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

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Abstract

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 study the daily and seasonal 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. 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.

Key words: Weather Shocks, Climate, Crime, Conflict, Gender.
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1 Introduction

There is now a robust body of evidence that weather variability has substantial impacts on the occurrence of a variety of crimes (see Hsiang et al., 2013 for a review). For developing countries, most research has been restricted to weather-crime associations at the annual level (Blakeslee and Fishman, 2017), where the economic logic of violence is the central driver of the relationship. Consequently, the importance of variations at the daily frequency of weather and crime and the potential underlying non-economic drivers of this relationship remain poorly understood. Since weather and crime data at a disaggregated spatial and temporal resolution has thus far only been available in developed economies, much of this research has focused on high income countries. However, 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. This paper is one of the first to ***simultaneously*** identify the daily and annual weather-crime relationship for both property and violent crimes, as well as various disaggregated types of crimes particularly salient 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 unique data which covers a wide variety of crimes allow us to examine the strength of the weather-crime relationship along two dimensions: (1) impacts of both daily and seasonal temperature and rainfall; and (2) the types of crime (property and violent). These dimensions are important because the theoretical implications of the observed weather-crime relationship will depend crucially on the type of crime being considered and temporal scale at which impacts are realized.

Under the Becker (1968) model, an individual engages in crime when the economic benefit of the crime (such as appropriation of economic property) outweighs its opportunity cost. The Baysan et al. (2019) framework expands the standard economic model of violence to include pure consumption value for the aggressor from using violence. This is captured by the "taste for violence," which is assumed to respond positively to increased temperatures. Based on these two models, crime increases when the summation of the economic benefit of crime and the consumption value from using violence exceeds the opportunity cost of crime. Therefore, opportunity cost plays a role in the occurrence of both property and violent crime. However, economic benefits play a larger role for ***property*** crime, whereas "taste for violence" plays a larger role for ***violent*** crime.

Temporally, both daily and seasonal variation in rainfall and temperature can affect crime through their effects on the benefits and opportunity costs of crime. Concurrent (same-year) seasonal weather variation in the form of low rainfall and high temperature reduce the ***opportunity cost*** of crime. This is because adverse seasonal weather reduces agricultural productivity, which lowers wages and increases unemployment for agricultural workers during the cultivation season (Blakeslee and Fishman, 2017). However, concurrent seasonal variation in temperature and rainfall are less likely to affect the economic ***bene ts*** of crime, as the conversion of higher agricultural output into expropriable assets occurs in the months after the crops have been harvested. Taken together, this leads to the following hypothesis for the seasonal weather-crime relationship: both property and violent crimes are likely to increase when changes in seasonal weather reduce the opportunity cost of crime.

Daily variation in weather, in contrast, has virtually no effect on agricultural productivity or employment, and therefore is unlikely to affect the economic benefits or opportunity cost of crime. However, higher temperatures may increase aggression levels and the "taste for violence" (Anderson, 2001; Baysan et al., 2019). Daily variation in rainfall on the other hand, affects the opportunity cost of crime, as higher rainfall may increase the logistical difficulty of committing a crime, and also lead to fewer social interactions (Miguel et al., 2004),[1] thereby reducing the number of potential targets for criminals and the opportunities for unplanned crimes. Overall, this leads to the hypotheses that daily increases in temperature increase the likelihood of violent crimes but not property crimes; while daily increases in rainfall lead to fewer crimes which arise from social interactions or require significant travel.

These theoretical arguments provide us with testable hypotheses for the directions of the daily and seasonal weather-crime relationships, and their dependence on the type of crime being considered. Previous research, while grounded in a similar theoretical framework, has generally focused on a single temporal dimension of the weather-crime relationship (sub-annual or annual frequency). Due to the unique spatio-temporal resolution of our data, we are able to simultaneously estimate the impacts of daily and seasonal weather variation, allowing us to test these hypotheses, and to assess the relative importance of daily and seasonal weather variation in driving the weather-crime relationship.

We begin our analysis by documenting substantial same-day increases in crime with

[1] Miguel et al. (2004) discuss this issue in the context of civil war in Africa. The authors raise the 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. Moreover, high rainfall can also lead to lower crime by the taste of violence channel through its effect on temperatures.

elevated daily temperature, and declines with elevated daily rainfall. Consistent with our hypotheses, we find that the same-day effects of temperature are present only for violent crimes and not for property crime. While it is theoretically ambiguous as to which types of crime would be most affected by daily rainfall, we find again that it is primarily violent crime which is affected. The effects of daily temperature and rainfall are consistent across a broad range of violent crimes, including forms of violence which are particularly salient in India, such as violence against socially vulnerable groups (women and low-caste individuals), as well as ethno-religious conflict.

Next, we show that high seasonal temperatures cause similar increases in both property and violent crimes, while low seasonal rainfall has large effects on property crime, but far smaller (and less precisely measured) impacts on violent crime. Importantly, when we estimate specifications that simultaneously include both the daily and seasonal weather variables, we find that property crimes are affected only by seasonal weather variation, whereas violent crimes respond primarily to daily weather variation.

Our results indicate that weather affects crime both through economic channels as well as non-economic channels. That property crimes are affected by seasonal variables but not daily variables suggests that income-related channels are the primary driver of the weather-crime relationship for property crime—an interpretation which is strengthened by the additional finding that these seasonal effects are stronger in areas with high agricultural employment. In contrast, the impact of weather on violent crime appears to operate through both economic and non-economic channels, with the latter being somewhat more important. While we emphasize the likely role of psychological responses to heat—i.e., a "taste for violence"—we do not rule out additional non-economic channels, such as general cognitive impairment (Garg et al., 2016; Park, 2016) or increased alcohol consumption (Cohen and Gonzalez, 2018).

This analysis represents an important extension of earlier research, which generally assumed economic channels to be the primary factor mediating the weather-conflict relationship across a broad range of types of conflict, including political and ethnic conflict (Bohlken and Sergenti, 2010; Iyer and Topalova, 2014; Mitra and Ray, 2014), gender-based violence (Miguel, 2005; Aizer, 2010; Sekhri and Storeygard, 2014), and violence against marginalized castes (Sharma, 2015). Several concurrent studies examine the weather-crime relationship in Mexico to identify non-economic effects of temperature on crime, including: Baysan et al. (2019), who study the effects of temperature on homicides, drug-related killings, and suicides; Garg et al. (2018), who focus on homicides; and Cohen and Gonzalez (2018), who study a broad range of crime types in Mexican municipalities. Our analysis complements these papers, while studying the weather-crime relationship at a higher temporal and spatial resolution—***daily*** crime and weather at the ***precinct*** level; and shedding light on many crime types particularly salient in developing countries, including ethnic conflict and crimes against women.

Our paper also contributes more broadly to the extensive literature on the economics of crime.[2] Among the topics addressed in this literature are: 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 (Kling, 2006; Raphael, 2010; Doleac and Hansen, forthcoming), and the effects of criminally accused politicians on local economic outcomes (Prakash et al., 2019).

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. In addition, temperatures in our study area are substantially higher (30–35 C throughout most of the year) than those found in most advanced economies, and are similar to those found in many other developing countries. This is important, as the effect of elevated temperatures may depend crucially on whether individuals are acclimatized to higher mean temperatures.

The remainder of the paper is structured as follows. In Section 2, we describe the data. 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. We also report results for crimes committed against women and marginalized groups, as well as inter-group conflict between Muslims and Hindus. In Section 5, we turn to a discussion of the potential mechanisms and conclude.

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.

[2]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.

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."[3] 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 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 inter-group. 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

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

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 pollution data and data from the demographic and economic censuses.

As an additional robustness test, we control for air pollution introducing a potential omitted variable bias. Emerging evidence shows a positive relationship between the level of pollution (especially particulate matter) and crime (Bondy et al., 2020; Burkhardt et al., 2019; Herrnstadt et al., 2020). Unlike the United States (Burkhardt et al., 2019; Herrnstadt et al., 2020), or United Kingdom (Bondy et al., 2020), high spatial resolution data for air pollution measured by terrestrial sensors are not available in our empirical context. We overcome this limitation by using satellite measurements. Remotely-sensed measurement of Aerosol Optical Depth (AOD) is well-established to be highly correlated with particulate matter (PM_{10}, and $PM_{2:5}$) pollution at a very high spatial resolution (Chu et al., 2003; Engel-Cox et al., 2004; Emili et al., 2010; Lin et al., 2015). We extracted AOD data from the MODIS (Moderate Resolution Imaging Spectroradiometer) instrument aboard the Terra satellite using the `MOD043K` product available from NASA at a 3 KM resolution (Levy et al., 2015).[4] We created an annual composite raster for 2013 (the mid-point year in our analysis), and extracted vectorized data for our police precinct boundaries.

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. As 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

[4] See https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MOD04_3K/ for a detailed description of this product.

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 estimating the impact of (i) *daily* weather fluctuations (ii) *seasonal* weather fluctuations, and (iii) *both* daily and seasonal weather fluctuations jointly, on the incidence of different types of crime.

For estimating the daily weather-crime relationship, 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:

$$Y_{P,D} = \exp(\beta(T_{P,D}) + \gamma(R_{P,D}) + f_P(D) + \alpha_P + \varepsilon_{P,D}), \tag{1}$$

where $Y_{P,D}$ is the number of crime incidents in precinct P on date D. Here, $\beta(T)$ and $\gamma(R)$ are functions of the daily maximum temperature T and rainfall R. The function $f_P(D)$ captures time trends that are potentially precinct-specific, and α_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.

To study the daily weather-crime relationship, we control for global month and year fixed effects $f_P(D) = \mu_m + \eta_y$. 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 $f_P(D) = \mu_m \times \eta_y$ as well as models that include precinct-month-year fixed effects $\lambda_{P,m,y}$.

Next, to study the seasonal weather-crime relationship, we estimate the following specification:

$$Y_{P,y} = \exp(\beta(T_{P,y}) + \gamma(R_{P,y}) + \eta_y + \alpha_P + \varepsilon_{P,y}), \tag{2}$$

where the unit of observation is at the precinct-year (P, y) level. $_y$ and $_{(P)}$ are year- and precinct-fixed effects, respectively. The seasonal variables are specified as 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. For our seasonal analysis, the months of monsoon are of primary interest because, in an agrarian setting, employment cycles, and hence the opportunity costs of crime, move in tandem with the monsoon season. We also define the seasonal rainfall/temperature using z-scores, based on the precinct-level weather distribution; as well as terciles (following Shah and Steinberg, 2017), which take a value of 1 if the z-score is above the 80th percentile, 0 if it is between 20th and 80th percentile, and -1 if it is less than the 20th percentile.

Next, Figures 1 and 2 provide further motivation for accounting for seasonal weather variables when studying the daily 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.[5] Therefore, we also simultaneously estimate the daily and seasonal impact of weather on crime. We, therefore, include precinct-specific seasonal cycles $_{P,m}$ such that we estimate a specification which includes seasonal and daily weather variables in a single regression.

In the subsequent analysis, we will focus on two broad categories of crime: property and violent. The main distinction between the two is whether the crime is being committed primarily for economic gain (property); or, instead, is motivated primarily by the "taste for violence," with little regard for pecuniary gain (violent). Property crimes include burglary, theft, robbery, and banditry. Violent crimes include murder, attempted murder, rape, fights, and violent assaults.

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 specification 1 we divide the range of observed daily temperatures (rainfall) into ten 2 C (2 mm) bins (denoted by j), and specify:

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

$$
\begin{aligned}
(T_{P;D}) &= \sum_{j=1}^{10} {}_j I_j^T(T) \\
(R_{P;D}) &= \sum_{j=1}^{10} {}_j I_j^R(R);
\end{aligned} \tag{3}
$$

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 ${}_j$ and ${}_j$ are the objects of estimation.

Non-parametric specifications of weather shocks such as specification 3 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 individual impact separately and directly.

Figure 3 presents a plot of the estimated coefficients ${}_j$ and ${}_j$ from specification 3 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 plot estimates derived from similar specifications that include alternative fixed effects, including global year-month-week and year-month-day fixed effects, as well as police station-specific year, month, and year-month 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.

All of these specifications yield virtually identical results.[6] 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

[6]The linear relationship is further confirmed by using a flexible restricted cubic spline in temperature and rainfall as illustrated in Appendix Figure A3.

paper.

4.2 Main 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 (T) and (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 (T) and (R) coefficients for property and violent crimes. The patterns strongly indicate that daily weather primarily affects the incidence of violent crime.

Daily Variation: Table 2 reports the resulting estimates using the linear measures of temperature and rainfall on all crimes (column 1), property (column 2) and violent crimes (column 3). In Panel A we use the entire sample, while in Panel B we limit the sample to the monsoon season (June–October), since little rainfall occurs outside of this period.

Panel A estimates suggest that an increase of 1 C in daily maximum temperature is associated with a 0.5% increase in the expected crime count on a given day. This effect is 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.

In Panel B we restrict our sample to monsoon season and find that in response to an increase in temperature by 1 C, incidence of all crimes increases by 0.6%, which is again driven primarily by the increase in violent crimes. An increase in rainfall also mimics our results from Panel A, where in response to 1mm increase in rainfall, all crimes reduce by 0.2% and violent crimes decrease by 0.3%. We find no statistically significant relation between daily weather and property crimes.

We also confirm these results using a number of robustness exercises. Our main results are based on standard errors clustered at the precinct level. In Appendix Table A1 we use alternative clustering for standard errors which includes: district clustering (Panel A); bootstrap clustering by drawing days with replacement (Panel B); and spatially, using Conley standard errors (Panel C).[7]

[7] For Panel C, we use an OLS specification rather than Poisson, due to the infeasibility of spatial clustering with the latter.

One potential confounder in the daily weather-crime relationship may be the level of pollution. This is because it tends to co-vary with maximum temperature (especially ozone) and there is evidence that pollution itself causes crime (Herrnstadt et al., 2020). Furthermore, the same logic is also consistent with rainfall decreasing crime as it washes out pollution. To address this concern, in Appendix Table A2 we estimate the daily effect of temperature and rainfall on crime in areas with higher and lower pollution levels based on the Aerosol Optical Depth (AOD) data from the Moderate Resolution Imaging Spectoradiometer (MODIS).[8] We find results similar to Table 2 confirming that the daily weather is primarily driving these results. However, we do find that the estimated impact of temperature (but not rainfall) is differentially larger in high relative to low pollution areas.

In the results shown thus far temperature and rainfall are specified as having linear effects on the outcomes of interest. However, one concern with our results could be that they are driven by extreme weather conditions, broadly defined by the tails of the distribution (see Figure 3). In Appendix Table A3 we drop extreme weather incidents in Panel A. Additionally, in Panel B we include minimum temperature as an additional variable in specification 1.[9] In all of these specifications, we find results similar to Table 2.

Taken together, these results are broadly consistent with our hypothesis that elevated daily temperatures increase the taste for violence, leading to an increase in violent crimes. The effect of daily rainfall on crime is consistent with an opportunity cost channel, with high rainfall reducing the number of social interactions (and thereby the number of victims) and increasing the costs of movement.

However, if households are sufficiently dependent on daily wages (as could be the case for the poorest households), and daily employment sufficiently dependent on daily weather conditions, then economic channels might be present even with the daily weather-crime relationship. To test this possibility, in Table A4 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 somewhat larger on non-working days than on working days, arguing against the presence of economic channels.[10] These results are in line with the hypothesis that the daily weather and crime relationship is primarily driven by non-pecuniary motivations.

Seasonal Variation: In Table 3 we study the effects of seasonal weather on all crimes (column 1), property crimes (column 2), and violent crimes (column 3). In panel A, we use

[8] More information on the data for pollution is given in Section 2.

[9] This allows us to consider if higher minimum temperatures may affect sleep quality making individuals more irritable and aggressive.

[10] The larger effect on weekends and holidays may indicate that alcohol consumption and social interactions, which are more common on these days, play an important mediating role in the daily weather-crime relationship.

the precinct-level mean temperature and rainfall during the monsoon season, in panel B we use the standardized deviations from the mean (z-scores), and in panel C we use the terciles for seasonal weather. Across all specifications, we find results consistent with our hypothesis that concurrent (same-year) seasonal temperature and rainfall affects all types of crimes by changing the opportunity cost of crime. Specifically, our results show that all crimes, both property and violent, go up with higher temperature and lower rainfall (though the effect of rainfall is imprecisely estimates for violent crimes).

Thus far, our results are consistent with the hypotheses discussed above regarding the economic and non-economic drivers of the weather-crime relationship, which are associated with seasonal and daily weather variation, respectively. However, the ***relative*** importance of these mechanisms is an open question, for which there exists little empirical evidence. We address this question next.

Daily and Seasonal Weather Variation: Figures 1 and 2 motivate the importance of analyzing the effects of daily and seasonal weather variation simultaneously. Specifically, violent crime moves in close tandem with temperatures, peaking in May when temperatures are highest, and falling during the cooler winter months. Because this time period encompasses both the non-agricultural summer season (March–May), as well as the agricultural monsoon season (June–October), it is likely that any analysis focusing only on daily or seasonal weather will conflate the impacts of the two. Property crime displays a slightly different seasonality, peaking towards the latter months of the monsoon season (late-August). Because the patterns for property crime again closely match the planting season, daily and seasonal effects of weather variation are likely to be conflated when looking at either category of weather independently.

In Table 4 we jointly estimate the impact of daily and seasonal weather on crime. For seasonal variables we use the precinct-level terciles for seasonal weather. We find that violent crime is affected by both daily and seasonal weather variation. However, a substantial share of the relationship between weather and violent crime is driven by daily variation, as evidenced by the smaller (and less significant) coefficients for seasonal weather relative to daily weather variables. For property crimes, which are primarily based on economic motivations, seasonal weather variation continues to matter even after controlling for daily weather variations (the latter showing no statistical significance). It is important to note that the loss of significance for some of the seasonal coefficients should not be interpreted as undermining the well-documented seasonal weather-crime relationship, as the data only spans five years, meaning that the seasonal analysis may be somewhat imprecise.

In Appendix Table A5 we also test for the differential effects of weather variation according to the fraction of non-agricultural population. For this exercise, we divide the sample into areas with non-agricultural labor forces above and below the sample median (23% of workers).[11] 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.

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 (agricultural) economic channels.

4.3 Impacts on Individual Crime Types

In Table 5 we show the results for a variety of individual crimes. Columns (1) and (2) give the temperature and rainfall coefficients when using the entire year, while columns (3) and (4) give the coefficients when limiting the sample to the monsoon months. 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 0.7 to a 1.2% increase in the probability of crime count with each additional 1 C increase in temperature. For property crimes, in contrast, the relationships are substantially smaller and (for heat) generally insignificant. 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 almost 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 unnatural deaths increase with higher rainfall.

The disaggregated results also help to rule out the possibility that the estimated effects of weather are being driven in part by changes in reporting and detection, rather than the incidence of crime. Specifically, researchers often cite violent crimes such as murder to be least susceptible to biases in reporting. In our analysis, we see that daily weather has statistically significant impacts on both murder and attempted murder; and, moreover, that the coefficients are of similar magnitude to those for other crimes. This suggests that the impacts being estimated reflect the true effects of daily weather variation on crime, and not merely the timing of reporting.

[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.

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 and seasonal weather shocks. We describe our results below.

4.4.1 Crimes against women

In Table 6 we explore the effects of daily weather variation (Panels A and B) and both daily and seasonal weather variations jointly (Panel C) 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. There are statistically significant increases in the expected count of non-dowry related abuse, harassment, and rape with elevated temperatures, consistent with the overall results found for violent crime. Elevated rainfall causes a decline in the public harassment of women, non-dowry abuse, and rape, again consistent with the results for violent crimes. Dowry-related crimes are unaffected by daily weather.

In Panel C, where we jointly include both daily and seasonal weather variables, we find that the results for daily weather variables are generally unaffected by the inclusion for seasonal variables. We also find little evidence for effects of seasonal weather variations on crime, save for a decline in harassment with elevated rainfall.

While increases in violence against women with elevated daily temperature follow straightforwardly from a "taste for violence" mechanism, the impacts of rainfall are more ambiguous. Specifically, whereas harassment and rape might be expected to decline with reduced social interactions, the decline of domestic abuse with elevated rainfall does not follow from a social interactions mechanism. The latter finding may, however, be consistent with a psychological mechanism, in which low rainfall affects domestic violence through an increase in stress levels, due to the importance of rainfall for agricultural incomes. Though a single day's rainfall will generally not affect agricultural output, it may affect ***beliefs*** about aggregate monsoon rainfall and output. 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.

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 inter-group 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 estimate the effect of daily weather variation on inter-group conflict. The results are given in Panel A of Table 7 for the full year, and in Panel B for the monsoon season. 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.

In Panel C of Table 7 we include both daily and seasonal weather variations jointly. We find that the effects of daily temperature and rainfall remain similar when we include seasonal weather. In contrast, seasonal weather variables do not have a statistically significant impact on these 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, much of the literature on Hindu-Muslim violence stresses the strategic and economic factors that underlie this phenomenon (Mitra and Ray, 2014).[12] The findings shown here indicate that inter-group conflict can be triggered by non-economic factors in much the same way as interpersonal violent crime. In addition, daily rainfall has a negative association with Hindu-Muslim conflict. We are unaware of other research showing such an effect of daily rainfall on inter-group violence.

5 Discussion and Conclusion

A large literature, mostly focused on the ***annual*** weather-crime relationship, has empirically confirmed the predictions of the Becker (1968) model, where criminal activity increases when there is a fall in the opportunity cost of crime. Recent theoretical and empirical work posits that non-economic channels, such as a psychologically driven "taste for violence," may also contribute to the impact of weather on crime (Baysan et al., 2019). This work focuses on the ***sub-annual*** weather-crime relationship, where economic factors are less likely to play a significant role.

[12] 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.

In this paper, we contribute to the existing literature using a novel data set covering all crimes at the ***daily*** level across the roughly 600 police stations in the state of Karnataka, India. Combining this dataset with daily weather data (temperature and rainfall), we provide important insights into the nature of the weather-crime relationship, and its implications for models based on economic and non-economic channels. We show that violent crimes increase with higher daily temperature and fall with higher daily rainfall, but that property crimes are largely unaffected by daily weather. Importantly, when we ***jointly*** estimate the effect of daily and seasonal weather on crime, we find that violent crimes are affected primarily by daily weather, whereas property crimes are affected only by seasonal weather variation.

While we cannot definitively identify the specific mechanisms at play, our results provide important insights on the the class of mechanisms likely present. The patterns presented in this paper for the relationship between daily temperature and daily crime suggest that non-economic mechanisms are at play, as elevated temperatures would only result in meaningful losses of income over time.[13] Though there are numerous non-economic channels by which temperature may affect crime, one likely factor is the psychological effect of elevated temperatures on aggression, as evidenced by the large effect of temperature on violent crimes (Tables 2 and 5) and the absence of such an effect for property crimes.

This does not preclude the presence of additional mechanisms driving the temperature-crime relationship, such as a general erosion of cognitive functioning. For example, several papers show that there is a general decline in cognitive functioning when temperatures are elevated (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 5). 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 previous research. One plausible channel is through the effect of rainfall on social interactions, with low rainfall facilitating more 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.[14] Though we are aware of no research verifying the effect of rainfall on

[13]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.

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

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.[15] 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 (depending on the locus of the item being stolen). An additional mechanism possibly at work is the effect of rainfall in reducing pollution levels, as pollution has been shown elsewhere to cause an increase in crime (Herrnstadt et al., 2020).

The larger effect of daily rainfall on violent than property crimes may also be indicative of a psychological channel. For example, rainfall may reduce aggression levels, either directly or indirectly through a reduction in 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 agricultural output, it may affect expectations of future weather events and the ultimate success of the cropping season.[16]

One potential concern is that daily weather shocks simply change the timing at which crimes are reported, for example if heavy rainfall makes it difficult for victims to report a crime. However, this is inconsistent with the fact that it is primarily violent crimes that decline with rainfall and increase with temperature, 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 weather (up to two days) has the same sign as same-day weather, whereas the sign should be flipped if daily weather is simply changing the timing of reporting.[17]

One significant aspect of our study is that it takes place in a region with persistently high temperatures, with seasonal temperatures ranging between 30–35 C throughout most of the year. Despite being accustomed to perennially high temperatures, individuals nonetheless continue to display a strong tendency for violence when a single day's temperature makes an unexpected rise. This may indicate that physiological acclimatization has limited potential

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

[16] 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.

[17] We do not employ the distributed lag model to formally study the displacement of crime, as we find strong evidence that, in this context, lag and lead coefficients are likely to be, at least in part, spurious. In results presented in the Online Appendix, we show that leads and lags have similarly signed, but smaller, coefficients as the same-day weather shocks. The reason for this is likely due to the extremely high serial correlation across consecutive days in the weather variables (the correlation in temperature between consecutive days is 0.85). When combined with even relatively small measurement error in the weather variables, this will cause the lead and lag coefficients to capture some of the variation in crime being generated by same-day weather shocks. Because we are not aware of any paper addressing this issue, we present a simulation exercise in the Online Appendix demonstrating this phenomenon.

to reduce the future impacts of rising temperatures on the incidence of crime.

However, even if the potential of economic or non-economic 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), decriminalization (Adda et al., 2014), and women police stations (Amaral et al., 2018). Identifying and evaluating such interventions, and assessing whether they may moderate the impact of daily weather shocks, is an important subject for future research.

References

Adda, J., B. McConnell, and I. Rasul (2014): "Crime and the depenalization of cannabis possession: Evidence from a policing experiment," Journal of Political Economy, 122, 1130–1202.

Aizer, A. (2010): "The Gender Wage Gap and Domestic Violence," American Economic Review, 100, 1847–59.

Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003): "Fractionalization," Journal of Economic Growth, 8, 155–94, o. Galor (ed.) (2011), Inequality and Economic Development: The Modern Perspective, Edward Elgar, UK.

Amaral, S., N. Prakash, and S. Bhalotra (2018): "Gender, Crime and Punishment: Evidence from Women Police Stations in India," Working Paper.

Anderson, C. A. (2001): "Heat and Violence," Current Directions in Psychological Science, 10, 33–38.

Baysan, C., M. Burke, F. Gonzalez, S. Hsiang, and E. Miguel (2019): "Non-economic factors in violence: Evidence from organized crime, suicides and climate in Mexico," Journal of Economic Behavior Organization, 168, 434 – 452.

Becker, G. S. (1968): "Crime and Punishment: An Economic Approach," Journal of Political Economy, 76, 169–217.

Blakeslee, D. S. and R. Fishman (2017): "Rainfall Shocks and Property Crimes in Agrarian Societies: Evidence from India," Journal of Human Resources.

Blattman, C., J. C. Jamison, and M. Sheridan (2017): "Reducing crime and violence: Experimental evidence from cognitive behavioral therapy in Liberia," American Economic Review, 107, 1165–1206.

Bohlken, A. T. and E. J. Sergenti (2010): "Economic Growth and Ethnic violence: An Empirical Investigation of Hindu-Muslim Riots in India," Journal of Peace Research.

Bondy, M., S. Roth, and L. Sager (2020): "Crime is in the air: The contemporaneous relationship between air pollution and crime," Journal of the Association of Environmental and Resource Economists, 7, 555–585.

Burke, M., S. M. Hsiang, and E. Miguel (2015): "Climate and Conflict," Annual Review of Economics, 7, 577–617.

Burkhardt, J., J. Bayham, A. Wilson, E. Carter, J. D. Berman, K. O'Dell, B. Ford, E. V. Fischer, and J. R. Pierce (2019): "The effect of pollution on crime: Evidence from data on particulate matter and ozone," Journal of Environmental Economics and Management, 98, 102267.

Card, D. and G. B. Dahl (2011): "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior," The Quarterly Journal of Economics, 126, 103.

Chalfin, A. and S. Raphael (2011): "Work and crime," in The Oxford Handbook of Crime and Criminal Justice, Oxford University Press New York, 444–76.

Chu, D. A., Y. Kaufman, G. Zibordi, J. Chern, J. Mao, C. Li, and B. Holben (2003): "Global monitoring of air pollution over land from the Earth Observing System-Terra Moderate Resolution Imaging Spectroradiometer (MODIS)," Journal of Geophysical Research: Atmospheres, 108.

Cohen, F. and F. Gonzalez (2018): "Understanding interpersonal violence: the impact of temperatures in Mexico," Center for Climate Change Economics and Policy Working Paper No. 326.

Coviello, L., Y. Sohn, A. D. Kramer, C. Marlow, M. Franceschetti, N. A. Christakis, and J. H. Fowler (2014): "Detecting emotional contagion in massive social networks," PloS one, 9, e90315.

Deschenes, O. and M. Greenstone (2007): "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather," American Economic Review, 97, 354–385.

Dhar, D., T. Jain, and S. Jayachandran (2018): "Reshaping Adolescents' Gender Attitudes: Evidence from a School-Based Experiment in India," Unpublished manuscript.

Doleac, J. and B. Hansen (forthcoming): "The unintended consequences of "ban the box": Statistical discrimination and employment outcomes when criminal histories are hidden," Journal of Labor Economics.

Draca, M. and S. Machin (2015): "Crime and economic incentives," Annual Review of Economics, 7, 389–408.

Emili, E., C. Popp, M. Petitta, M. Riffler, S. Wunderle, and M. Zebisch (2010): "PM10 remote sensing from geostationary SEVIRI and polar-orbiting MODIS sensors over the complex terrain of the European Alpine region," Remote sensing of environment, 114, 2485–2499.

Engel-Cox, J. A., C. H. Holloman, B. W. Coutant, and R. M. Hoff (2004): "Qualitative and quantitative evaluation of MODIS satellite sensor data for regional and urban scale air quality," Atmospheric environment, 38, 2495–2509.

Fougere, D., F. Kramarz, and J. Pouget (2009): "Youth unemployment and crime in France," Journal of the European Economic Association, 7, 909–938.

Garg, T., M. Jagnani, and V. Taraz (2016): "Human Capital Costs of Climate Change," Unpublished Manuscript.

Garg, T., G. C. McCord, and A. Montfort (2018): "Losing your Cool: Psychological Mechanisms in the Temperature-Crime Relationship in Mexico," Tech. rep., Mimeo.

Gould, E. D., B. A. Weinberg, and D. B. Mustard (2002): "Crime rates and local labor market opportunities in the United States: 1979–1997," Review of Economics and Statistics, 84, 45–61.

Gronqvist, H. (2013): "Youth unemployment and crime: Lessons from longitudinal population records," Swedish Institute for Social Research, mimeo.

Herrnstadt, E., A. Heyes, E. Muehlegger, and S. Saberian (2020): "Air pollution and criminal activity: Microgeographic evidence from Chicago," American Economic Journal: Applied Economics.

Hsiang, S. M. (2010): "Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America," Proceedings of the National Academy of Sciences, 107, 15367–15372.

Hsiang, S. M., M. Burke, and E. Miguel (2013): "Quantifying the Influence of Climate on Human Conflict," Science, 341.

Iyer, L. and P. B. Topalova (2014): "Poverty and crime: evidence from rainfall and trade shocks in India," Harvard Business School BGIE Unit Working Paper.

Kenrick, D. T. and S. W. MacFarlane (1986): "Ambient Temperature and Horn Honking a Field Study of the Heat/Aggression Relationship," Environment and Behavior, 18, 179–191.

Kling, J. R. (2006): "Incarceration length, employment, and earnings," American Economic Review, 96, 863–876.

Levitt, S. D. and T. J. Miles (2006): "Economic Contributions to the Understanding of Crime," Annual Review of Law and Social Science, 2, 147–164.

Levy, R., C. Hsu, et al. (2015): MODIS Atmosphere L2 Aerosol Product, NASA MODIS Adaptive Processing System, Goddard Space Flight Center, USA.

Lin, C., Y. Li, Z. Yuan, A. K. Lau, C. Li, and J. C. Fung (2015): "Using satellite remote sensing data to estimate the high-resolution distribution of ground-level PM2. 5," Remote Sensing of Environment, 156, 117–128.

Lin, M.-J. (2008): "Does unemployment increase crime? Evidence from US data 1974–2000," Journal of Human Resources, 43, 413–436.

Lochner, L. and E. Moretti (2004): "The effect of education on crime: Evidence from prison inmates, arrests, and self-reports," American Economic Review, 94, 155–189.

Machin, S., O. Marie, and S. Vujic (2011): "The crime reducing effect of education," The Economic Journal, 121, 463–484.

Machin, S. and C. Meghir (2004): "Crime and economic incentives," Journal of Human resources, 39, 958–979.

Miguel, E. (2005): "Poverty and Witch killing," The Review of Economic Studies, 72, 1153–1172.

Miguel, E., S. Satyanath, and E. Sergenti (2004): "Economic shocks and civil conflict: An instrumental variables approach," Journal of Political Economy, 112, 725–753.

Mitra, A. and D. Ray (2014): "Implications of an economic theory of conflict: Hindu-Muslim violence in India," Journal of Political Economy, 122, 719–765.

Park, J. (2016): "Human Stress and Human Capital Production," Unpublished Manuscript, Harvard University Economic Department, Working Paper.

Prakash, N., M. Rockmore, and Y. Uppal (2019): "Do criminally accused politicians affect economic outcomes? Evidence from India," Journal of Development Economics, 102370.

Ranson, M. (2014): "Crime, Weather, and Climate Change," Journal of Environmental Economics and Management, 67, 274–302.

Raphael, S. (2010): "Improving employment prospects for former prison inmates: Challenges and policy," in Controlling crime: Strategies and tradeoffs, University of Chicago Press, 521–565.

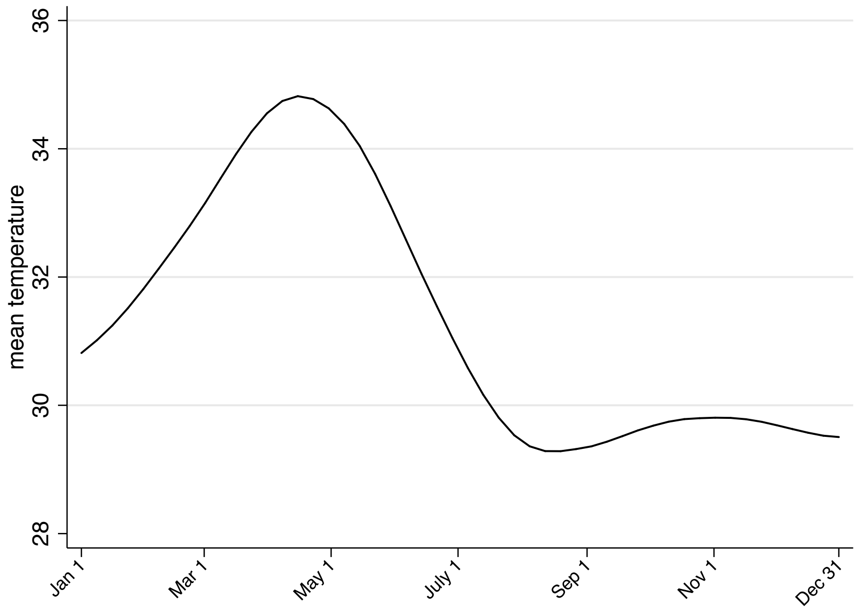
Raphael, S. and R. Winter-Ebmer (2001): "Identifying the effect of unemployment on crime," The Journal of Law and Economics, 44, 259–283.

Sekhri, S. and A. Storeygard (2014): "Dowry Deaths: Response to Weather Variability in India," Journal of Development Economics, 111, 212–223.

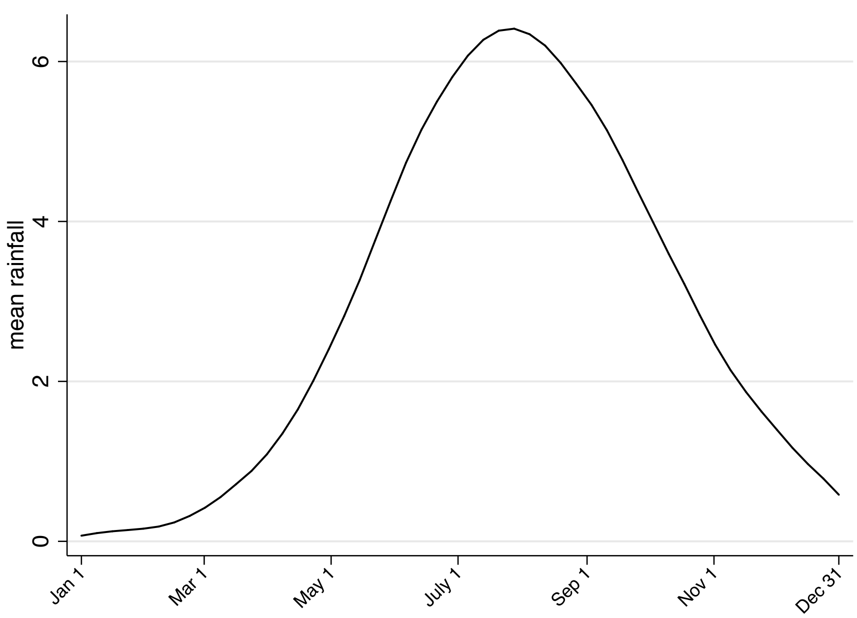
Shah, M. and B. M. Steinberg (2017): "Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital," Journal of Political Economy, 125, 527–561.

Sharma, S. (2015): "Caste-based crimes and economic status: Evidence from India," Journal of Comparative Economics, 43, 204–226.

Figure 1: Daily Weather



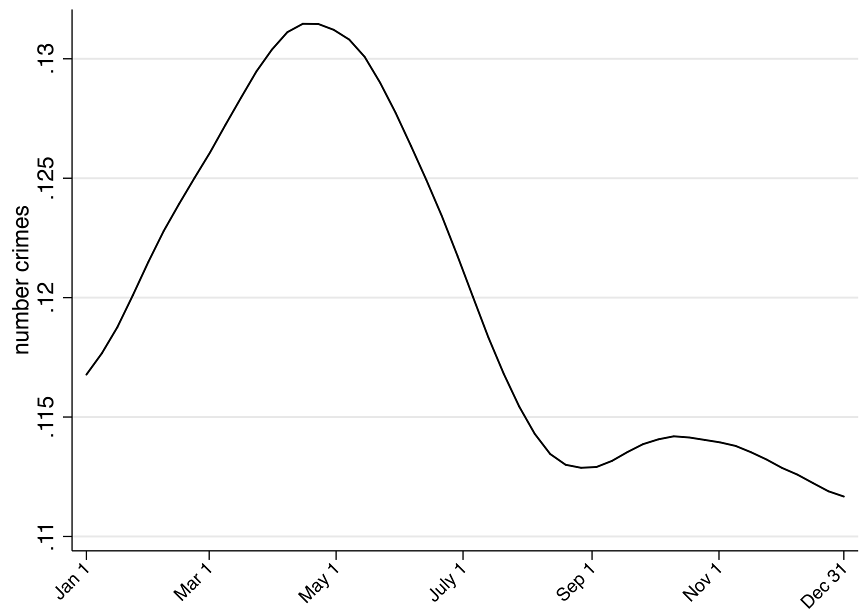
1.1: Mean Daily (Max) Temperature



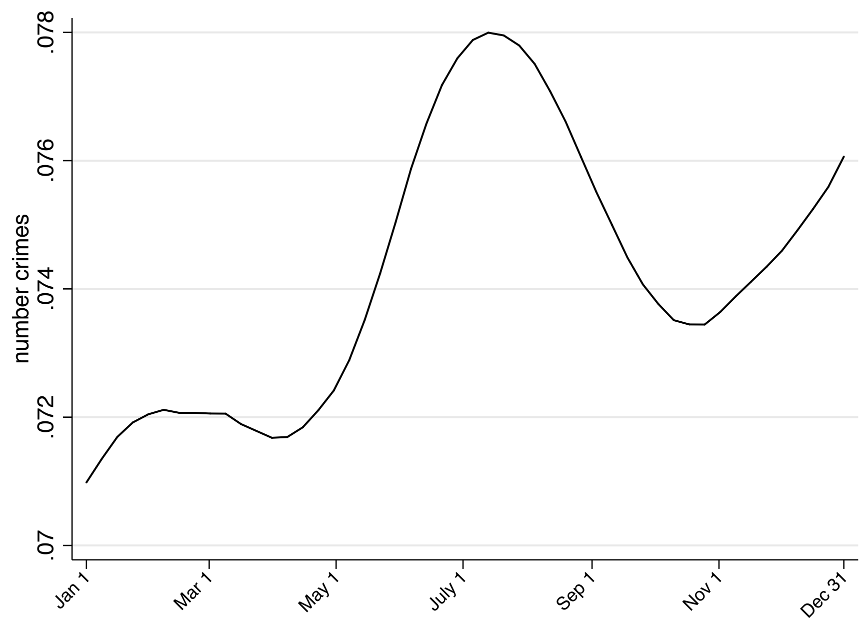
1.2: Mean Daily Rainfall

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



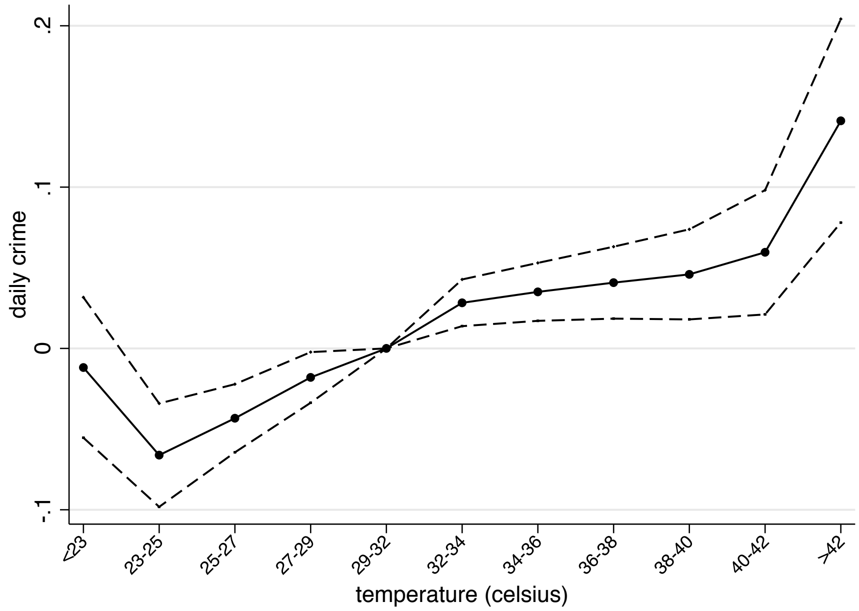
2.1: Violent Crime



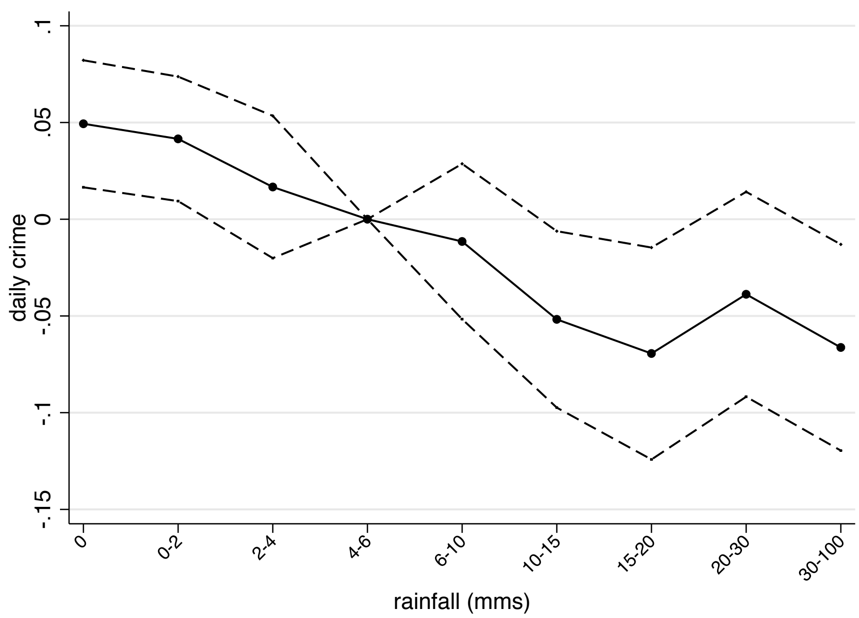
2.2: Property Crime

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



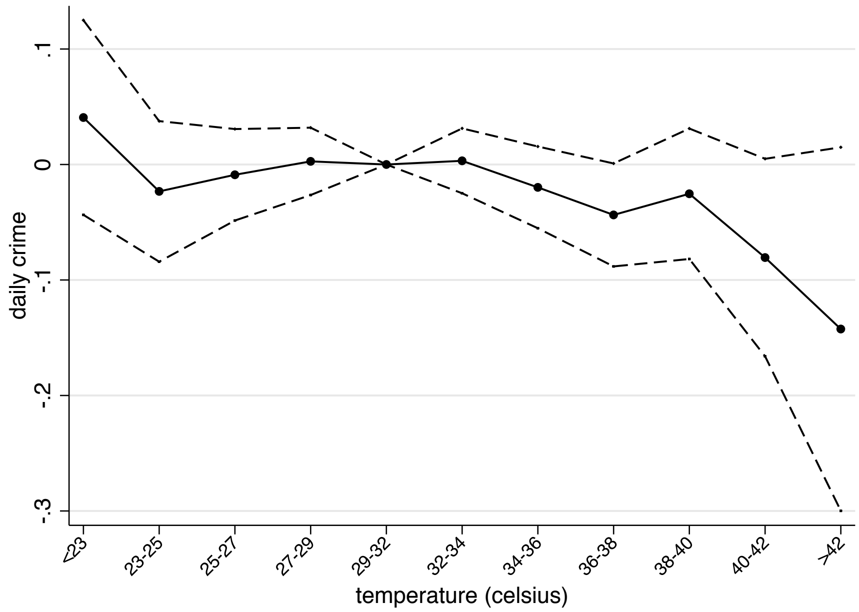
3.1: Maximum Temperature and Crime



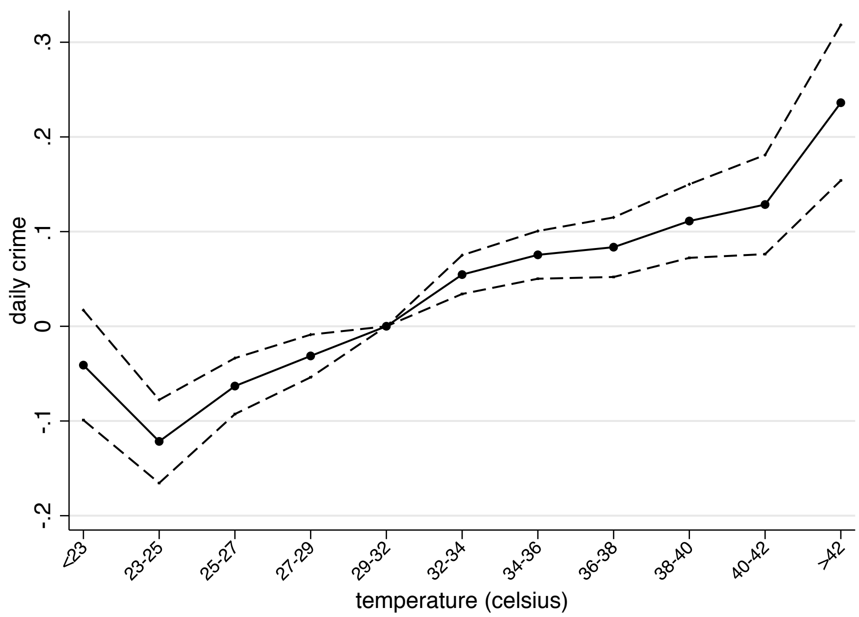
3.2: Rainfall and Crime

Notes: Figure 3 plots the estimated impacts of daily (maximum) temperature on crime incidence, as per specification 3. The figures are based on estimates obtained from a regression of daily crime on daily temperature/rainfall, with dummies used for daily temperatures/rainfall falling within the indicated intervals. Figure 3.1 plots temperature bin coefficients, with temperature of 29–32 degrees Celsius as the reference category, and Figure 3.2 plots 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



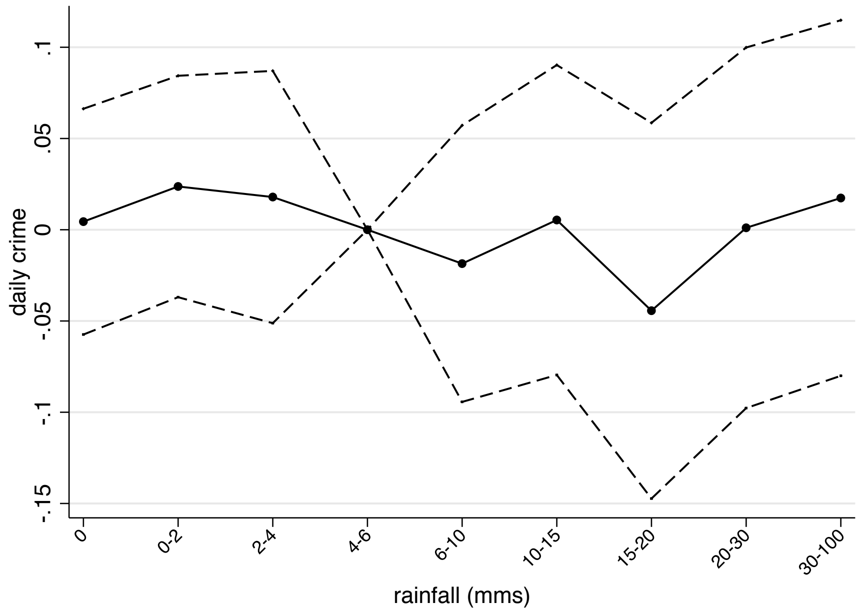
4.1: Property Crime



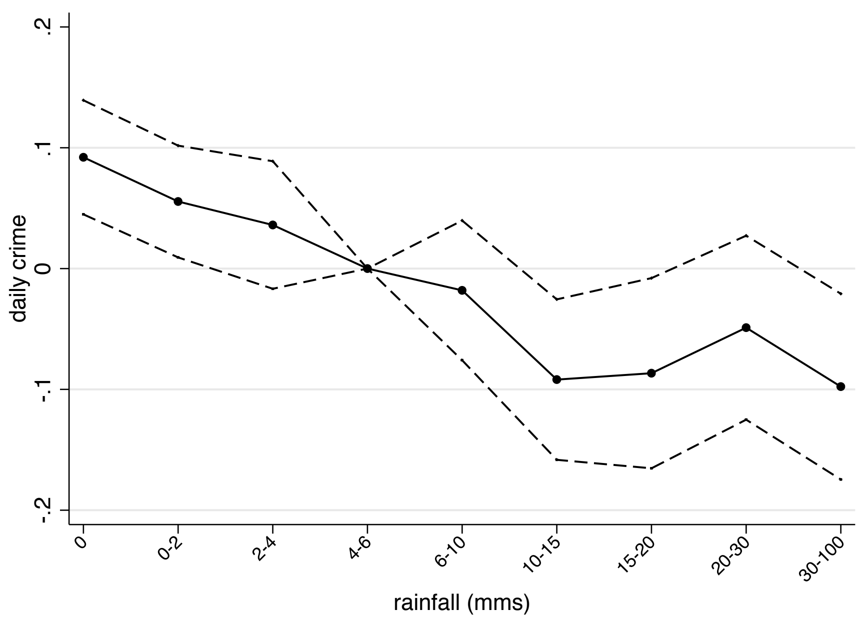
4.2: Violent Crime

Notes: Figure 4 plots the estimated impacts of daily (maximum) temperature on property (Figure 4.1) and violent (Figure 4.2) crime separately, as per specification 3, 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 3, 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)	Season: Monsoon (3)	Season: Winter (4)
Weather, Daily Mean				
Rainfall (mms)	2.79	1.50	5.41	0.45
	(5.11)	(1.53)	(6.93)	(1.07)
Max Temperature (C)	31.52	35.27	29.82	30.41
	(3.68)	(3.21)	(2.74)	(2.66)
Crime, Monthly Mean				
Property				
Burglary	0.43	0.40	0.48	0.41
	(0.94)	(0.90)	(0.99)	(0.91)
Banditry	0.03	0.03	0.03	0.03
	(0.20)	(0.20)	(0.19)	(0.20)
Theft	0.77	0.78	0.78	0.74
	(1.54)	(1.53)	(1.54)	(1.56)
Robbery	0.10	0.11	0.11	0.10
	(0.40)	(0.41)	(0.42)	(0.38)
Violent				
Murder	0.14	0.16	0.14	0.12
	(0.40)	(0.44)	(0.39)	(0.38)
Attempted Murder	0.17	0.20	0.17	0.15
	(0.47)	(0.51)	(0.48)	(0.43)
Rape	0.07	0.08	0.07	0.07
	(0.30)	(0.34)	(0.28)	(0.28)
Assault	1.79	2.14	1.72	1.62
	(2.42)	(2.72)	(2.33)	(2.24)
Fight	0.03	0.03	0.03	0.03
	(0.19)	(0.20)	(0.19)	(0.20)
Gender				
Dowry-related	0.15	0.15	0.15	0.14
	(0.47)	(0.45)	(0.47)	(0.49)
Domestic Abuse (non-dowry)	0.25	0.27	0.25	0.24
	(0.68)	(0.68)	(0.72)	(0.63)
Harassment	0.38	0.42	0.40	0.34
	(0.86)	(0.92)	(0.88)	(0.79)
Intergroup				
Attack on SC/ST	0.17	0.18	0.16	0.17
	(0.47)	(0.49)	(0.45)	(0.48)
Hindu-Muslim violence	0.03	0.02	0.02	0.04
	(0.34)	(0.17)	(0.18)	(0.53)
Other				
Riots	0.65	0.73	0.65	0.58
	(1.23)	(1.27)	(1.22)	(1.21)
Kidnapping	0.12	0.13	0.12	0.11
	(0.41)	(0.44)	(0.40)	(0.38)
Auto Accident	3.87	4.43	3.57	3.84
	(5.48)	(5.88)	(5.09)	(5.62)
Arson	0.04	0.05	0.02	0.04
	(0.21)	(0.28)	(0.16)	(0.21)
Gambling	1.00	1.01	1.07	0.91
	(1.80)	(1.81)	(1.85)	(1.74)
Unnatural Death	1.07	1.23	1.08	0.95
	(1.44)	(1.51)	(1.46)	(1.35)
Negligence Death	0.03	0.04	0.03	0.02
	(0.17)	(0.20)	(0.16)	(0.14)

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 weather, 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 (1)	Property (2)	Violent (3)
Panel A: Full Sample			
Temperature	0.005***	-0.003*	0.008***
	(0.001)	(0.002)	(0.001)
Rainfall	-0.003***	-0.000	-0.005***
	(0.000)	(0.001)	(0.001)
Mean	0.149	0.056	0.093
N	910304	910304	910304
Panel B: Monsoon			
Temperature	0.006***	0.002	0.008***
	(0.001)	(0.002)	(0.001)
Rainfall	-0.002***	-0.001	-0.003***
	(0.000)	(0.001)	(0.001)
Mean	0.147	0.057	0.090
N	373439	373439	373439

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are separately reported for all crimes (Columns 1), property crimes (Columns 2) and violent crimes (Columns 3). Panel A reports estimates for temperature and rainfall for all days in the sample; and Panel B reports the same estimates for 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: Seasonal Weather and Crime, Monsoon Season

	All Crime	Property	Violent
	(1)	(3)	(5)
Panel A: Seasonal Raw			
Temperature	0.020***	0.020**	0.020***
	(0.006)	(0.009)	(0.007)
Rainfall	-0.010	-0.017	-0.006
	(0.007)	(0.011)	(0.008)
N	2613	2613	2613
Panel B: Seasonal Z-Score			
Temperature	0.015***	0.017**	0.012*
	(0.006)	(0.008)	(0.006)
Rainfall	-0.032**	-0.049**	-0.023
	(0.013)	(0.020)	(0.015)
N	2437	2435	2437
Panel C: Seasonal Terciles			
Temperature	0.047***	0.049**	0.043***
	(0.013)	(0.020)	(0.015)
Rainfall	-0.038**	-0.052*	-0.031
	(0.017)	(0.027)	(0.020)
N	2437	2435	2437

Note: This table gives the estimated coefficients from a linear specification of model 2 for precinct-year sample. Estimates are separately reported for all crimes (Columns 1), property crime (Columns 2) and violent crimes (Columns 3). Panel A uses raw mean values, Panel B uses z-scores and Panel C uses terciles (using precinct specific distribution) for seasonal weather variables which are specified during the monsoon months (June–October). All specifications include precinct fixed effects and year fixed effects. Standard errors are clustered at the precinct level. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 4: Daily and Seasonal Weather and Crime

	All Crime			Property			Violent		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily Weather									
Temperature	0.006***		0.006***	0.002		-0.001	0.008***		0.008***
	(0.001)		(0.001)	(0.003)		(0.003)	(0.001)		(0.001)
Rainfall	-0.002***		-0.003***	-0.001		-0.001	-0.003***		-0.004***
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Seasonal Weather									
Temperature		0.047***	0.022*		0.049**	0.035*		0.043***	0.014
		(0.013)	(0.013)		(0.020)	(0.021)		(0.015)	(0.014)
Rainfall		-0.038**	-0.025		-0.052*	-0.029		-0.031	-0.024
		(0.017)	(0.017)		(0.027)	(0.027)		(0.020)	(0.020)
N	373439	2437	348166	373439	2435	347968	373439	2437	348166

Note: This table gives the estimated coefficients from a linear specification of model 1, model 2 and model 1 while controlling for precinct-specific seasonal cycles ($_{P;m}$). Estimates are separately reported for all crimes (Columns 1–3), property crime (Columns 4–6) and violent crimes (Columns 7–9). Columns (1), (4), and (7) report estimates from a model that includes daily seasonal weather variables (temperature and rainfall) and uses monsoon months (June–October); and Columns (2), (5), and (8) reports the estimates from a model that includes precinct-specific seasonal cycles ($_{P;m}$); columns (3), (6) and (9) include both daily and seasonal variables jointly and uses monsoon months (June–October). All specifications include precinct fixed effects, year fixed effects. For daily analysis and joint analyses, we also include month fixed effects. Standard errors are clustered at the precinct level. *** p<0.01, ** p<0.05, and * p<0.1. *** p<0.01, ** p<0.05, and * p<0.1.

Table 5: Disaggregated Crimes

	Full Year		Monsoon Season	
	Temperature	Rainfall	Temperature	Rainfall
	(1)	(2)	(3)	(4)
Property				
Burglary	-0.004	0.002**	-0.007	0.000
	(0.004)	(0.001)	(0.005)	(0.001)
Theft	-0.005	-0.002**	0.005*	-0.002
	(0.003)	(0.001)	(0.003)	(0.001)
Robbery	0.005	-0.001	0.005	-0.000
	(0.005)	(0.002)	(0.006)	(0.003)
Banditry	0.008**	-0.010*	0.004	-0.012*
	(0.003)	(0.006)	(0.008)	(0.006)
Violent				
Murder	0.009***	-0.006***	0.008***	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
Attempted Murder	0.011***	-0.008***	0.009***	-0.006**
	(0.001)	(0.002)	(0.002)	(0.003)
Rape	0.007	-0.005	0.010**	-0.005
	(0.005)	(0.003)	(0.005)	(0.003)
Assault	0.007***	-0.004***	0.007***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Fight	0.012***	-0.012**	0.008**	-0.013*
	(0.003)	(0.005)	(0.004)	(0.007)
Other				
Auto Accident	0.002**	-0.000	0.002*	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Arson	0.014***	-0.008	0.011***	0.005
	(0.003)	(0.006)	(0.003)	(0.005)
Unnatural Death	0.007***	0.001*	0.006***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Negligence Death	-0.005	0.003	-0.013	-0.005
	(0.012)	(0.004)	(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. Columns (1)–(2) report estimates from a model that includes the full sample and Columns (3)–(4) report estimates for 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: Crime Against Women

	All	Dowry-Related		Non-Dowry	Rape	Harassment
		Murder	Abuse	Abuse		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Daily (Full Sample)						
Temperature	0.007***	0.007	0.004	-0.001	0.007	0.011***
	(0.002)	(0.008)	(0.005)	(0.004)	(0.005)	(0.001)
Rainfall	-0.003***	-0.006	-0.004	-0.004***	-0.005	-0.003***
	(0.001)	(0.008)	(0.005)	(0.001)	(0.003)	(0.001)
N	910341	597525	514394	898491	840885	906995
Panel B: Daily (Monsoon)						
Temperature	0.007***	0.003	-0.012	0.008**	0.010**	0.008**
	(0.003)	(0.014)	(0.021)	(0.003)	(0.005)	(0.003)
Rainfall	-0.003***	-0.004	-0.005	-0.006***	-0.005	-0.003*
	(0.001)	(0.009)	(0.007)	(0.002)	(0.003)	(0.001)
N	372827	161527	133348	355960	281675	364842
Panel B: Daily & Seasonal (Monsoon)						
Temperature	0.006**	0.002	-0.011	0.004	0.010**	0.009***
	(0.003)	(0.016)	(0.022)	(0.004)	(0.005)	(0.003)
Rainfall	-0.004***	-0.006	-0.003	-0.005***	-0.006*	-0.003*
	(0.001)	(0.010)	(0.007)	(0.002)	(0.004)	(0.002)
Monsoon Temperature	0.008	-0.065	-0.119	0.007	0.090	-0.024
	(0.021)	(0.103)	(0.120)	(0.032)	(0.061)	(0.033)
Monsoon Rainfall	-0.001	0.034	-0.055	-0.006	0.062	-0.082*
	(0.028)	(0.124)	(0.160)	(0.045)	(0.079)	(0.044)
N	347842	148306	119681	328777	258868	340244

Note: This table gives the estimated coefficients from a linear specification of model 1 which includes precinct-specific seasonal cycles ($_{P;m}$) 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 includes all days in the sample; Panel B and Panel C include 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: Group Conflict

	All	SC/ST	Communal
	(1)	(2)	(3)
Panel A: Daily (Full Sample)			
Temperature	0.009***	0.008***	0.013***
	(0.002)	(0.002)	(0.003)
Rainfall	-0.005**	-0.002	-0.025***
	(0.002)	(0.002)	(0.008)
N	900242	897140	493999
Panel B: Daily (Monsoon)			
Temperature	0.009***	0.009***	0.011**
	(0.002)	(0.002)	(0.005)
Rainfall	-0.004*	-0.003	-0.017***
	(0.002)	(0.002)	(0.006)
N	348236	341994	130396
Panel C: Daily & Seasonal (Monsoon)			
Temperature	0.009***	0.008***	0.010
	(0.002)	(0.002)	(0.006)
Rainfall	-0.004*	-0.003	-0.017**
	(0.002)	(0.003)	(0.007)
Monsoon Temperature	0.000	-0.000	0.081
	(0.038)	(0.040)	(0.104)
Monsoon Rainfall	-0.090	-0.072	-0.192
	(0.057)	(0.059)	(0.165)
N	322414	315983	117181

Note: This table gives the estimated coefficients from a linear specification of model 1 which includes precinct-specific seasonal cycles ($_{P;m}$) for inter-group violence. Estimates are reported separately for all such crimes, attacks on scheduled castes and tribes (SC/ST) (Columns 2) and Hindu-Muslim violence. (column 3). Panel A includes all days in the sample; Panel B and Panel C include 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.

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

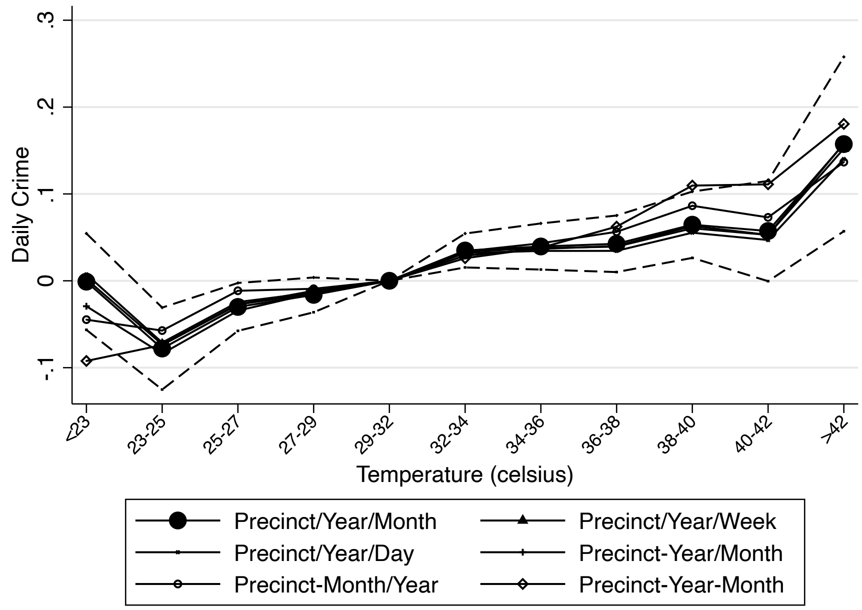
Karnataka's climate presents an exceptional diversity. Given the geographical variation in Karnataka ranging from hilly and Plateau regions to plain regions, the climate also demonstrate high diversity. There are three main climatic zones in Karantaka based on the topography. The first is the coastal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

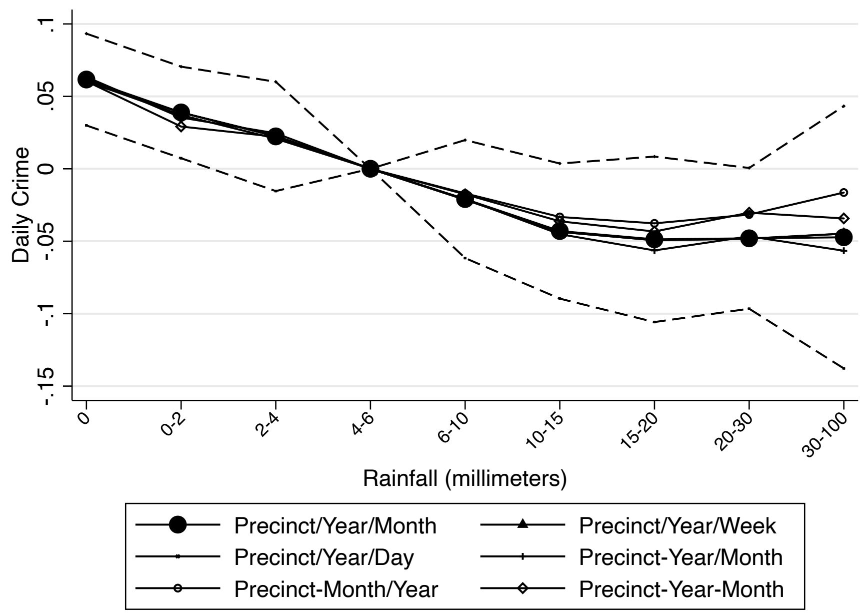
The monsoon season starts from June and lasts until September. During this season with the frequent showers and rainfall, the temperature drops while the humidity stays high. This season is predominant in the entire coastal belt and adjoining areas. This region can experience extremely heavy rainfall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



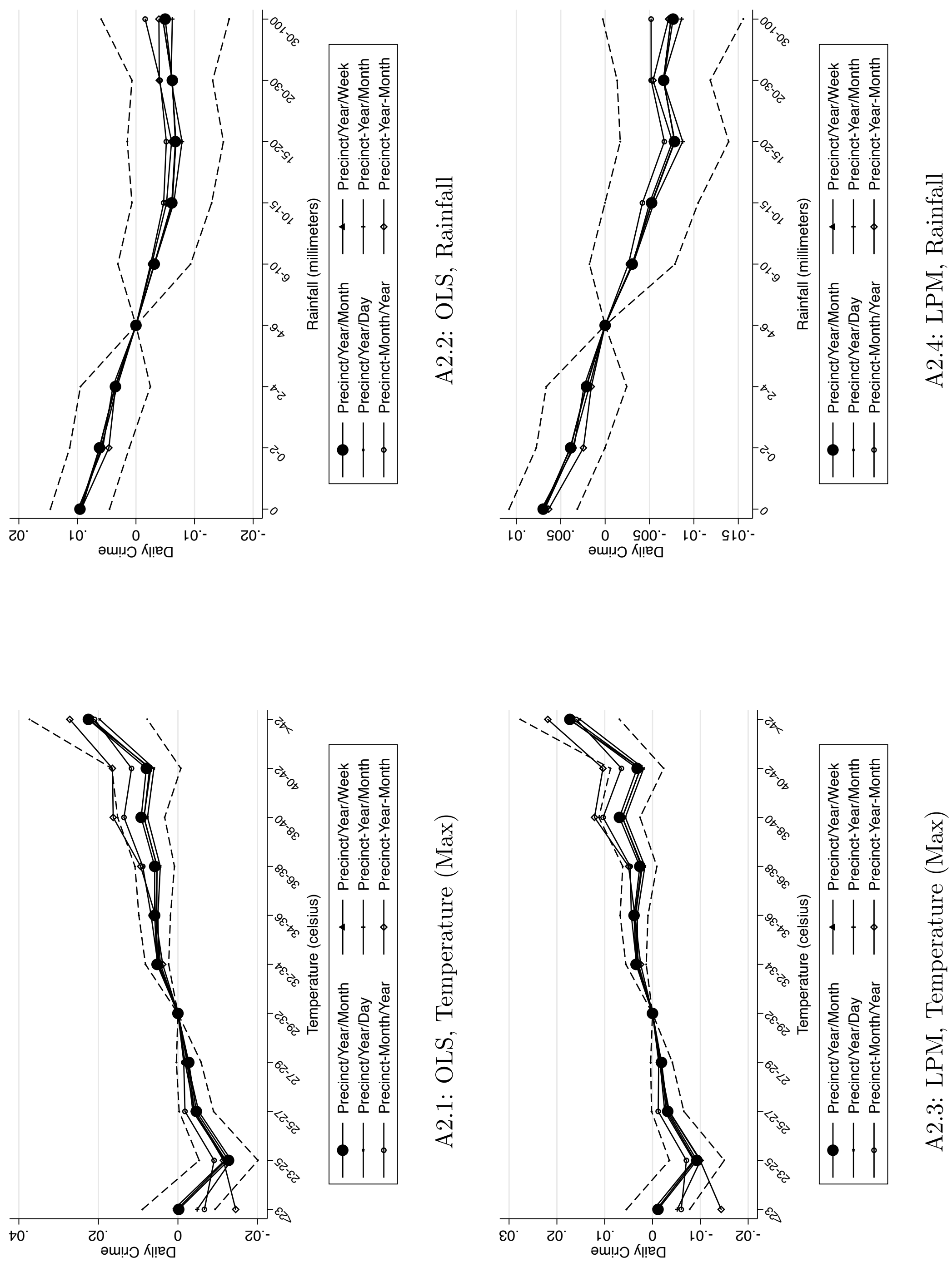
A1.1: Poisson, Temperature (Max)



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 the legend. Dashed lines indicate the 95% confidence interval for specifications including precinct, year, and month fixed effects.

Figure A2: Alternative Specifications



A2.1: OLS, Temperature (Max)

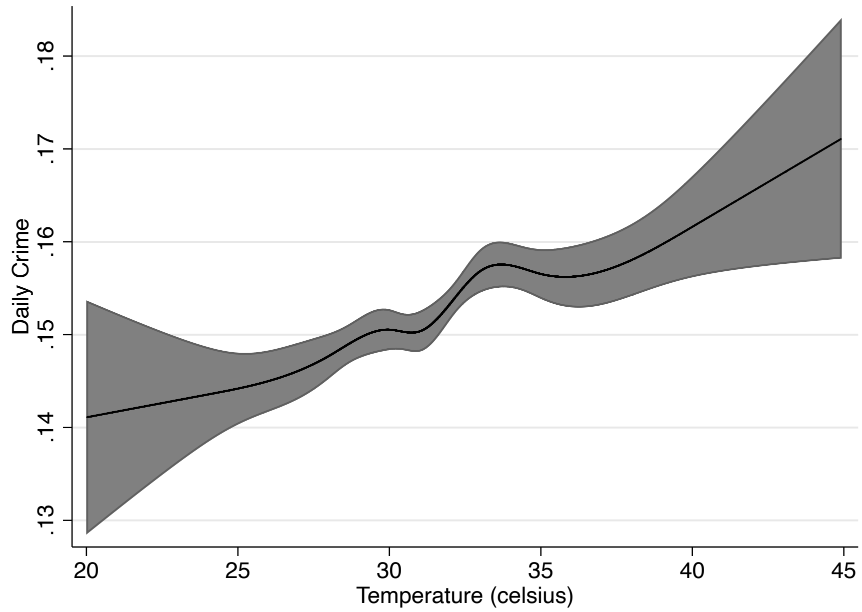
A2.2: OLS, Rainfall

A2.3: LPM, Temperature (Max)

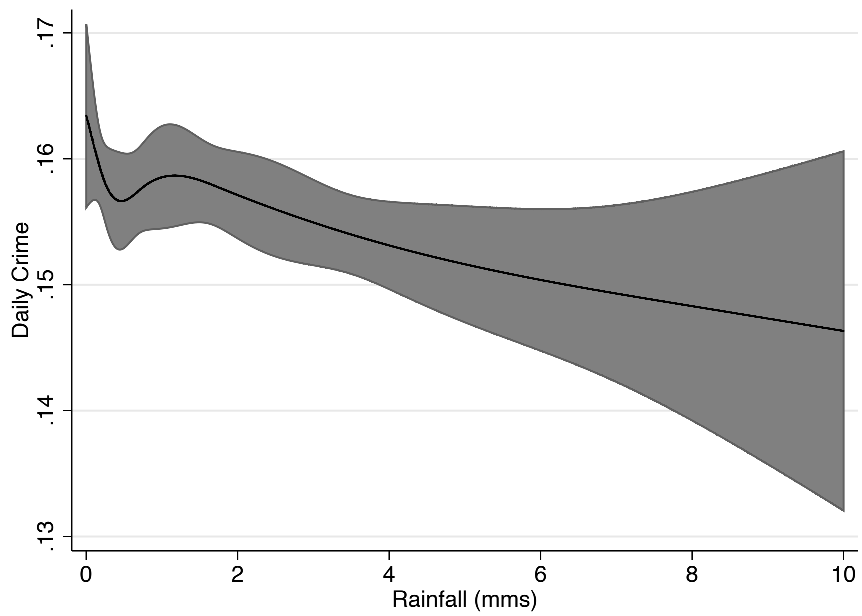
A2.4: LPM, Rainfall

Notes: Figure A2 plots the estimated impacts of daily temperature and rainfall on crime incidence for specifications including alternative fixed effects. All figures use an OLS specification. Figures A2.1 and A2.2 use the number of daily crimes as the outcome variable; while Figures A2.3 and A2.4 use an indicator for any crime being committed as the outcome variable. Figures A2.1 and A2.3 show temperature bin coefficients, with temperatures of 29–32 degrees Celsius as the reference category. Figures A2.2 and A2.4 show rainfall bin coefficients, with daily rainfall of 4–6 millimeters as the reference category. Included fixed effects are indicated in the legend. Dashed lines indicate the 95% confidence interval for specifications including precinct, year, and month fixed effects.

Figure A3: Flexible Cubic Spline



A3.1: Temperature (Max)



A3.2: Rainfall

Notes: Figure A3 plots restricted cubic spline (in maximum temperature in Figure A3.1 and rainfall in Figure A3.2) regression lines with seven knots for temperature, and six knots for rainfall. The grey area indicates the 95% confidence interval for specifications including precinct, year, and month fixed effects.

Table A1: Daily Weather and Crime, Alternative Clustering

	All (1)	Property (2)	Violent (3)
Panel A: District Clustering			
Temperature	0.005***	-0.003*	0.008***
	(0.001)	(0.002)	(0.001)
Rainfall	-0.003***	-0.000	-0.005***
	(0.000)	(0.001)	(0.000)
N	910341	910341	910341
Panel B: Bootstrap			
Temperature	0.005***	-0.003	0.008***
	(0.001)	(0.002)	(0.001)
Rainfall	-0.003***	-0.000	-0.005***
	(0.000)	(0.001)	(0.001)
N	910341	910341	910341
Panel C: Conley Clustering (Linear Model)			
Temperature	0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)
Rainfall	-0.000***	-0.000*	-0.000***
	(0.000)	(0.000)	(0.000)
	0.000	0.000	0.000
N	910341	910341	910341

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are separately reported for all crimes (Columns 1), property crime (Columns 2) and violent crimes (Columns 3). Panel A is based on standard errors clustered by district; Panel B uses bootstrap clustering by drawing days with replacement and; Panel C uses Conley standard errors (with a linear model). 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 A2: Daily Weather Shocks, by Pollution Level

	All Crime			Property Crime			Violent Crime		
	Pollution		Full	Pollution		Full	Pollution		Full
	Low	High	Sample	Low	High	Sample	Low	High	Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Daily Variables									
Temperature	0.003***	0.008***	0.003***	-0.004	-0.003	-0.004	0.006***	0.011***	0.006***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Rainfall	-0.003***	-0.003***	-0.003***	-0.001	0.000	-0.001	-0.004***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Interaction Terms									
X Temp			0.004**			0.001			0.005***
			(0.002)			(0.005)			(0.002)
X Rain			0.000			0.001			-0.001
			(0.001)			(0.001)			(0.001)
N	477504	432837	910341	477504	432837	910341	477504	432837	910341

Note: This table gives the estimated coefficients from a linear specification of model 1 that includes daily weather variables and their interactions with the indicator for above median pollution level (measure by Aerosol Optical Depth). 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 precincts with below median pollution level; 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 weather variables with the indicators for above median pollution level. 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 A3: Daily Weather and Crime, Alternative Specifications

	All (1)	Property (2)	Violent (3)
Panel A: Dropping Extreme Weather			
Temperature	0.007***	-0.003	0.012***
	(0.001)	(0.002)	(0.002)
Rainfall	-0.011***	0.000	-0.017***
	(0.002)	(0.003)	(0.003)
N	805903	805903	805903
Panel B: Including Minimum Temperature			
Temperature Max	0.005***	-0.003	0.007***
	(0.001)	(0.002)	(0.001)
Temperature Min	0.002	-0.004	0.005***
	(0.002)	(0.003)	(0.002)
Rainfall	-0.003***	-0.000	-0.005***
	(0.000)	(0.001)	(0.001)
N	909569	909569	909569

Note: This table gives the estimated coefficients from a linear specification of model 1. Estimates are separately reported for all crimes (Columns 1), property crime (Columns 2) and violent crimes (Columns 3). Panel A reports estimates for temperature and rainfall for all days excepts days where extreme weather is recorded (temperature below 23 and above 42 degrees or rainfall above 8 mms); and Panel B reports the same estimates but including minimum temperature along with maximum 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 A4: Daily Weather and Crime Across Days of Week and Holidays

	Mean (1)	Temperature (2)	Rainfall (3)
Holiday	0.090	0.016**	-0.006**
		(0.006)	(0.002)
Monday	0.094	0.011***	-0.005***
		(0.004)	(0.001)
Tuesday	0.096	0.017***	-0.005***
		(0.004)	(0.001)
Wednesday	0.094	0.007*	-0.006***
		(0.004)	(0.001)
Thursday	0.093	0.004**	-0.005***
		(0.002)	(0.001)
Friday	0.091	0.006***	-0.001
		(0.002)	(0.001)
Saturday	0.092	0.013***	-0.005***
		(0.003)	(0.001)
Sunday	0.090	0.019***	-0.006***
		(0.004)	(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) reports mean crimes, column (2) reports the estimates for temperature and column (3) for rainfall. All specifications include police station fixed effects, year fixed effects, and month fixed effects. Standard errors are clustered at the police station level. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table A5: 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	0.007***	0.005***	0.007***	0.003	-0.003	0.003	0.008***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.005)	(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)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Seasonal Variables									
Temperature	0.042**	-0.001	0.042**	0.076***	0.003	0.076***	0.025	-0.001	0.025
	(0.018)	(0.019)	(0.017)	(0.029)	(0.030)	(0.029)	(0.020)	(0.020)	(0.020)
Rainfall	-0.049**	0.004	-0.049**	-0.046	-0.008	-0.046	-0.050*	0.005	-0.050*
	(0.024)	(0.025)	(0.024)	(0.038)	(0.038)	(0.038)	(0.029)	(0.028)	(0.029)
Interaction Terms									
X Daily Temp			-0.002			-0.006			-0.001
			(0.002)			(0.006)			(0.002)
X Daily Rain			-0.001			-0.002			-0.001
			(0.001)			(0.002)			(0.002)
X Seasonal Temp			-0.043*			-0.074*			-0.026
			(0.026)			(0.041)			(0.028)
X Seasonal Rain			0.053			0.037			0.055
			(0.035)			(0.054)			(0.040)
N	178944	169222	348166	178944	169024	347968	178944	169222	348166

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 a 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.

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

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This Online Appendix presents the results of a simulation exercise demonstrating that lead and lag coefficients may be spurious in a context where there is extremely high serial correlation across consecutive days in the weather variables coupled with even relatively small measurement error in the weather variables. Because we are not aware of any other paper addressing this issue, we present a simulation demonstrating that these two factors can generate the patterns shown above.

It is important to note that this issue is more salient in our paper than in other contexts, due to the extremely high temporal frequency of the data being used. Specifically, other papers typically use weather data at the level of the month, season, or year, where the correlation in temperature (for example) between successive time intervals will be far less than is the case for days. That being said, even where monthly data is being used, statistically significant leads can also be found, potentially due to these issues (see, for example, Figure 6b in Baysan et al., 2019).

To motivate this exercise, we present Appendix Figure B1, which shows the coefficients from regressions of both temperature and crime on distributed lead and lag temperature variables using the observed data. For the regression with crime as the outcome, the regression is specified as a poisson; and for regression with temperature as the outcome, the regression is OLS. As is apparent, the patterns across the two sets of regressions are highly similar. The coefficients for lead and lag temperature using crime as the outcome show similar patterns, being large and statistically significant for 1- and 2-day leads and lags, and decaying quickly as one moves further from same-day temperature. Moreover, these patterns closely mirror those using same-day temperature as the outcome.

The two key parameters of our simulation exercise are the size of the measurement error in temperature and the size of the correlation coefficient between temperature on successive days. As before, we specify crime to be a function of same-day temperature, and additionally specify temperature at time $t+1$ to be a function of temperature at time t:

$$Crime_{pt} = \ {}_0 + \ {}_1 Temp_{pt} + {}''_{pt}$$

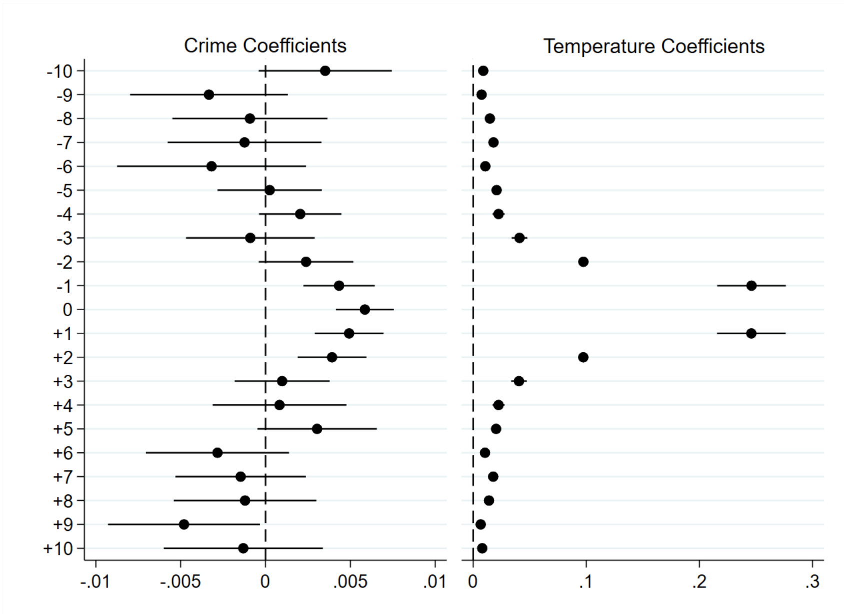
$$Temp_{pt+1} = \ {}_0 + \ {}_1 Temp_{pt} + \ {}_{pt+1}:$$

For our purposes, we assume that ${}_1 = 0.006$, which is taken from the results given in Panel B of Table 2.[18] Empirically, the observed relationship between temperature on successive days using a linear regression is $PredTemp_{pt+1} = 4.73 + 0.849 Temp_{pt}$.

The first of the key parameters is the measurement error of temperature. We specify the

[18]It should be noted latter coefficient is from a poisson regression, whereas in this exercise we are estimating linear regressions.

Figure B1: Distributed Lead and Lag Coefficients



Notes: Figure B1 plots the coefficients from regressions of both temperature and crime on distributed lead and lag temperature variables using the observed data. For the regression with crime as the outcome, the regression is specified as a poisson; and for regression with temperature as the outcome, the regression is OLS.

measurement error in temperature to be a normally distributed term u_{pt} $N(0; \ )$, with the observed temperature given by $ObsTemp_{pt} = Temp_{pt} + u_{pt}$. We allow the standard deviation to be equal to $\ 2\ f0, 0.25, 0.50, 0.75, 1g$. We lack data on the true level of measurement error: however, with a mean maximum daily temperature of 31.52 degrees Celsius, the measurement error assumed for this exercise is relatively small.

The second of the key parameters is the $_1$ coefficient. As noted above, the observed relationship between temperatures on successive days is $PredTemp_{pt+1} = 4.73 + 0.849Temp_{pt}$, where $_1 = 0{:}849$. We therefore test specifications using $_1\ 2\ f0.10, 0.50, 0.90g$, to account for how the strength of the correlation in temperature across consecutive days affects the estimated parameters.

To test for impact of these factors on spurious leads in the results given above, we estimate the specification:

$$Crime_t = \ _0 + \ _1 ObsTemp_{pt} + \ _2 ObsTemp_{pt+1} + "_t{:}$$

The results are given in the following table. As is apparent, as the correlation coefficient approaches 0.90—which is approximately equal to the observed coefficient of 0.85—even a relatively small measurement error ($= 0.50$) yields a spurious lead coefficient that is quantitatively large and statistically significant ($_{2}$), and also causes an attrition in the same-day temperature coefficient ($_{1}$).

This exercise should be taken as suggestive: it is not possible to verify that the proposed mechanisms are driving the spurious lead coefficients observed above. Nonetheless, the striking correspondence in the patterns for for crime and temperature shown in Appendix Figure B1, coupled with the relatively parsimonious assumptions required for generating such a correspondence, suggests the likelihood of such a mechanism.

Table B1: Simulation: Serial Correlation and Measurement Error

Measurement Error (degrees C)		Between Day Temperature Correlation		
		0.1	0.5	0.9
0	1	0.006***	0.006***	0.006***
		(0.000)	(0.000)	(0.000)
	2	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
0.25	1	0.006***	0.006***	0.006***
		(0.000)	(0.000)	(0.000)
	2	0.000*	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
0.50	1	0.006***	0.006***	0.005***
		(0.000)	(0.000)	(0.000)
	2	0.000***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
0.75	1	0.006***	0.005***	0.004***
		(0.000)	(0.000)	(0.000)
	2	0.000***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
1	1	0.005***	0.005***	0.004***
		(0.000)	(0.000)	(0.000)
	2	0.000***	0.001***	0.002***
		(0.000)	(0.000)	(0.000)

Note: This table gives the estimated coefficients from a linear specification of model 5. Estimates are reported for all crimes. Column (1)-(3) varies the between day temperature correlation ($_1$), and panels vary the measurement error in temperature ( ). *** p<0.01, ** p<0.05, and * p<0.1.