(0.007)		(0.006)	(0.007)		(0.006)	(0.006)
Rainfall			-0.001			-0.001			-0.000
			(0.003)			(0.003)			(0.003)
Temp X Fem Ownership		-0.012	-0.017					-0.012	-0.015
		(0.013)	(0.025)					(0.013)	(0.024)
Temp X Fem Employment					-0.008	-0.026		-0.009	-0.025
					(0.010)	(0.018)		(0.010)	(0.017)
Rain X Fem Ownership			-0.004						-0.004
			(0.007)						(0.007)
Rain X Fem Employment						-0.004			-0.003
						(0.005)			(0.005)
Female Ownership	0.024						-0.010		
	(0.105)						(0.104)		
Female Employment				0.304***			0.308***		
				(0.084)			(0.084)		
N	1165500	571964	329350	1167600	573105	330031	1165500	571964	329350
Full Year	yes			yes			yes		
Hot Seasons		yes			yes			yes	
Monsoon Season			yes			yes			yes

Note: This table gives the estimated impacts on crimes against women from a model that includes linear daily temperature and rainfall and their interactions with indicators of female economic participation (employment and firm ownership). Estimates are reported for harassment (Panel A), rape (Panel B) and dowry related violence (Panel C). Columns 1-3 include interactions with female firm ownership, Columns 4-6 include interactions with female employment and Columns 7-9 include both interactions. Within each of these groups, the first Column (1,4,7) reports the un-interacted level effects of female economic participation; the second Column (2,5,8) includes only temperature and its interaction; and the third Column (3,6,9) includes interactions with both rainfall and temperature. All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1.

Table 6: Group Conflict

	All	Attack on SC/ST	Hindu-Muslim Violence
	(1)	(2)	(3)
Panel A: Hot Seasons			
Temperature	0.009***	0.009***	0.015***
	(0.003)	(0.003)	(0.006)
N	598121	591475	268775
Panel B: Monsoon Season			
Temperature	0.008**	0.008**	0.011
	(0.004)	(0.004)	(0.011)
Rainfall	-0.004**	-0.003	-0.017**
	(0.002)	(0.002)	(0.008)
N	348129	341887	130390

Note: This table gives the estimated coefficients from a linear specification of model 1 for inter-group violence. Estimates are reported separately for on all such crimes, attacks on scheduled castes and tribes (SC/ST) (Columns 2) and Hindu-Muslim violence. (column 3). Panel A reports a temperature-only model and includes all days in "hot" months (March-October); Panel B reports a model with both temperature and rainfall controls and therefore only includes days in the monsoon months (June–October). All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1.

Table 7: Daily and Seasonal Weather Shocks

	All Crime		Property Crime		Violent Crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monsoon Season						
Daily Variables						
Temperature		0.005***		-0.002		0.007***
		(0.001)		(0.003)		(0.001)
Rainfall		-0.003***		-0.001*		-0.004***
		(0.000)		(0.001)		(0.001)
Seasonal Variables						
Temperature	0.017***	0.011***	0.015***	0.017***	0.018***	0.010**
	(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)
Rainfall	-0.014***	-0.010**	-0.018***	-0.013*	-0.012**	-0.009*
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.005)
N	2613	373418	2613	373418	2613	373418
Panel B: Post-Monsoon Season						
Daily Variables						
Temperature		0.002		-0.011***		0.009***
		(0.002)		(0.003)		(0.002)
Seasonal Variables						
Temperature	0.010***	0.004	0.024***	0.024***	0.002	-0.007
	(0.003)	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)
Rainfall	-0.004	0.002	-0.012*	-0.002	-0.001	0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.005)
N	2613	325888	2613	325888	2613	325888

Note: This table gives the estimated coefficients from a linear specification of model 1 that also includes seasonal climatic indicators (mean temperature and rainfall during the Monsoon season). Estimates are separately reported for all crimes (Columns 1 and 2), property crime (Columns 3 and 4) and violent crimes (Columns 5 and 6). Columns (1), (3), and (5) report estimates from a model that only includes seasonal variables; and Columns (2), (4), and (6) also control for both daily and seasonal variables. Panel A uses the monsoon season (June-October) as the sample, while Panel B uses the post-monsoon season (November-February). All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level.
*** p<0.01, ** p<0.05, and * p<0.1.

Table 8: Daily and Seasonal Weather Shocks, Economic Disaggregations

	All Crime			Property Crime			Violent Crime		
	Non-Ag Workforce		Full	Non-Ag Workforce		Full	Non-Ag Workforce		Full
	Low	High	Sample	Low	High	Sample	Low	High	Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily Variables									
Temperature	0.006***	0.005***	0.006***	-0.001	-0.003	-0.001	0.007***	0.007***	0.007***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.001)	(0.002)
Rainfall	-0.002***	-0.003***	-0.002***	0.001	-0.002**	0.001	-0.003***	-0.004***	-0.003***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Seasonal Variables									
Temperature	0.024***	-0.001	0.020***	0.024**	0.010	0.020**	0.025***	-0.004	0.022***
	(0.006)	(0.005)	(0.005)	(0.010)	(0.008)	(0.010)	(0.007)	(0.006)	(0.006)
Rainfall	-0.034***	-0.001	-0.037***	-0.046***	-0.002	-0.051***	-0.030***	-0.001	-0.027***
	(0.008)	(0.005)	(0.007)	(0.014)	(0.008)	(0.012)	(0.010)	(0.006)	(0.009)
Interaction Terms									
X Daily Temp			-0.001			-0.001			-0.000
			(0.002)			(0.005)			(0.002)
X Daily Rain			-0.001			-0.003*			-0.000
			(0.001)			(0.001)			(0.001)
X Seasonal Temp			-0.018***			-0.008			-0.024***
			(0.007)			(0.012)			(0.009)
X Seasonal Rain			0.035***			0.048***			0.022**
			(0.008)			(0.013)			(0.010)
N	192161	181257	373418	192161	181257	373418	192161	181257	373418

Note:
This table gives the estimated coefficients from a linear specification of model 1 that includes both daily and seasonal weather indicators and their interactions with the share of the non-agricultural labor force (as fraction of overall labor force). Estimates are separately reported for all crimes (Columns 1-3), property crime (Columns 4-6) and violent crimes (Columns 7-9). Within each group of models, the first column (1,4,7) reports estimates based on police precincts with below median non-agricultural labor shares; the second column (2,5,8) reports estimates from the sample of precincts with above median levels; and the third column reports estimates from a model which interacts all weather indicators with the non-agricultural labor share. All specifications include precinct fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the precinct level.*** p<0.01, ** p<0.05, and * p<0.1.

Appendix A

Background

Crime rate in Karnataka

Total crimes in India have gone by 9.84% since 2012 reaching 2.65 million reported crimes in 2013. Both violent crimes and property crimes have increased by 11.63% and 9.6%, respectively making Karnataka State 11th in all crime records in 2013, 9th in number of murders, 14th in number of rapes, 4th in number of robberies, 9th in number of thefts, 6th in number of dacoities, 14th in number of kidnappings and 4th in number of riots. On average Karnataka has a comparable crime rate of 223.73 (per 100,000 persons) relative to the average national crime rate of 218.67 (per 100,000 persons) in 2013. Karanataka therefore provide us with a representative state of India in terms of the reported crime rates.

Within Karnataka there is heterogeneity in the reported crime rates. It is noticable that Bangalore has the highest crime rate while Gadag has the least crime rate. Given this heterogeneity, we lay out our empirical strategy that accounts for police station fixed effects to absorb such geographical variation.

Climate in Karnataka

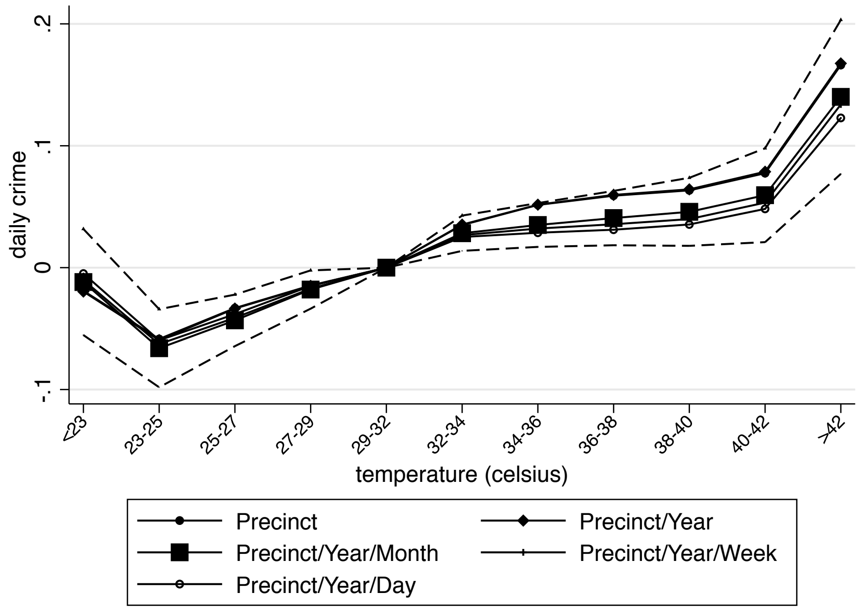
Karnataka's climate presents an exceptional diversity. Given the geographical variation in Karnataka ranging from hilly and Plateau regions to plain regions, the climate also demonstrate high diversity. There are three main climatic zones in Karantaka based on the topography. The first is the coastal region which includes Dakshina Kannada and Uttara Kannada districts. The second contains North Interior Karnataka, which includes: Belgaum, Bidar, Bijapur, Dharwad, Gulbarga and Raichur districts. Finally the third region is the South Interior Karnataka, which includes: the remaining districts of Bangalore Rural, Bangalore, Bellary, Chikmagalur, Chitradurga, Kodagu, Hassan, Kolar, Mysore, Mandya, Shimoga and Tumkur districts.

On average the weather in the state is dry and warm. The summer season starts from the month of April and lasts till the end of May. While these months are the hottest months of the year, the humidity percentage is low. However, the humidity elevates at the start of June as the monsoon starts to kick in. The average temperature during this month is around 34 degree Celsius with a high humidity content.

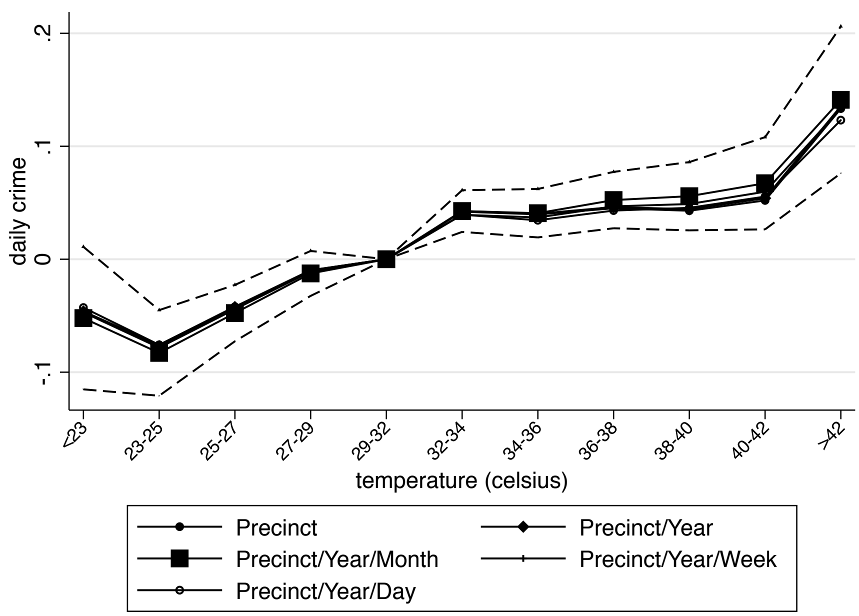
The monsoon season starts from June and lasts until September. During this season with the frequent showers and rainfall, the temperature drops while the humidity stays high. This season is predominant in the entire coastal belt and adjoining areas. This region can experience extremely heavy rainfall of 3456 mm annually while the North interior Karnataka and its adjoining areas; Bijapur, Bagalkot, Belgaum, Haveri, Gadag, Dharwad, Gulbarga, Bellary, Koppal and Raichur districts only experience normal rainfall of 731mm annually. On the other side, the South interior Karnataka receives a a reasonable shower of monsoon annually of 1126 mm.

The winter season starts from January and lasts until the end of February, however there are no harsh winters in Karnataka in any of the three climatic regions. The climate in general remains pleasant where the average temperature is 20 degree Celsius. During winter Karnataka also receives delightful rain in October and November.

Figure A1: Daily Temperature and Crime



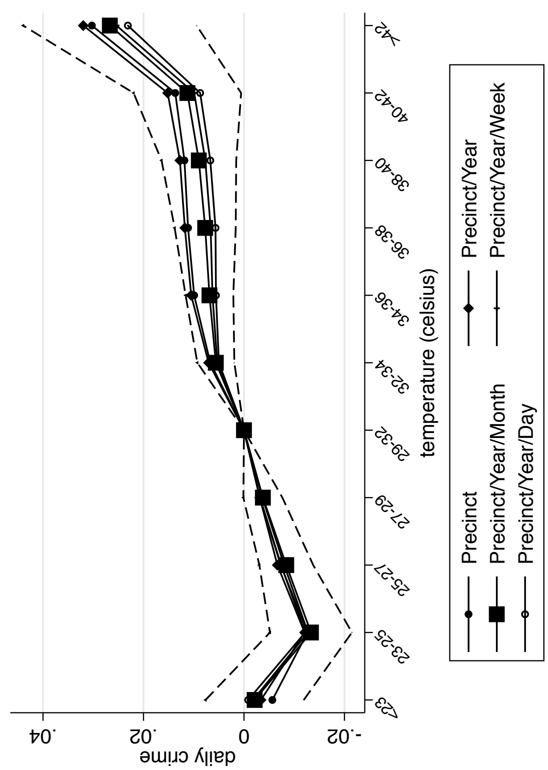
A1.1: Poisson



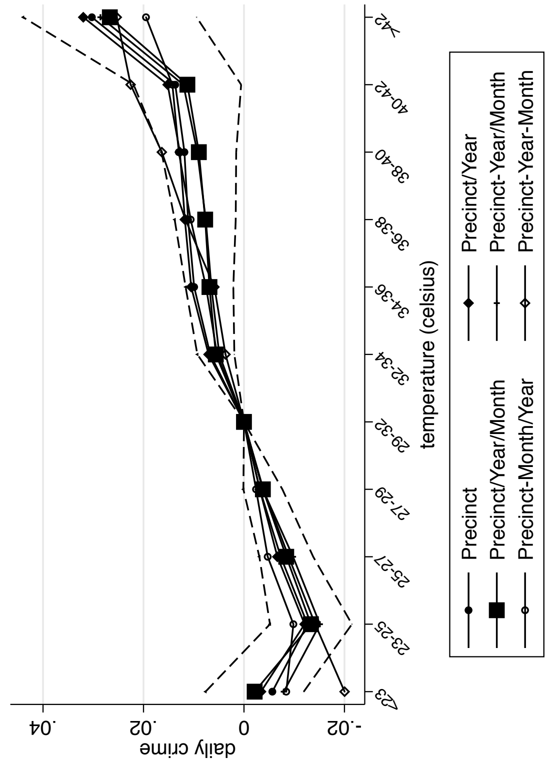
A1.2: Poisson, Hot Months

Notes: Figure A1.1 plots the coefficients. The dashed lines indicate the 95% confidence interval.

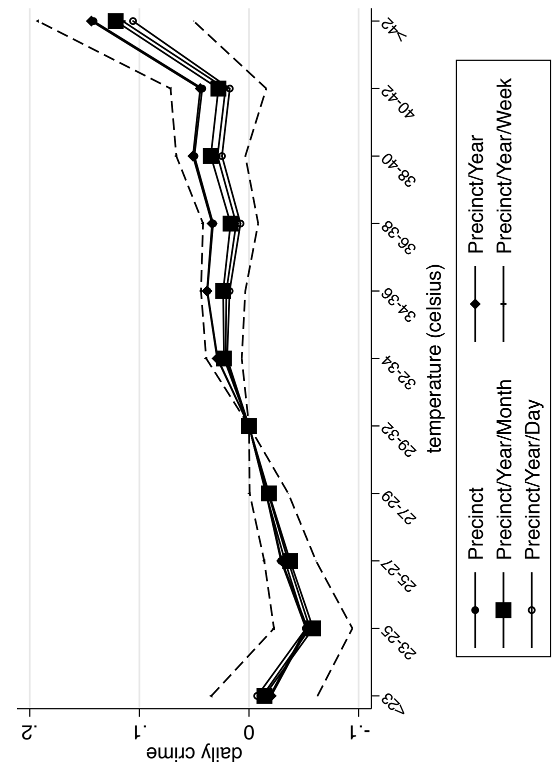
Figure A2: Alternative Temperature Specifications



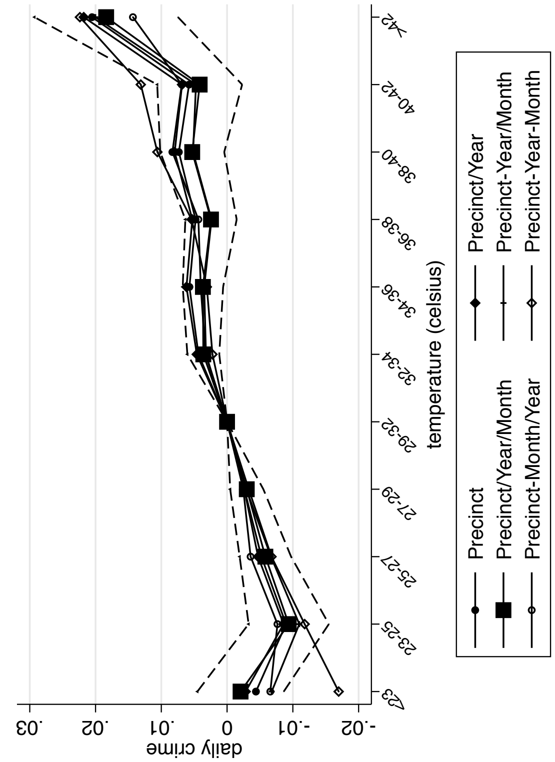
A2.1: OLS



A2.2: OLS, Alternative Controls

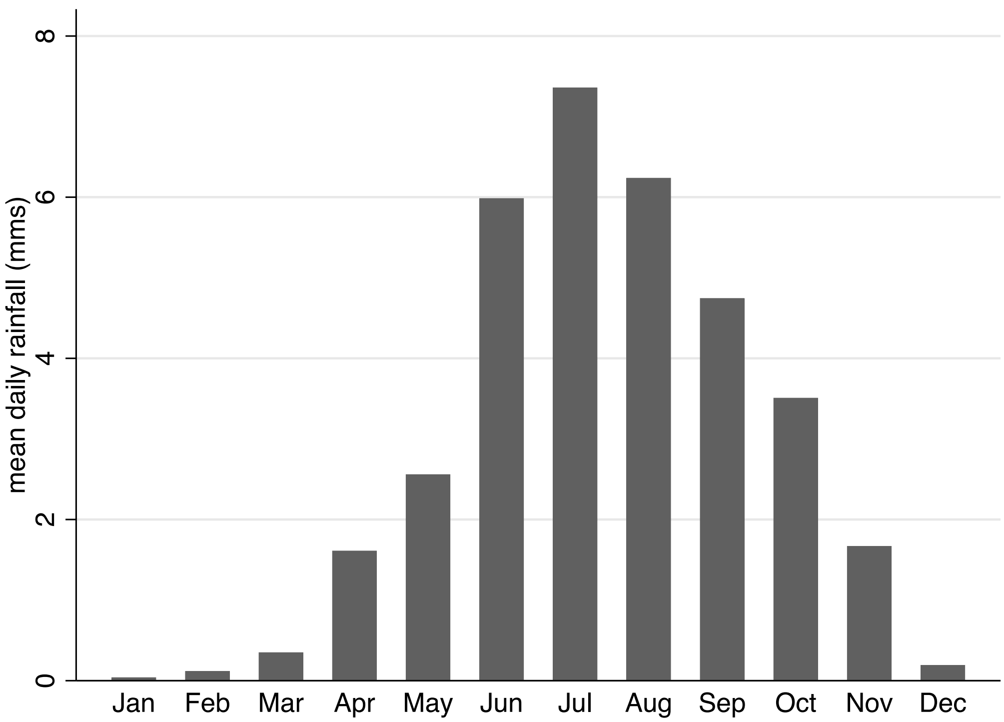


A2.3: LPM



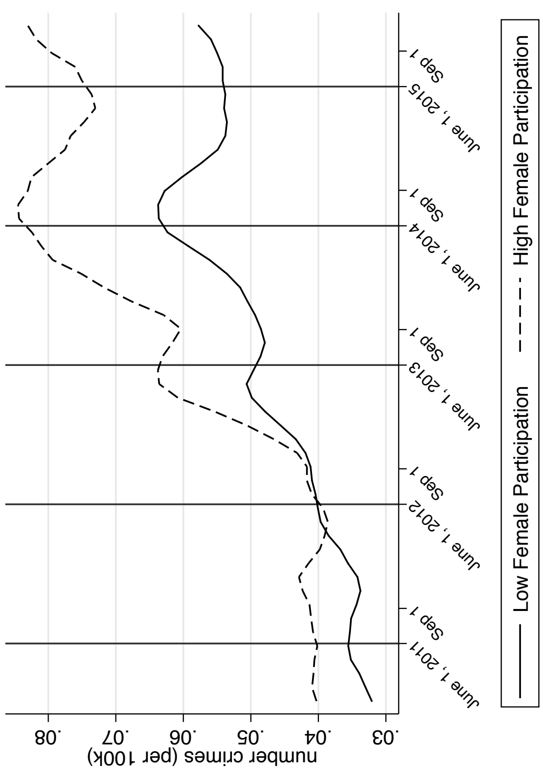
A2.4: LPM, Alternative Controls

Figure A3: Monthly Rainfall

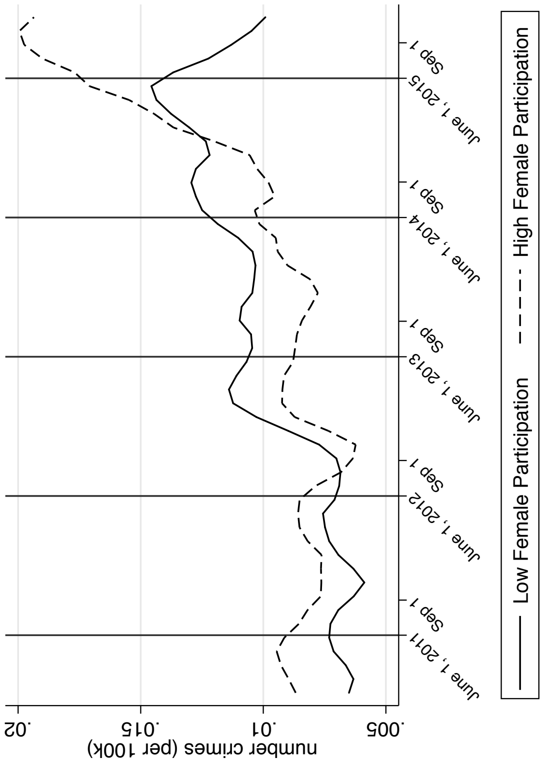


Notes: Figure A3 shows the average daily rainfall in millimeters for the study period disaggregated by month.

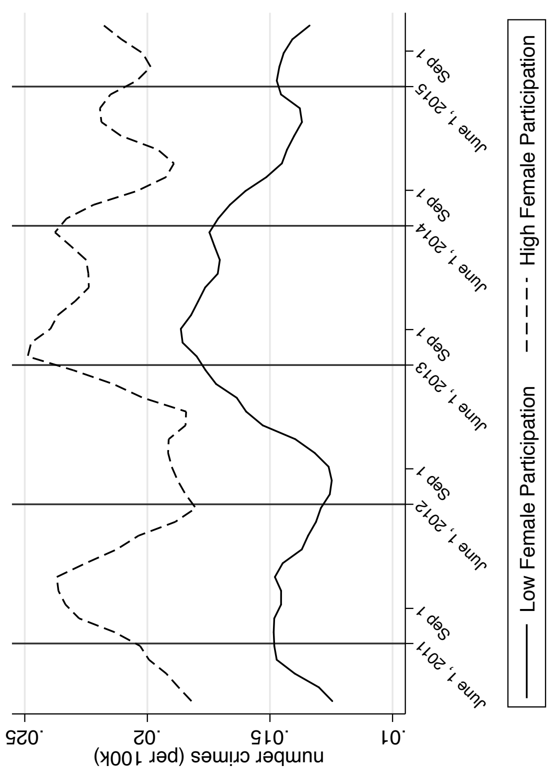
Figure A4: Female Employment and Crimes Against Women



A4.1: Harassment

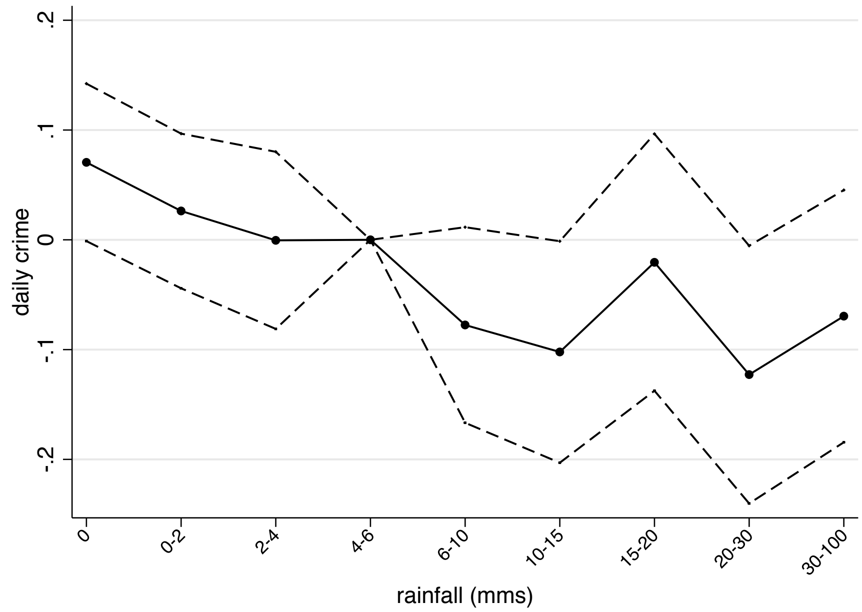


A4.2: Rape

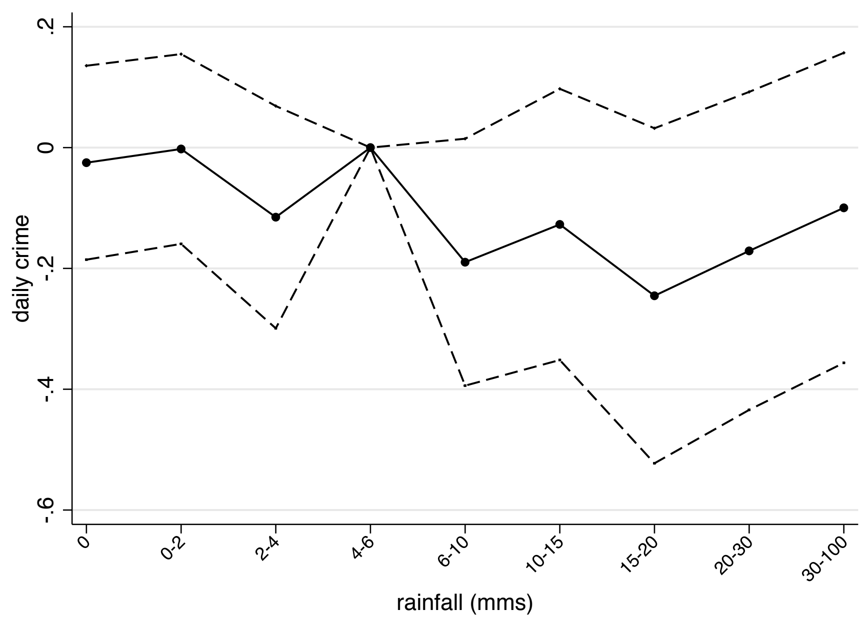


A4.3: Dowry

Figure A5: Daily Rainfall and Crime



A5.1: Gender-related Crime



A5.2: Intergroup Crime

Notes: Figure A5 plots the estimated impacts of daily rainfall on crime incidence, as per specification 2 and plots 2mm daily rainfall bins with 4–6 millimeters as the reference category. Dashed lines indicate the 95% confidence interval.

Table A1: Daily Weather and Crime Across Seasons

	All Crime (1)	Property (2)	Violent (3)
Panel A: Summer			
Temperature	0.006***	-0.011***	0.010***
	(0.001)	(0.003)	(0.001)
N	245038	244609	245038
Panel B: Monsoon			
Temperature	0.006***	0.001	0.008***
	(0.001)	(0.002)	(0.001)
Rainfall	-0.003***	-0.001*	-0.004***
	(0.000)	(0.001)	(0.001)
N	373418	373418	373418
Panel C: Winter			
Temperature	0.001	-0.005	0.005*
	(0.002)	(0.003)	(0.003)
N	291911	291911	291911

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are reported for all crimes in column (1), property crimes in column (2) and violent crimes in column (3). Panel A is a temperature-only model and includes all days in "hot" months (March-October); Panel B reports a model with both temperature and rainfall controls and therefore only includes days in the monsoon months (June–October). Panel C is a temperature-only model and includes all days in "winter" months (November-February). All specifications include police station fixed effects, year fixed effects, and month fixed effects. Error terms are clustered at the police station level. *** p<0.01, ** p<0.05, and * p<0.1.

Table A2: Daily Weather and Crime Across Days of Week and Holidays

	Violent Crime		
	Hot Seasons	Monsoon Season	
	Temperature	Temperature	Rainfall
	(1)	(2)	(3)
Holiday	0.018***	0.015***	-0.007***
	(0.005)	(0.006)	(0.002)
Monday	0.010***	0.009***	-0.006***
	(0.003)	(0.003)	(0.001)
Tuesday	0.018***	0.016***	-0.005***
	(0.003)	(0.003)	(0.001)
Wednesday	0.009***	0.007**	-0.007***
	(0.003)	(0.003)	(0.001)
Thursday	0.004***	0.004**	-0.005***
	(0.001)	(0.002)	(0.001)
Friday	0.008***	0.007***	-0.002*
	(0.002)	(0.002)	(0.001)
Saturday	0.012***	0.011***	-0.005***
	(0.002)	(0.002)	(0.001)
Sunday	0.020***	0.018***	-0.006***
	(0.003)	(0.003)	(0.001)

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are reported for violent crimes on holidays, and each day of the week. Column (1) includes all days in "hot" months (March-October); Panel B includes days in the monsoon months (June–October). Panel C is a rainfall-only model and includes all days in "monsoon" months (June-October). All specifications include police station fixed effects, year fixed effects, and month fixed effects. Error terms are clustered at the police station level. *** p<0.01, ** p<0.05, and * p<0.1.

Table A3: Crime and Lagged Weather

	All Crime							
	Full Sample				Monsoon Season			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature								
Same Day	0.006***	0.004***	0.004***	0.004***	0.006***	0.005***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag 1		0.004***	0.004***	0.004***		0.005***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Lag 2			0.000	0.001			0.003**	0.003**
			(0.001)	(0.001)			(0.001)	(0.001)
Lag 3				-0.002				-0.000
				(0.001)				(0.002)
Rainfall								
Same Day					-0.003***	-0.002***	-0.002***	-0.002***
					(0.000)	(0.000)	(0.000)	(0.000)
Lag 1						-0.000	-0.000	-0.000
						(0.000)	(0.000)	(0.000)
Lag 2							-0.001*	-0.001
							(0.000)	(0.000)
Lag 3								-0.000
								(0.000)
N	910364	909061	908118	907335	373410	372905	372651	372498

Note: This table gives the estimated coefficients from a linear specification of model 1 with additional day-lags. Estimates are reported for all crimes. Column (1) - (4) includes all days in “hot” months (March-October); columns (5) - (8) includes days in the monsoon months (June–October) so we also provide the estimates for rainfall for this sample. All specifications include police station fixed effects, year fixed effects, and month fixed effects. Error terms are clustered at the police station level. *** p<0.01, ** p<0.05, and * p<0.1.

Table A4: Economic Disaggregations

	Violent Crime			
	(1)	(2)	(3)	(4)
Panel A: Hot Seasons				
Temperature	0.008***	0.008***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Interactions				
Temp X Non-Ag	0.002			0.003*
	(0.001)			(0.001)
Temp X Density		0.003*		0.003**
		(0.001)		(0.001)
Temp X Literacy			-0.001	-0.002
			(0.001)	(0.001)
N	618456	618456	618456	618456
Panel B: Monsoon Season				
Temperature	0.009***	0.007***	0.013***	0.012***
	(0.001)	(0.001)	(0.002)	(0.002)
Rainfall	-0.004***	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Interactions				
Temp X Non-Ag	-0.003			-0.000
	(0.002)			(0.002)
Rain X Non-Ag	0.000			0.000
	(0.001)			(0.001)
Temp X Density		0.003		0.003
		(0.002)		(0.002)
Rain X Density		-0.001		-0.001
		(0.001)		(0.001)
Temp X Literacy			-0.007***	-0.007***
			(0.002)	(0.002)
Rain X Literacy			0.000	0.000
			(0.001)	(0.001)
N	373418	373418	373418	373418

This table gives the estimated coefficients from a linear specification of model 1. Estimates are reported for violent crime. Panel A is a temperature-only model and includes all days in "hot" months (March-October); Panel B reports a model with both temperature and rainfall controls and therefore only includes days in the monsoon months (June–October). All specifications include police station fixed effects, year fixed effects, and month fixed effects. Error terms are clustered at the police station level. *** p<0.01, ** p<0.05, and * p<0.1.

Table A5: Daily and Seasonal Weather Shocks, Gender and Integroup Violence

	Gender				Group			
	Dowry		Rape		SC/ST		Hindu-Muslim	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Daily Variables								
Temperature		-0.005		0.009*		0.008**		0.010
		(0.009)		(0.005)		(0.004)		(0.012)
Rainfall		-0.002		-0.005		-0.003		-0.016**
		(0.002)		(0.003)		(0.002)		(0.008)
Seasonal Variables								
Temperature	0.012	0.023	0.022**	0.018	0.000	-0.004	0.005	0.008
	(0.008)	(0.021)	(0.011)	(0.028)	(0.008)	(0.020)	(0.018)	(0.045)
Rainfall	0.018*	0.021	-0.093***	-0.094***	-0.013	-0.001	-0.167***	-0.113*
	(0.011)	(0.026)	(0.013)	(0.032)	(0.010)	(0.022)	(0.026)	(0.061)
N	11665	330061	10110	281678	12045	341975	4785	130395

Note: This table gives the estimated coefficients from a linear specification of model 1 that also includes seasonal climatic indicators (mean temperature and rainfall during the Monsoon season). Estimates are separately reported for all crimes (Columns 1 and 2), property crime (Columns 3 and 4) and violent crimes (Columns 5 and 6). Columns (1), (3), and (5) report estimates from a model that only includes seasonal variables; and Columns (2), (4), and (6) also control for both daily and seasonal variables. Panel A uses the monsoon season (June-October) as the sample, while Panel B uses the post-monsoon season (November-February). All specifications include police station fixed effects, year fixed effects, and month fixed effects. Error terms are clustered at the police station level.
*** p<0.01, ** p<0.05, and * p<0.1.