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 underlying mechanisms remain imperfectly understood. Using daily data on the universe of crimes from 600 police stations in Karnataka, India between 2011–2016, and daily weather data from a dense network of monitoring stations, we disentangle the economic and non-economic channels 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 inter-group conflict. Economic development, in the form of a larger non-agricultural labor force, does not attenuate the non-economic impacts of weather on violent crime.

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—in particular, 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.

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–where the motivation is primarily one of animus, rather than economic gain–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. We also find that elevated daily rainfall leads to a decline in daily crime, a novel result in the climate-conflict literature. As with temperature, the relationship is observed primarily for violent crimes, which may suggest a psychological channel. It is also likely that elevated rainfall leads to a decline in crime through a reduction in social interactions, akin to the conjecture of Miguel et al. (2004) with respect to civil war in Africa.

These findings call into question the attribution of inter-annual associations between seasonal weather and *violent* crime in developing countries solely to agricultural income shocks (Sekhri and Storeygard, 2014; Blakeslee and Fishman, 2017). On the other hand, they provide new evidence to support the emphasis on agricultural income shocks in mediating the effect of seasonal weather in the case of *property* crimes (Blakeslee and Fishman, 2017), as the latter are unaffected by either daily temperature or rainfall.

To more directly test this interpretation, we estimate specifications simultaneously accounting for daily and seasonal climatic variability. 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. 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.

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, and is the first to clearly document non-economic channels driving the effect of rainfall on crime. 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) seek to disentangle the economic and non-economic drivers of homicide by an analysis of the separate effects of daily and seasonal temperature fluctuations. Baysan et al. (2018) use monthly data to demonstrate non-economic impacts of temperatures on conflict between drug trafficking organizations, which they show to be similar to the effects of temperature on crimes such as homicides and suicides.

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 and criminal records on labor market outcomes (Raphael, 2010; Kling, 2006; Doleac and Hansen, forthcoming). Other papers have focused on policy interventions for reducing crime, which often appeal to non-economic factors for their efficacy. Among these are: 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 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

[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 times.

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 results for crimes 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, a crime might be broadly classified as domestic violence, with the "crime head" specifying that it was related to dowry.

In Table 1 we present summary statistics on a variety of crime types included in the crime

[2] The records also indicate the identity of the victim, the accused, and the complainant. However, for anonymity purposes, this data was not collected.

data, disaggregated by season. These crimes constitute a subset of all the crimes included in the data set, but are among the most important and most common. The crimes are grouped into the categories: property, violent, gender, and intergroup. In addition, we include crimes that are ambiguous in their classification, which are labeled as "other." These categories are self-explanatory, though some crimes span multiple categories. Below we give greater detail on the various categories.

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.

Figures 1.1 and 1.2 show the time series of daily mean temperature and rainfall 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 declines 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 summer months of March through May, 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 use 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. before, these variables are reported at the village level, which we then aggregate to the level of the precinct.

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.

In Figure 2 we show the time series of daily crime incidents (per 100,000 people) for violent and property crimes separately. Though the patterns are somewhat similar, violent crimes peak slightly earlier in the year than do property crimes.

3 Empirical Strategy

Our analysis is focused on 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), and the outcome variable is the number of crime incidents. 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 1.2). 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.

In our benchmark specifications, we control for global month and year fixed effects $f_P(D) = \alpha_m + \beta_y$. Here, we decompose each date as $D = d, m, y$, where $1 \leq d \leq 31$ is the day of the month, $1 \leq m \leq 12$ 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 $f_P(D) = \alpha_m \times \beta_y$ as well as models that control for precinct-specific seasonal cycles $\delta_{P,m}$, and even models that include precinct-month-year fixed effects $\delta_{P,m,y}$.

In the subsequent analysis, we will focus on two broad categories of crime: property and violent. The principal distinction between the two is whether the crime is being committed primarily for economic gain (property); or instead is motivated by the desire to cause physical harm to other individuals, or otherwise employs violence for non-pecuniary objectives (violent). Property crimes include burglary, theft, robbery, and banditry.[3] Violent crimes include murder, attempted murder, rape, fights, and violent assaults. Several categories of crime are ambiguous, and are therefore not included in either of these two categories. For example, riots may sometimes occur for the purpose of looting; but at other times will be highly violent with no specific economic ends. Similarly, kidnapping will sometimes be conducted for the purpose of extorting ransoms, but at other times will be for the purpose of abusing victims. We show results giving the effects of weather variation for these crimes individually.

4 Results

4.1 Non-Parametric Specification

We begin by estimating a non-parametric form of the relationship between daily maximum 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

$$\begin{aligned} \tau(T_{P,D}) &= \sum_{j=1}^{10} \tau_j I_j^T(T) \\ \rho(R_{P,D}) &= \sum_{j=1}^{10} \rho_j I_j^R(R), \end{aligned} \tag{2}$$

where I_j^T and I_j^R are binary indicators of whether the values of maximum 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.

[3]While both robbery and banditry include violence, we classify them as property crimes, as they are motivated primarily by economic gain.

Figure 3 presents a plot of the estimated coefficients τ_j and ρ_j from specification 2 with global month and year fixed effects. Figure 3.1 plots the temperature coefficients, using the 29–32°C as the reference category. Figure 3.2 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.

In Appendix Figure A1 we report estimates derived from similar specifications that include alternative fixed effects, including global year-month-week and year-month-day fixed effects. In Figures A2 and A3 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 using a Poisson count model with precinct, year, and month fixed effects (specification 1). We therefore use the latter for the remainder of the paper.

4.2 Baseline 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 °C) and rainfall (in mm), respectively. For this analysis, we also estimate effects for property and violent crimes separately. Figures 4 and 5 show the $\tau(T)$ and $\rho(R)$ coefficients property and violent crimes. The patterns strongly indicate that daily weather primarily affects the incidence of violent crime.

Table 2 reports the resulting estimates using the linear measures of temperature and rainfall. 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 1°C in daily maximum temperature is associated with a 0.6% 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% increase in probability of an additional crime with each $1°C$ temperature increase. In fact, there is a small decline in property crimes with higher temperatures, which as shown in Figure 4.1 is driven by an (imprecisely measured) decline at temperatures above $40°C$. Rainfall displays similar effects, with each 1mm increase in rainfall causing a 0.3% decline in the probability of an additional crime, which is again driven by the effect for violent crime.

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 entire year, while columns (2) and (3) give the temperature and rainfall coefficients when limiting the sample to the monsoon months. For property crimes, there is virtually no relationship between daily crime and weather, save for a small decline in theft 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 0.8 to a 1.3% increase in the probability of crime count with each additional $1°C$ increase in temperature. In addition, riots, 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 crimes. We also see that riots and gambling decline with higher levels of rainfall, while unnatural deaths increase with higher rainfall.

4.4 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 (Alesina et al., 2003), 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. We describe our results below.

4.4.1 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 1.1 and 0.8% 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), consistent with the results found for other types of violent crime.

Rainfall has a negative relationship with the public harassment of women, consistent with the results for violent crimes. We also see a decrease in domestic abuse and rape with higher levels of rain, which is also consistent with the results for violent crimes.

4.4.2 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 5. 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 five 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).[4] 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,

[4] 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.

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).

5 Mechanisms

5.1 Drivers of Daily Weather-Crime Association

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, which we argue are largely non-economic in nature.

The patterns with respect to daily temperature variation and daily crime are strongly suggestive of a psychological mechanism being at play, consistent with previous research. First of all, because the increase in crime occurs on the same day as the elevated temperature, it is unlikely that it is being caused by the economic effects of temperature, as these would only result in meaningful losses of income over time.[5] Further evidence for a psychological channel comes from the fact that the effect of temperature on crime are stronger and more consistent for violent crimes (Tables 2 and 3).

An additional mechanism driving the temperature-crime relationship may be through a general erosion of cognitive functioning. 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 crimes having no clear relationship with elevated aggression, such as unnatural deaths 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" (Kenrick and MacFarlane, 1986), while diminished cognitive functioning leads to a general deterioration in driving ability.

The mechanisms driving the daily rainfall results are necessarily more speculative, due to the novelty of this finding and the concomitant lack of research. One plausible channel is through the effect of rainfall on social interactions, with low rainfall allowing more social interactions, and high rainfall fewer. Such a mechanism has been suggested by Miguel et al. (2004), who cite it as one reason the exclusion restriction may fail when using rainfall to instrument for income.[6] Though we are aware of no research verifying the effect of rainfall on

[5]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.

[6]Miguel et al. (2004) discuss this issue in the context of civil war in Africa. The authors raise the

social interactions, it is a phenomenon well-attested in the Indian press, where the flooding of roads and break-down of transport are a defining feature of the monsoon season.[7] Some evidence that this mechanism is at work can be seen in the fact that the effect of rainfall occurs primarily for violent crimes, as social interactions are arguably more important for violent than for property crimes.

The larger effect of rainfall on violent than property crimes would also be consistent with a psychological channel, as argued above for temperature. For example, rainfall may directly reduce aggression levels, though we are aware of no research on this topic. Even if rainfall has no independent effect on aggression, if it causes temperatures to fall, it may indirectly reduce aggression by reducing the number of hours during which temperatures are near to the daily maximum. Alternatively, higher rainfall may reduce stress levels due to the dependence of agricultural livelihoods on rainfall. Though a single day's rainfall will generally not affect yields, it may affect *beliefs* about aggregate monsoon rainfall and yields.[8]

Another possibility is that rainfall simply causes a delay in the reporting of crime, and that this is what drives the rainfall results. However, this is inconsistent with the fact that it is primarily violent crimes that decline with rainfall, with little effect on property crimes. Given the greater severity of the violent crimes, one would expect that victims would be *less* likely to delay reporting due logistical difficulties. In addition, in results not shown, we find that lagged rainfall up to two days has no effect on crime, arguing against rainfall's causing a delay in reporting.

The decline in the public harassment of women with high rainfall is consistent with a social interactions channels. The effects of rainfall on domestic violence and rape, however, seem to be inconsistent with a social interactions mechanism, as high rainfall would be expected to increase the probability that potential abusers remain in their homes, increasing the exposure of women to such crimes.[9] These effects are more consistent with a psychological mechanism, in which low rainfall affects domestic violence through an increase in stress levels. The effect of stress on domestic violence has been shown in previous research by Card and Dahl (2011), where domestic abuse in America is negatively related to the success of the favored sports team.

We have argued that the effects of daily weather variation are unlikely to be driven by

possibility that high rainfall could wash our roads and thereby impede the interactions of government and rebel forces, though they find no evidence of this.

[7]For an example, see Indian Express (2018).

[8]Coviello et al. (2014) find that rainfall in the US leads to a worsening of emotional states. In India, however, rainfall is crucial to agricultural incomes, and therefore would likely elicit a positive emotional response. Indeed, the economic importance and psychological significance of the monsoon rain are a central theme in popular culture.

[9]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.

economic channels, due to the absence of effects for property crimes, as well as the fact that incomes have little dependence on single-day weather events. However, if households are sufficiently dependent on daily wages, as could be the case for the poorest households, then economic channels might be present even with the daily weather-crime relationship.

To test this possibility, in Table 6 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 generally larger on Sundays and holidays than it is on working days. This provides additional evidence against there being an economic channel mediating the daily weather-crime relationship. The higher temperature effect on weekends and holidays is potentially due to larger social gatherings and/or more alcohol consumption, which could amplify the temperature effect.

5.2 Daily and Seasonal Weather Variation

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.

Our results have established that there is a substantial increase in *violent* crime with daily elevated temperatures and deficient rainfall, and little effect on *property* crime. 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.

Figures 1 and 2 provide further suggestive evidence for the factors driving the weather-crime relationship for property and violent crimes. 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. Significantly, the patterns for property crime closely match the planting season.[10]

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

[10] A second monsoon occurs in some parts of the state during October–December.

the mean daily temperature and rainfall 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), (3), and (5) the regression is estimated at the precinct-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 1.9 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 1.1 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 temperature variation are relatively similar for property crime, but become small and insignificant for violent crime. The inclusion of daily weather variables reduces the estimated effect of seasonal rainfall on property crime by half, and renders it statistically insignificant. However, we will see below that seasonal rainfall effects are robust to the inclusion of daily weather variables when looking at areas where a large share of workers are involved in agricultural production.

Three findings stand out. First, property crime is primarily 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.

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 A1. 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, indicating that economic factors play a large role in such crimes.

5.3 Heterogeneity by Labor Force Composition

An important question is whether higher levels of economic development may help to mitigate the effect of weather variation on crime. This is important both for understanding the channels driving the weather-crime relationship, as well as for predicting the effects of climate change on conflict. There is some reason to expect that economic development may dampen the effects of weather variation on conflict. 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 therefore test for the differential effects of weather variation according to the level of economic development. For this exercise, we disaggregate the sample into areas with non-agricultural labor forces above and below the sample median (23% of workers).[11] Areas with larger non-agricultural labor forces would be less dependent on weather for income generation, and therefore less susceptible to income-driven effects of weather variation on crime. Insofar as the mechanisms cited above are correct—non-economic factors driving the daily weather results, and economic factors the seasonal weather results—we would therefore expect the size of the non-agricultural labor force to be more important in mediating the effects of seasonal weather variation than daily weather variation.

In Table 8 we give the results. We estimate the effects separately for precincts with non-agricultural labor forces below and above the median. We then run a regression including all precincts, and interact the daily and seasonal weather variables with an indicator for precincts with a non-agricultural labor force above the median. The effect of daily weather variation on crime is relatively similar in precincts where the non-agricultural workforce is below and above the median.

The effect of seasonal weather variation on crime, however, occurs entirely in precincts with non-agricultural labor forces below the median. Each $1°C$ increase in mean daily temperature is associated with a 3.0 percent increase in crime in areas with a smaller non-agricultural labor force, but has no effect where the non-agricultural labor force is larger. A similar pattern holds for rainfall, with each additional mm of mean daily rainfall being associated with a 3.2 percent decline in crime count in precincts with a smaller non-agricultural labor force, but no effect where the non-agricultural labor force is above the median. The differences for both the seasonal temperature and rainfall coefficients across low- and high-non-agricultural workforce precincts, shown in column (3), are statistically significant at the 5 percent level.

[11] It should be noted that our sample consists of largely rural areas, and excludes urban areas where non-agricultural labor forces are far higher.

The lack of any differential effect of daily weather variation according to the size of the agricultural labor force is consistent with these effects being driven by non-economic mechanisms. This contrasts sharply with the findings for seasonal weather variation, where the effects on crime occur only in areas with larger agricultural work forces, as would be expected if seasonal weather affects crime through economic channels.

6 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 detailed crime and weather 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 relationship, as demonstrated by a remarkably robust association between daily weather fluctuations (both temperature and rainfall) and the occurrence of a wide variety of crime types. These results hold not only for "classic" violent crimes such as murder and assault, 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.

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. 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 for assessing 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 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$^{\circ}C$ 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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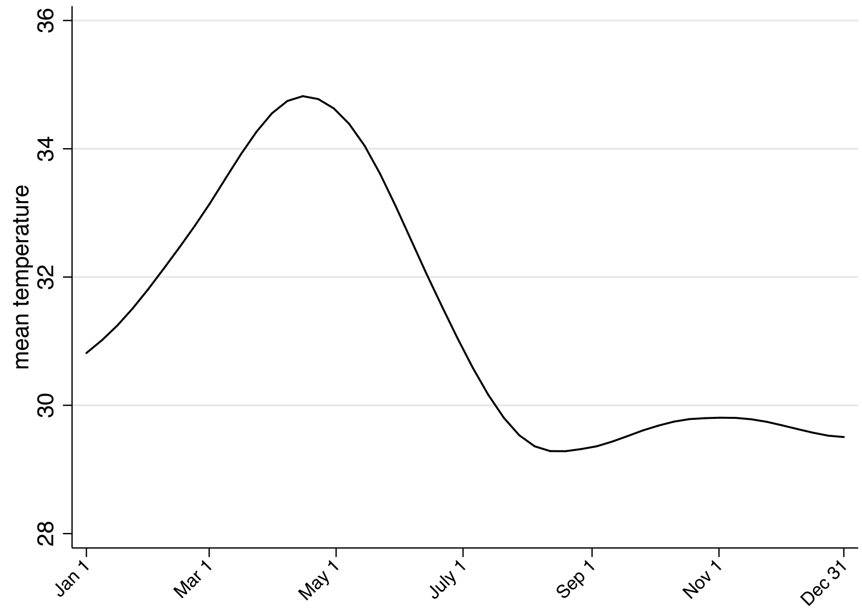
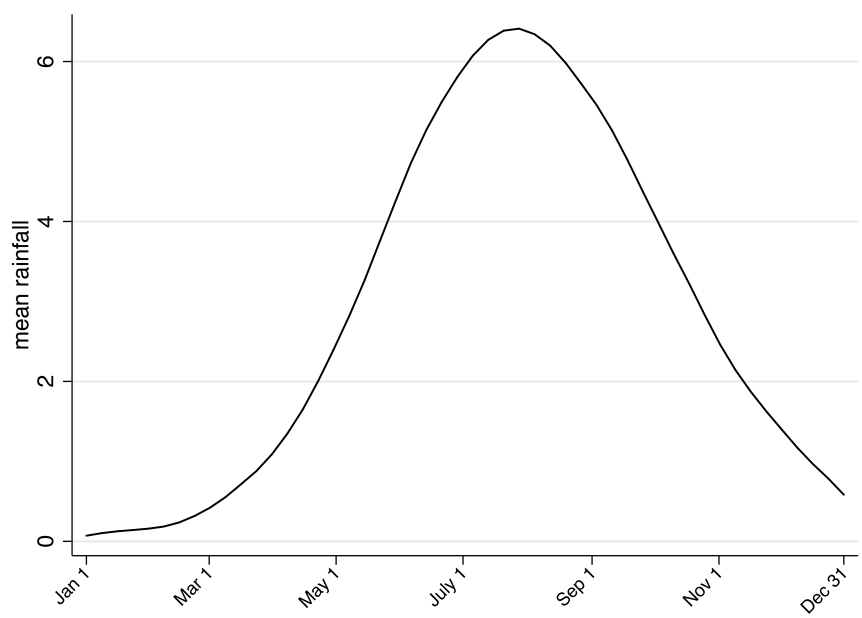
Figure 1: Daily Weather



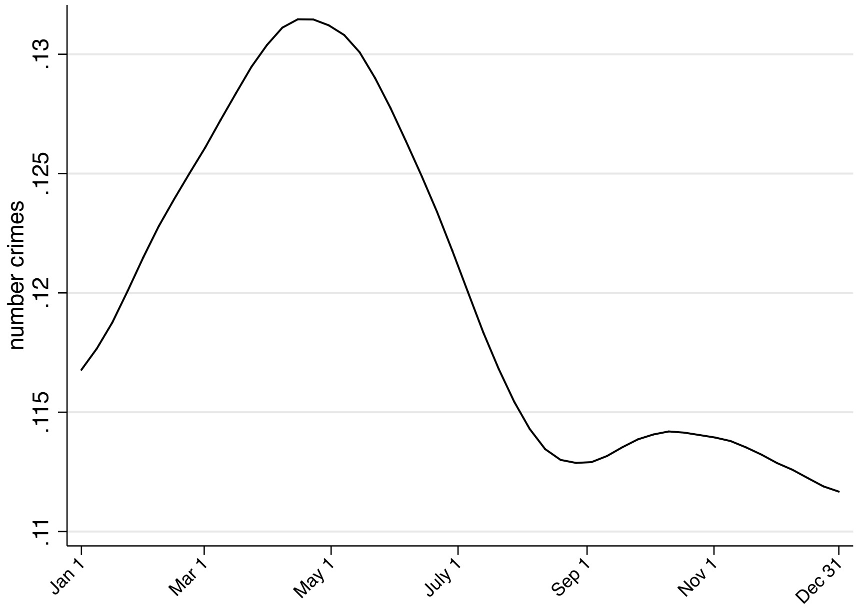
1.1: Mean Daily (Max) Temperature



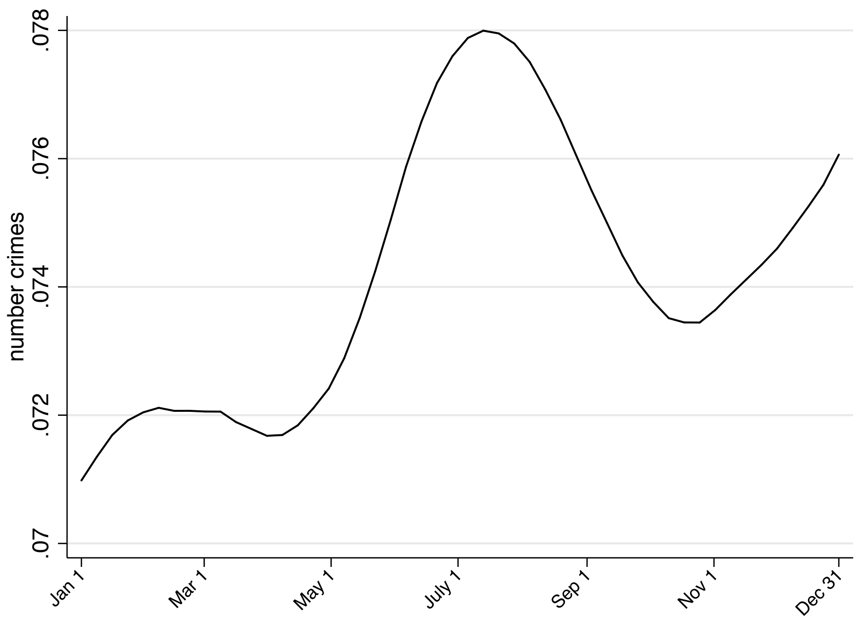
1.2: Mean Daily Rainfall

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

Figure 2: Statewide Daily Crime



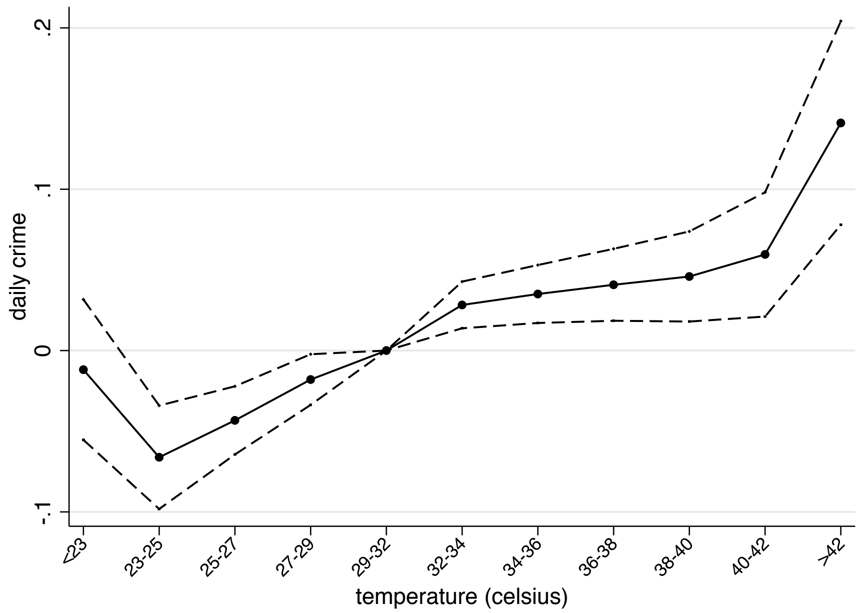
2.1: Violent Crime



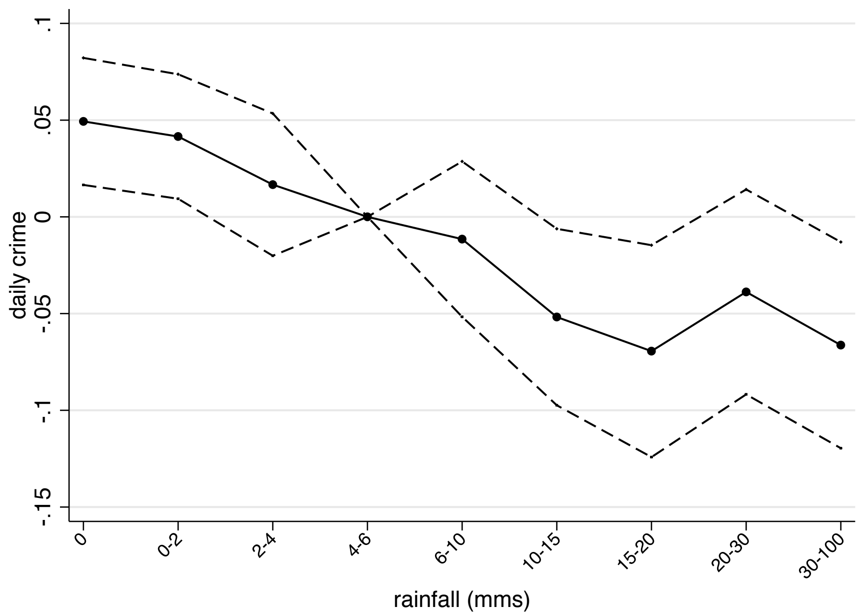
2.2: Property Crime

Notes: Figure 2 shows the precinct-level average daily incidence of crime for the study period. Figure 2.1 shows violent crime, and Figure 2.2 shows property crimes.

Figure 3: Daily Weather and Crime



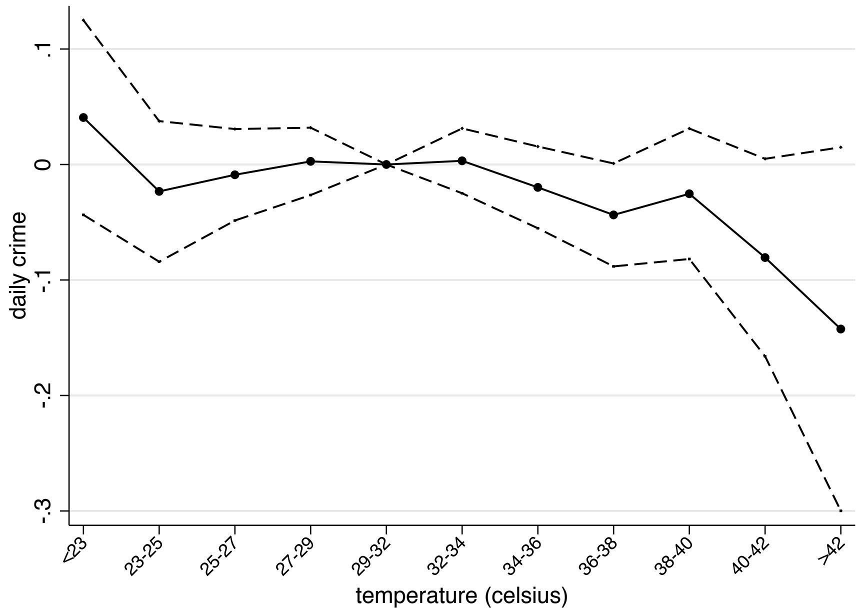
3.1: Temperature and Crime



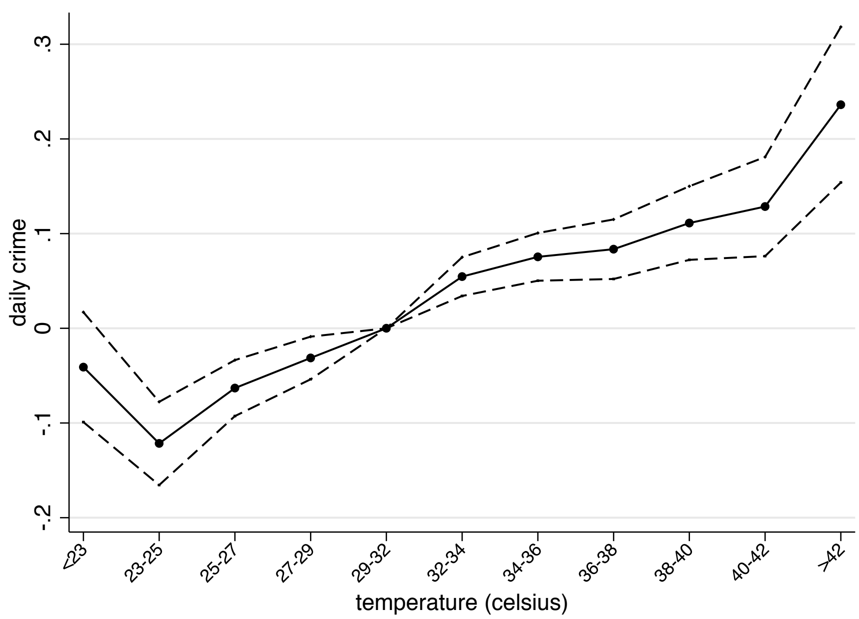
3.2: Rainfall and Crime

Notes: Figure 3 plots the estimated impacts of daily temperature on crime incidence, as per specification 2. Figure 3.1 plots temperature bin, with temperature of 29–32 degrees Celsius as the reference category, and Figure 3.2 shows rainfall bin coefficients, with daily rainfall of 4–6 millimeters as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 4: Daily Temperature and Crime



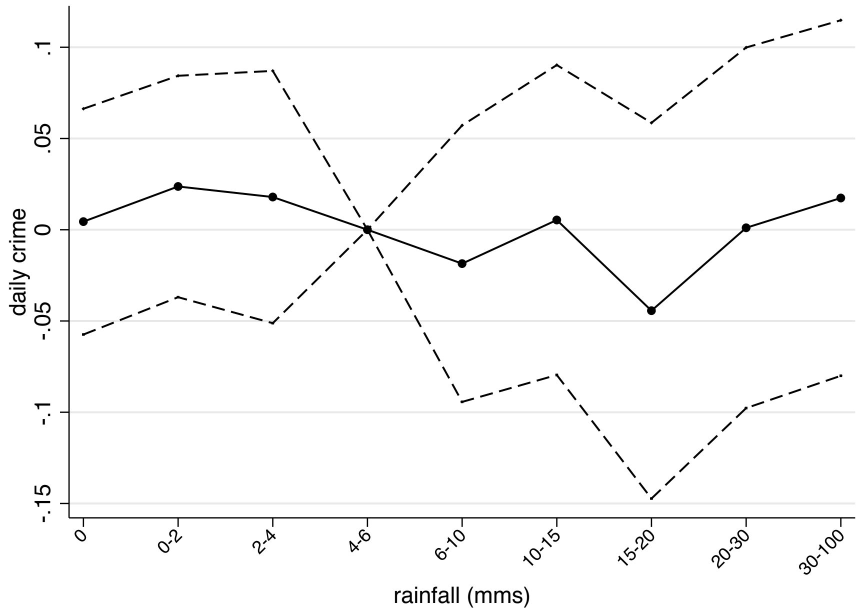
4.1: Property Crime



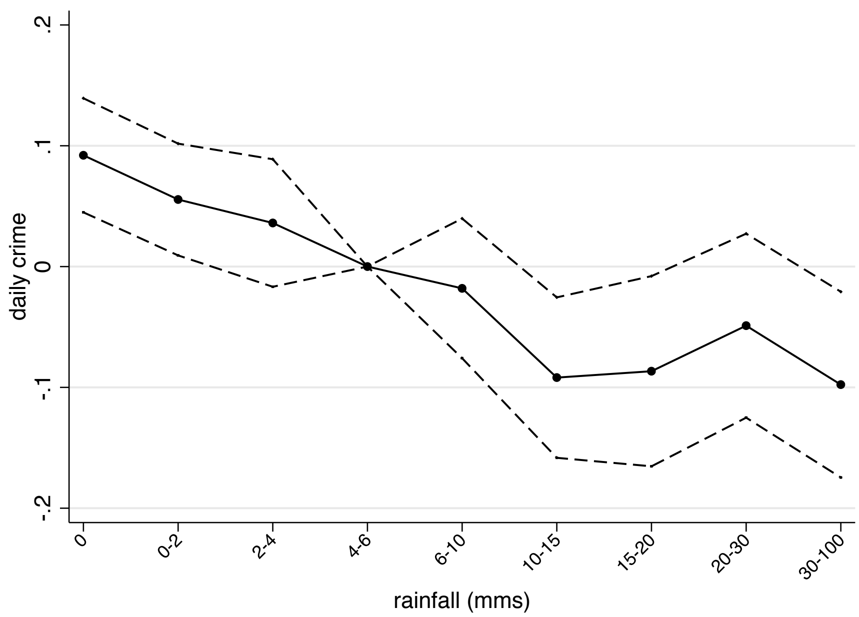
4.2: Violent Crime

Notes: Figure 4 plots the estimated impacts of daily temperature on property (Figure 4.1) and violent (Figure 4.2) crime separately, as per specification 2, with temperatures of 29–32 degrees Celsius as the reference category. Dashed lines indicate the 95% confidence interval.

Figure 5: Daily Rainfall and Crime



5.1: Property Crime



5.2: Violent Crime

Notes: Figure 5 plots the estimated impacts of daily rainfall on property (Figure 5.1) and violent (Figure 5.2) crime separately, as per specification 2, with daily rainfall of 4–6 millimeters as the reference category. Dashed lines indicate the 95% confidence interval.

Table 1: Summary Stats

Variable	All (1)	Season: Summer (2)	Monsoon (3)	Winter (4)
Weather, Daily Mean				
Rainfall (mms)	2.82	1.50	5.49	0.46
	(4.89)	(1.14)	(6.61)	(0.74)
Max Temperature (C)	31.29	35.08	29.79	30.31
	(3.31)	(2.88)	(2.37)	(2.24)
Crime, Monthly Mean				
Property				
Burglary	3.04	2.98	3.27	2.81
	(3.77)	(3.80)	(3.91)	(3.54)
Banditry	0.20	0.23	0.21	0.17
	(0.58)	(0.60)	(0.62)	(0.51)
Theft	5.43	5.62	5.60	5.10
	(7.51)	(7.71)	(7.64)	(7.17)
Robbery	0.78	0.82	0.81	0.72
	(1.68)	(1.69)	(1.81)	(1.49)
Violent				
Murder	1.02	1.13	1.02	0.95
	(1.29)	(1.35)	(1.30)	(1.22)
Attempted Murder	1.20	1.41	1.20	1.05
	(1.66)	(1.87)	(1.65)	(1.48)
Rape	0.52	0.56	0.51	0.50
	(0.87)	(0.93)	(0.88)	(0.79)
Assault	12.76	14.90	12.45	11.59
	(10.86)	(12.55)	(10.38)	(9.79)
Fight	0.24	0.27	0.23	0.23
	(0.58)	(0.59)	(0.58)	(0.57)
Gender				
Dowry-related	1.03	1.13	1.06	0.94
	(1.65)	(1.80)	(1.64)	(1.55)
Domestic Abuse (non-dowry)	1.78	2.00	1.78	1.62
	(2.91)	(3.11)	(2.97)	(2.66)
Harassment	2.78	3.03	2.84	2.54
	(3.12)	(3.40)	(3.13)	(2.86)
Intergroup				
Attack on SC/ST	1.18	1.24	1.20	1.10
	(1.51)	(1.57)	(1.52)	(1.44)
Hindu-Muslim violence	0.18	0.16	0.15	0.22
	(0.79)	(0.64)	(0.48)	(1.14)
Other				
Riots	4.65	5.30	4.70	4.12
	(4.58)	(5.12)	(4.55)	(4.12)
Kidnapping	0.83	0.90	0.85	0.74
	(1.37)	(1.47)	(1.39)	(1.26)
Auto Accident	27.10	30.56	25.37	26.75
	(29.74)	(32.11)	(28.58)	(29.10)
Arson	0.25	0.34	0.17	0.28
	(0.64)	(0.70)	(0.59)	(0.64)
Gambling	7.03	7.15	7.58	6.29
	(7.67)	(8.52)	(7.81)	(6.71)
Unnatural Death	7.58	8.70	7.62	6.72
	(5.92)	(6.76)	(5.72)	(5.32)
Negligence Death	0.18	0.21	0.18	0.16
	(0.48)	(0.52)	(0.48)	(0.43)

Variable	(5)
Socio-Demographic	
Population (10,000)	7.18
	(3.48)
Pct Workers Non-Ag	0.33
	(0.24)
Pct Ag Workers Laborers	0.45
	(0.15)
Pct Illiterate	0.31
	(0.08)
Pct Population SC	0.21
	(0.12)
Pct Population ST	0.09
	(0.09)
Population density	2.52
	(1.46)
Sex Ratio	1.02
	(0.05)
Light Density	9.03
	(5.96)

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***	-0.003*	0.002	0.008***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Rainfall		-0.003***		-0.001		-0.003***
		(0.000)		(0.001)		(0.001)
N	910386	373419	910386	373419	910386	373419
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

	Full Sample	Monsoon Season	
	Temperature	Temperature	Rainfall
	(1)	(2)	(3)
Property			
Burglary	-0.004	-0.006	0.000
	(0.003)	(0.005)	(0.001)
Banditry	0.009	0.003	-0.012*
	(0.006)	(0.014)	(0.006)
Theft	-0.005**	0.005*	-0.002*
	(0.002)	(0.003)	(0.001)
Robbery	0.005	0.006	-0.000
	(0.005)	(0.007)	(0.003)
Violent			
Murder	0.009***	0.006	-0.006**
	(0.003)	(0.005)	(0.003)
Attempted Murder	0.012***	0.009***	-0.006**
	(0.002)	(0.003)	(0.002)
Rape	0.008**	0.010**	-0.006*
	(0.004)	(0.005)	(0.003)
Assault	0.008***	0.007***	-0.003***
	(0.001)	(0.001)	(0.001)
Fight	0.013***	0.008	-0.013**
	(0.004)	(0.008)	(0.006)
Other			
Riots	0.009***	0.009***	-0.003***
	(0.001)	(0.002)	(0.001)
Kidnapping	0.001	0.004	0.001
	(0.006)	(0.007)	(0.003)
Auto Accident	0.002**	0.003*	0.000
	(0.001)	(0.001)	(0.000)
Arson	0.015***	0.010	0.006
	(0.005)	(0.009)	(0.005)
Gambling	-0.001	-0.002	-0.003***
	(0.002)	(0.003)	(0.001)
Unnatural Death	0.007***	0.006***	0.002**
	(0.001)	(0.002)	(0.001)
Negligence Death	-0.005	-0.011	-0.004
	(0.012)	(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 temperature alone and is estimated for all days during the year. Columns (2)–(3) 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: Full Sample						
temperature	0.007***	0.008	0.005	0.000	0.008**	0.011***
	(0.001)	(0.010)	(0.008)	(0.004)	(0.004)	(0.001)
N	910386	597563	514418	898536	840917	907040
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 the sample; 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: Group Conflict

	All	Attack on SC/ST	Hindu-Muslim Violence
	(1)	(2)	(3)
Panel A: Full Sample			
Temperature	0.009***	0.008***	0.014***
	(0.002)	(0.003)	(0.004)
N	900287	897185	494013
Panel B: Monsoon Season			
Temperature	0.009**	0.009**	0.011
	(0.004)	(0.004)	(0.011)
Rainfall	-0.004**	-0.003	-0.016**
	(0.002)	(0.002)	(0.008)
N	348212	341970	130368

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 the sample; 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 6: Daily Weather and Crime Across Days of Week and Holidays

	Violent Crime		
	Full Sample	Monsoon Season	
	Temperature	Temperature	Rainfall
	(1)	(2)	(3)
Holiday	0.018***	0.014	-0.005
	(0.006)	(0.011)	(0.004)
Monday	0.013***	0.017***	-0.004***
	(0.003)	(0.006)	(0.002)
Tuesday	0.020***	0.024***	-0.003**
	(0.004)	(0.006)	(0.002)
Wednesday	0.007**	0.014**	-0.005***
	(0.004)	(0.006)	(0.002)
Thursday	0.004***	0.002	-0.003*
	(0.002)	(0.002)	(0.002)
Friday	0.007***	0.017***	0.000
	(0.002)	(0.006)	(0.001)
Saturday	0.014***	0.015***	-0.004**
	(0.003)	(0.003)	(0.002)
Sunday	0.019***	0.022***	-0.005***
	(0.004)	(0.006)	(0.002)

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 the sample; 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 7: Daily and Seasonal Weather Shocks

	All Crime		Property Crime		Violent Crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Monsoon Season						
Daily Variables						
Temperature		0.005***		-0.002		0.007***
		(0.001)		(0.003)		(0.001)
Rainfall		-0.002***		-0.001		-0.003***
		(0.000)		(0.001)		(0.001)
Seasonal Variables						
Temperature	0.019***	0.014***	0.019***	0.021***	0.020***	0.012**
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.005)
Rainfall	-0.011**	-0.005	-0.018**	-0.009	-0.007	-0.003
	(0.004)	(0.005)	(0.008)	(0.008)	(0.006)	(0.006)
N	2613	373391	2613	373391	2613	373391

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. The sample includes only the monsoon (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 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***	0.004***	0.006***	0.002	-0.005	0.002	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Rainfall	-0.002**	-0.003***	-0.002**	0.001	-0.002*	0.001	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Seasonal Variables									
Temperature	0.030***	0.000	0.023***	0.033***	0.012	0.025**	0.029***	-0.003	0.024***
	(0.006)	(0.005)	(0.006)	(0.012)	(0.009)	(0.011)	(0.008)	(0.007)	(0.007)
Rainfall	-0.032***	0.006	-0.032***	-0.035**	0.001	-0.038***	-0.030***	0.007	-0.026***
	(0.009)	(0.006)	(0.008)	(0.016)	(0.009)	(0.014)	(0.011)	(0.007)	(0.010)
Interaction Terms									
X Daily Temp			-0.002			-0.007			-0.001
			(0.002)			(0.006)			(0.002)
X Daily Rain			-0.001			-0.002			-0.000
			(0.001)			(0.002)			(0.001)
X Seasonal Temp			-0.020**			-0.009			-0.025**
			(0.008)			(0.014)			(0.010)
X Seasonal Rain			0.034***			0.037**			0.027**
			(0.009)			(0.015)			(0.011)
N	192132	181259	373391	192132	181259	373391	192132	181259	373391

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

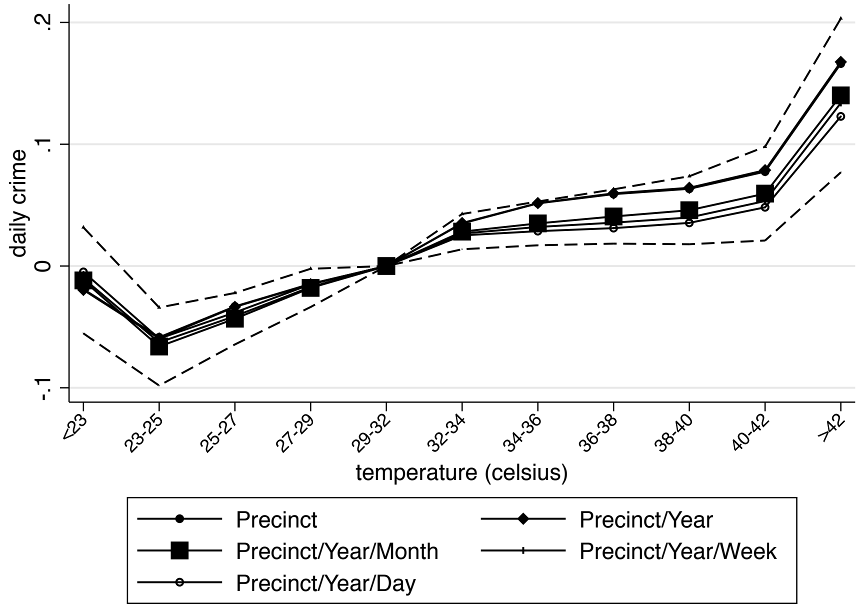
Karnataka's climate presents an exceptional diversity. Given the geographical variation in Karnataka ranging from hilly and Plateau regions to plain regions, the climate also demonstrate high diversity. There are three main climatic zones in Karantaka based on the topography. The first is the coastal 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.

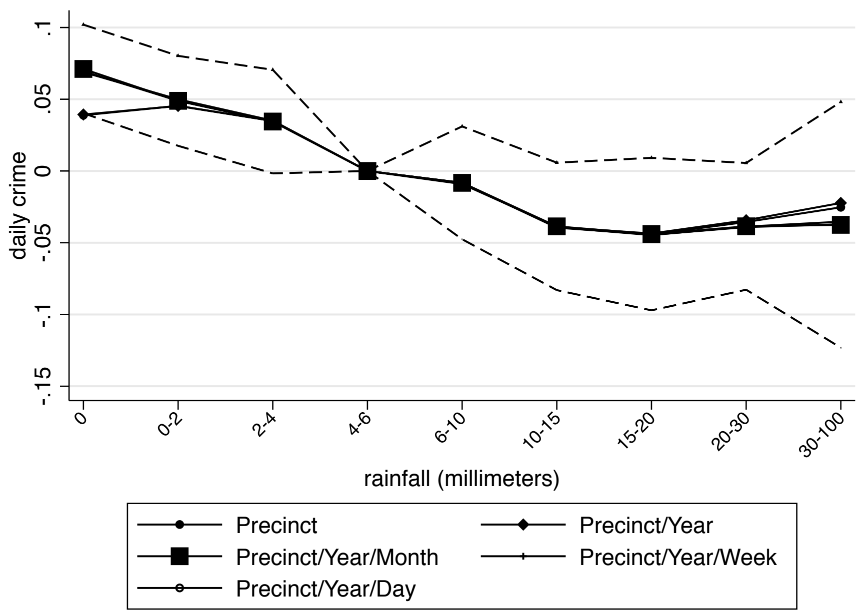
The monsoon season starts from June and lasts until September. During this season with the frequent showers and rainfall, the temperature drops while the humidity stays high. This season is predominant in the entire coastal belt and adjoining areas. This region can experience extremely heavy rainfall 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 Weather and Crime



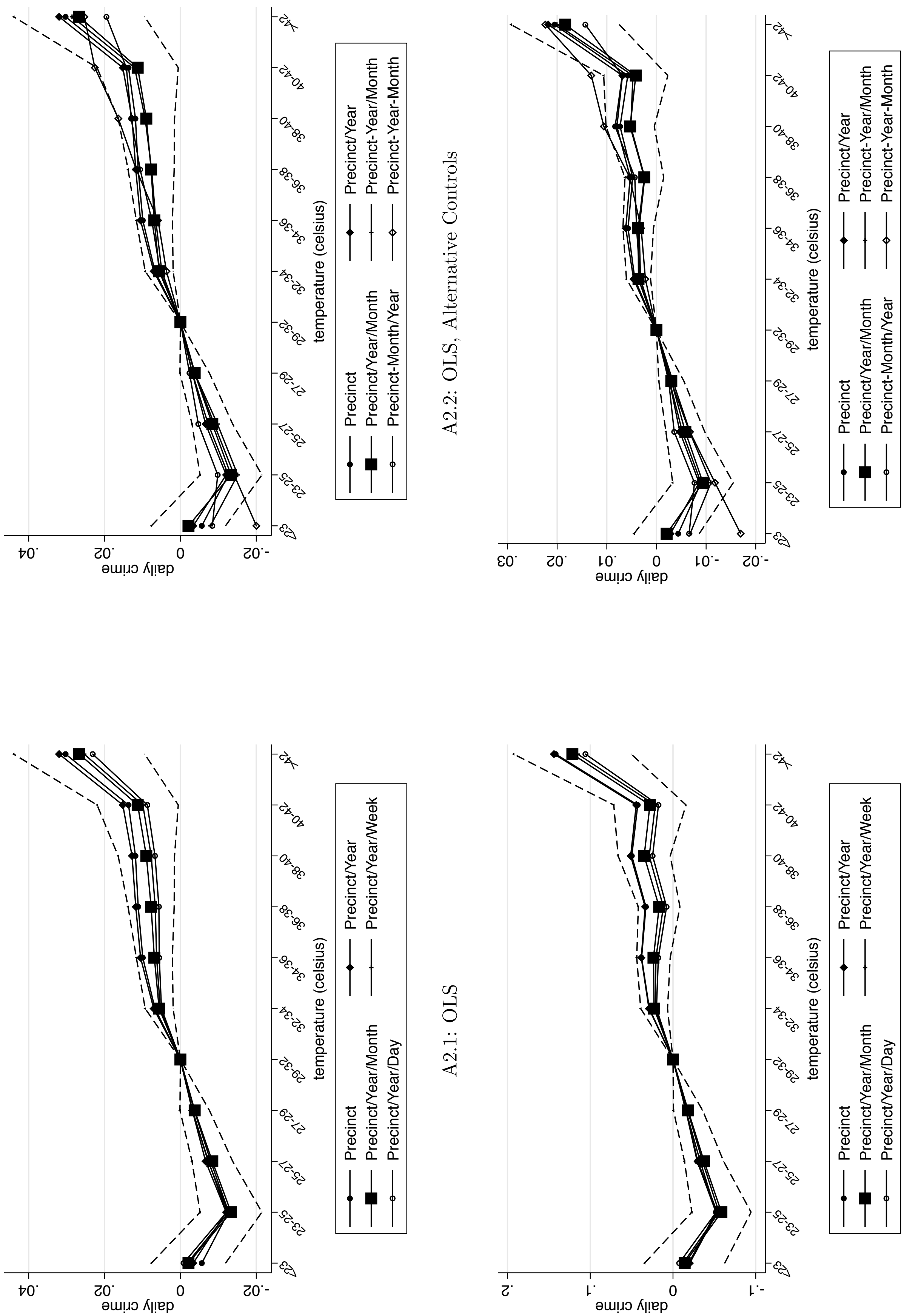
A1.1: Poisson, Temperature



A1.2: Poisson, Rainfall

Notes: Figure A1 plots the estimated impacts of daily temperature and rainfall on crime incidence for specifications including alternative fixed effects. Figure A1.1 shows temperature bin coefficients, with temperatures of 29–32 degrees Celsius as the reference category. Figure A1.2 shows rainfall bin coefficients, with daily rainfall of 4–6 millimeters as the reference category. Included fixed effects are indicated in legend. Dashed lines indicate the 95% confidence interval for specifications including precinct, year, and month fixed effects.

Figure A2: Alternative Temperature Specifications



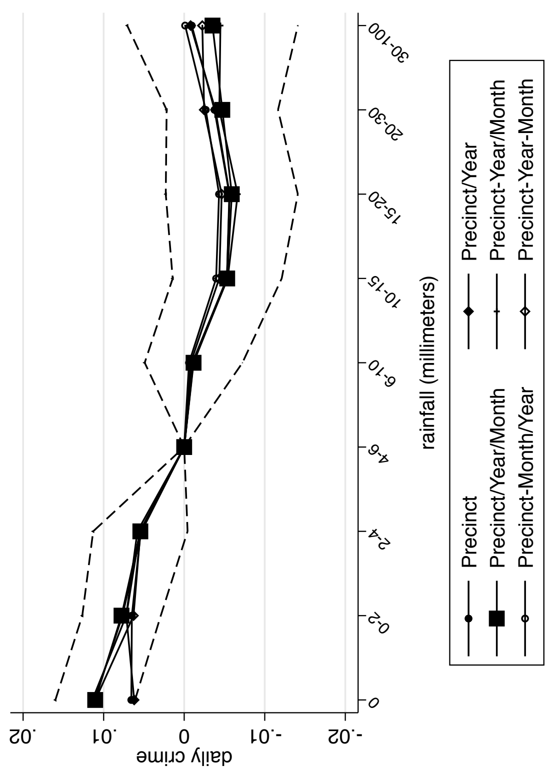
A2.1: OLS

A2.2: OLS, Alternative Controls

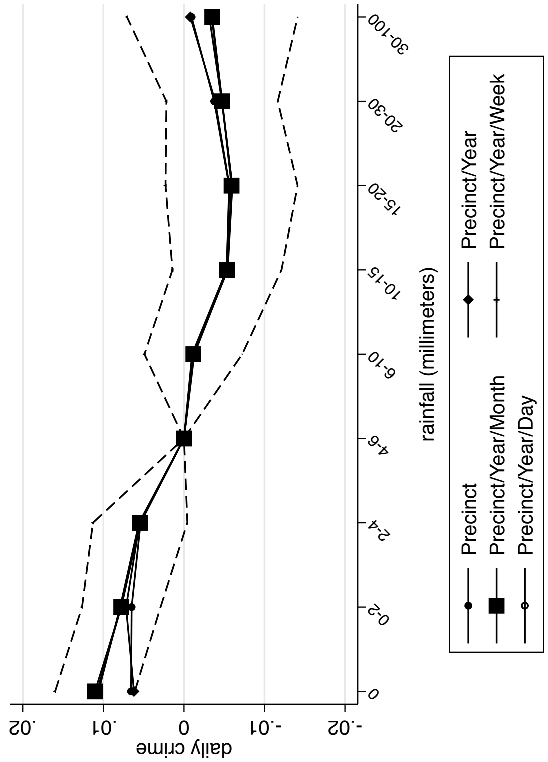
A2.3: LPM

A2.4: LPM, Alternative Controls

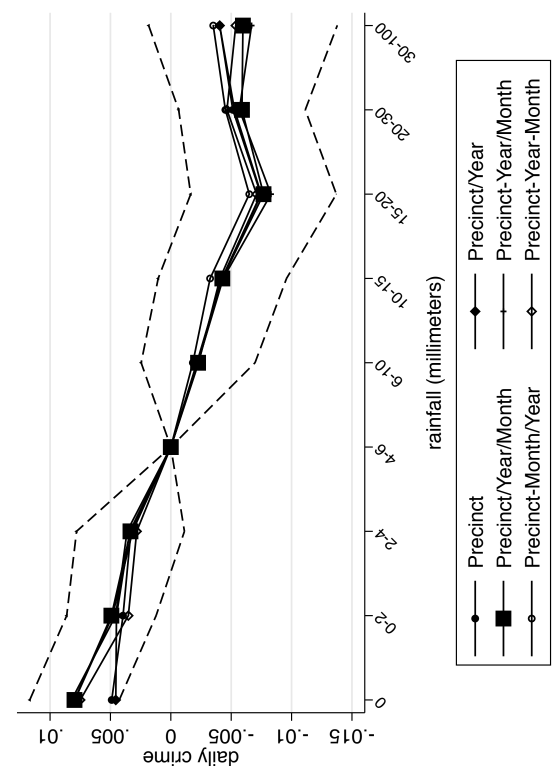
Figure A3: Alternative Rainfall Specifications



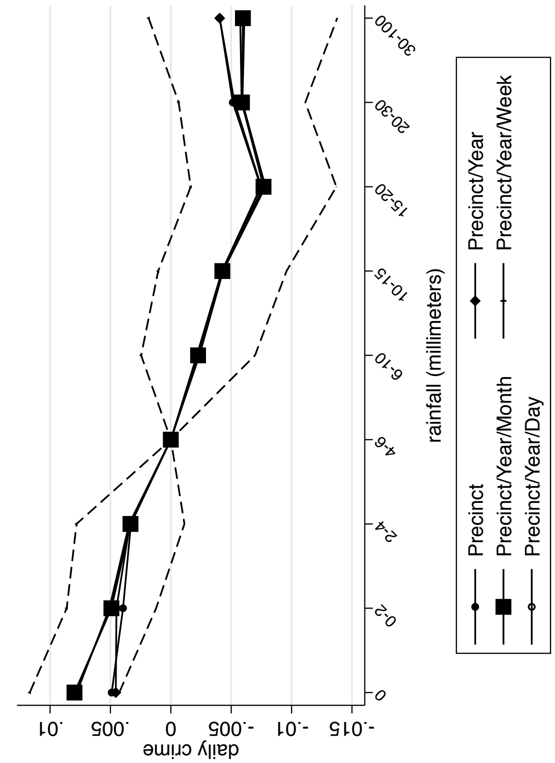
A3.1: OLS



A3.2: OLS, Alternative Controls



A3.3: LPM



A3.4: LPM, Alternative Controls

Table A1: 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. The sample includes only the monsoon season (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.