Weather Shocks, Crime, and Agriculture:

Evidence from India[1]

November 25, 2014

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This paper provides some of the first evidence from contemporary developing countries on the causal relationship between weather, income, and crime. Using detailed crime and weather data from India during the years 1971-2000, we show that weather shocks that reduce agricultural output, low rainfall and high temperatures, increase most types of crimes. These effects are larger and more uniform for property crimes than for violent crimes. The patterns are consistent with economic models of crime, and strongly suggest agricultural income shocks to be driving the weather-crime relationship. High temperatures, however, have an effect on crime that is disproportionally high given their agricultural impacts, potentially indicating a role for non-income linkages observed in industrialized countries. In addition, the effect of agricultural income shocks is highly non-symmetric: while negative shocks are almost always associated with increases in crime, positive agriculture shocks are *never* associated with a decrease. Finally, despite the significant economic changes taking place in India during these years, and even though the incidence of crime has in general declined, the effect of weather shocks on crime has remained remarkably stable.

Keywords: Crime, Income Shocks, Weather Shocks, Climate, Agriculture
JEL Codes: O10, O13, Q54

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[1] An earlier version of this paper, dated January 29, 2013, was entitled "Rainfall Shocks and Crime in Agrarian Societies: Evidence from India."
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1 Introduction

This paper presents some of the first rigorous empirical evidence on the causal relationship between weather, income, and crime in a contemporary developing country, over a long time period of substantial social change. Using detailed data on weather, crime, and agricultural production from India over the three decades spanning 1971-2000, we establish strong causal connections between weather shocks and crime, and provide evidence that agricultural income shocks drive most, but not all, of this association.

Starting with Becker (1968), an extensive literature has explored the economic determinants of crime. Based on the microeconomics of individual optimization, this literature has emphasized the costs and benefits to criminal activity in explaining the decision to engage in illicit income generation. Particular emphasis is given to the opportunity costs of engaging in crime, which consist of the foregone income and other penalties in the event of capture, with the general prediction that reductions in legal income due to economic shocks will reduce the opportunity cost of crime and thereby increase its incidence.

A substantial literature has sought to empirically test the income-crime relationship (see Freeman, 1999, for a review). Most of these studies have focused on the effect of unemployment rates on crime, though a few have estimated the effects of fluctuations in *wages* on crime, generally finding a negative relationship between the two (Gould, Weinberg and Mustard, 2002; Machin and Meghir, 2004; Grogger 1998). Virtually all of these studies are based on industrialized countries, however, with the result that little is known about how income shocks affect crime in those parts of the world (developing countries) most susceptible to such shocks, and in which individuals are least able to insure themselves against large drops in income. This omission is likely due to the relative dearth of reliable, and sufficiently fine-grained, crime and income data in developing countries.

In addition, the fundamental endogeneity of crime prevalence and labor market conditions remains a persistent challenge to causal inference. Lacking convincing sources of exogenous variation, researchers have sought identification through the inclusion of an extensive vector of controls, the use of panel data, or, in a few cases, using instrumental variables designs, with varying degrees of success.[4] Faced with similar identification challenges, researchers in the related literature on economic shocks and large-scale civil conflict have in recent years turned to weather shocks to generate exogenous variation in incomes (Miguel, Satyanath, and Sergenti, 2004),[5] a strategy well-suited to developing, agriculture-dependent economies, where incomes remain closely tied to annual weather patterns.[6] This approach has yielded

[4] Cross sectional correlations between crime and other social characteristics are likely to be biased given the deep inter-dependence between these variables (Hsiang *et al*., 2013). Even inference from panel data may be difficult to interpret because of the slow-moving nature of the variables of interest, which thereby lack sufficient variation, and lead to the suspicion that what variation exists involves substantial measurement error.

[5] In addition to their inherent interest, such shocks are generally deemed sufficiently similar to secular income changes as to provide important evidence for the effects of the latter. It must be emphasized, however, that economic shocks are different than long run economic growth, and may operate through other channels – a distinction sometimes elided in the civil conflict literature.

[6] Miguel and Satyanath (2011), for example, find that, whereas rainfall was a strong instrument for economic growth prior to 1999, it becomes a weak instrument thereafter, which the authors speculate is due to high growth rates in non-agricultural sectors, as well as improvements in policy due to the spread of democratic institutions.

a consistent and robust body of evidence on the effects of income shocks on civil conflict, and even societal collapse (Hsiang, Burke, and Miguel, 2013; Hsiang and Burke, 2014).[7]

Far fewer studies, however, have examined the effects of weather-induced income shocks on crime (Hsiang, Burke and Miguel, 2013), a social phenomenon that is different from civil conflict in many ways, and yet hypothesized to be responsive to similar economic factors.[8] These include Miguel (2005), who shows that negative rainfall shocks decrease consumption and increase murder rates ("witch killing") in rural Tanzania; Mehlum *et al.* (2005), who use rainfall shocks in 19th century Bavaria to establish a causal connection between rye prices and crime; and Sekhri and Storeygard (2010), who find an association between negative rainfall shocks and crimes against women and vulnerable minorities in India between 2002-2007. A separate strand of literature, spurred in part by the surging interest in the impact of future climate change, has established a direct causal connection, likely driven more by psychological than income channels, between high temperatures and crime, most of it in the US (Anderson *et al*., 2000; Auliciems and DiBartolo, 1995; Card and Dahl, 2011; Cohn and Rotton, 1997; Jacob *et al*., 2007; Kenrick and MacFarlane, 1986; Larrick *et al*., 2011; Mares, 2013; Ranson, 2012;

[7] In fact, this approach was also used by Bohlken and Sergenti (2010) to relate rainfall shocks and Hindu-Muslim riots in India using a state level panel.
[8] The mechanisms invoked for explaining the incidence of civil war are quite similar to those proposed in the literature on the economic determinants of crime.

Rotton and Cohn, 2000).[9]

Using detailed crime data in a panel of over 400 Indian districts between 1971-2000, we first conduct an analysis of weather-crime linkages that spans a tempo-spatial range of observation substantially larger than that of other existing studies in developing countries. We find a socially and statistically significant increase in most types of crime rates with negative rainfall shocks and positive temperature shocks occurring during the main agricultural season. During years in which rainy season precipitation is more than one standard deviation below the long-term mean ("negative rainfall shock"), or rainy season temperatures are one standard deviation above the long-term mean ("positive temperature shock"), crime rates increase by about 4-6% (an effect that is similar in magnitude to accumulated evidence from other studies reviewed by Hsiang *et al.*, 2013)..[10]

Given the high dependency of Indian agricultural productivity (Guiteras, 2009; Fishman, 2012), wages, and employment (Jayachandran, 2006; Kaur, 2012) on weather shocks throughout the period covered in this study,[11] it is natural to hypothesize an income mechanism to be driving our results. Consistent with this interpretation and with economic models of crime, we find that the effects of

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[9] Because this literature focuses on crime effects in developing countries, agricultural channels will generally be absent, though other income channels are possible.

[10] Corroboration of these results was recently provided in a working paper on the relationship between trade, consumption, and crime in India (Iyer and Topolova, 2014). Our own original results were first presented in a working paper posted in January, 2013 (Blakeslee and Fishman, 2013).

[11] According to the 2011 Indian census, 56% of India's workers still rely on agriculture as their main source of income, and their share among the rural poor is much higher.

weather shocks on property crimes are larger, more uniform, and of generally greater statistical significance than for non-property crimes.[12] However, even though exogenous weather shocks allow for causal inference of the weather-crime relationship, establishing rigorously whether income shocks drive the relationship is challenging. First, income is often hard to observe directly, and high-frequency data at the required resolution generally lacking. Second, weather, and particularly temperature, may affect crime rates through other channels. For example, Sudarshan and Tewari (2013) show high temperature shocks reduce labor productivity and wages in manufacturing; while another literature, cited above, has established a psychological mechanism for the relationship between high temperature and crime rates.

One popular empirical approach, used in a number of the papers cited above (e.g. Miguel, Satyanath, and Sergenti, 2004; Mehlum *et al.* ,2005), is to instrument income with rainfall shocks. For reasons cited above, it is likely that such a strategy will fail the exclusion restriction, which in this case would lead to a conflation of the effects of agriculture with other, non-agricultural channels, thereby biasing upwards the estimated effect of agricultural production on crime. Though we will later also estimate a regression using rainfall as an instrument for agricultural production, we refrain from giving this line of analysis precedence in our interpretation, due to

[12] Our sample size only allows us to reject an equal impact of high temperatures on property and non-property crimes at conventional statistical confidence levels (p=0.01). We can reject an equal effect of rainfall shocks only at marginal significance levels (p=0.16).

uncertainties surrounding the validity of the instrument.[13]

Instead, our preferred and principal empirical strategy is to compare the reduced form patterns relating weather (both temperature and precipitation) and crime, and those relating weather and agricultural production, and then to assess the correspondence between the two relationships. We find that the effects of (seasonally disaggregated) weather shocks on crime are closely paralleled by their effect on agricultural production: Rainfall and temperature shocks that decrease agricultural output also lead to increases in crime. In contrast, temperature shocks that occur outside the main agricultural season (the monsoon season, in which almost all rainfall occurs) are not associated with increases in crime, even when they occur during times that are as hot, on average, as the main cultivation season. Interestingly, while negative agriculture shocks are nearly always associated with an increase in crime, positive agriculture shocks are *never* associated with a decline, indicating an important asymmetry in the effect of income shocks on crime, and one which would not be expected based on standard economic models of crime. We regard the consistency of the correspondence between the crime and agriculture effects, using even highly disaggregated measures of weather events, to provide compelling evidence for agricultural income shocks' being one of the key mechanisms driving the weather-crime relationship.

A revealing qualification to this correspondence is that the effects of high temperature on crime are much larger relative to their effect on agricultural product

[13] As we will discuss later, the validity of weather as an instrument for agricultural production is more tenuous for temperature than for rainfall.

than those of low rainfall. Both types of weather shocks increase crime rates by about 4-5%, whereas the impact of a negative rainfall shocks (21%) is twice as high as that of a positive temperature shock (11%). This suggests that additional, non-agricultural mechanisms may also be operative, among the plausible candidates for which being: the demonstrated influence of elevated temperatures on manufacturing in India (Sudarshan and Tewari, 2013); and the heightened aggression attendant upon elevated temperatures as found in the psychological literature.[16] Both these mechanisms receive qualified corroboration in heterogeneities in impacts found across socio-economic characteristics in our sample.

We also find that, while average crime rates have declined over time, the relationship between crime and weather has remained remarkably stable, despite the considerable economic development and structural change occurring across these years. Negative rainfall leads to an approximately 5% increase in crime across all three decades of our sample. The effect of temperature shocks declined somewhat between the 1970s and 1980s, but has since remained stable at about 4%.

The disparity between changes in average crime rates and in their responsiveness to weather shocks is further reflected in heterogeneity of impacts with respect to several key socio-economic characteristics. For example, we find evidence to indicate that the expansion of irrigation, likely the most important rural economic transformation occurring in India during the period of this study, has

[16] See Anderson (2000) and Hsiang *et al.* (2013) for a summary of this literature.

reduced average incidence of crime; and that reductions in inequality and in the share of landless agricultural labor in the workforce are associated with reductions in crime rates. However, we find no evidence to indicate that the expansion of irrigation has reduced the *sensitivity* of crime to weather shocks. The effect of positive temperature shocks, however, seems to be amplified where there is more labor engaged in manufacturing, a higher share of young men in the population, and higher levels of inequality. A potential explanation of these patterns is that the burden of income shocks continues to be borne disproportionately by those segments of society most prone to criminal adaptation, even though the share of the population characterized by such extreme vulnerability may have decreased over time (Deaton and Kozel, 2005).

The contribution of this paper is three-fold. First and foremost, we provide a substantial addition to the surprisingly scarce evidence on the important subject of income shocks and crime. This contribution is of general relevance to the crime literature, but even more so for developing countries, where such research is almost entirely lacking. Moreover, the tempo-spatial breadth of our sample gives us the statistical power to identify even relatively small effects with precision, and to explore the *mechanisms* driving the observed effects. Our analysis shows the importance of both agricultural, as well as other, mechanisms by which weather shocks translate to changes in crime rates, and reveals a startling asymmetry in the effect of negative and positive weather-induced agriculture shocks. Second, because our panel spans three decades of momentous change in India – from a time of "Hindu rates of growth" to India's emergence as a dynamic economy with enviously high growth rates – we are able to explore how the relationship between crime and weather has evolved with structural change, rising incomes, and improvements in human development. Given the climatic changes predicted for the coming decades, the extent to which economic development helps to mitigate the effects of elevated temperatures and deficient rainfall is a question of fundamental importance. The final contribution of our paper is one of scope: India is the world's second largest country, its largest democracy, and country of immense interest to development economists. Our analysis, therefore, sheds light on the relationship between weather, income, and crime in a country central to the discipline's evolving understanding the causes and consequences of economic development.

2 Data

Data on crime rates was obtained from India's National Crime Records Bureau (INCRB), housed under the Ministry of Home Affairs. INCRB produces annual documents on national and sub-national crime trends, including detailed statistics on the incidence of various crimes at the district levels, beginning in 1971.[17] The data provides a rich accounting of a wide variety of crimes. Among the crimes included are burglary, robbery, banditry, theft, riots, murder, rape, kidnapping, cheating, counterfeiting, and homicide.[18]

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[17] Crime data is also available before 1971, but only at the state level.

[18] More recently, data has been collected on dowry-related deaths, and kidnapping has been disaggregated according to whether the victim was male or female.

Monthly weather data is based on gridded precipitation and temperature data produced by the Indian Meteorological Department (Rajeevan *et al*. 2005, Srivastava *et al.* 2009) and converted to district-wise figures by area-weighted averaging over grid points falling within a given district. Below we detail how the monthly data is converted the seasonal variables used in this paper.

Agricultural district-wise data on the production of various crops were obtained from the Indian Harvest database produced by the Center for the Monitoring of the Indian Economy (see Fishman, 2012, for a complete description).

An important issue in empirical studies on India for which the unit of observation is the district is the substantial partitioning (and sometimes re-combination) of districts that has occurred over time. This creates myriad challenges for determining the correct assignment of data to observations, as well as for the correct identification of the relevant unit for capturing time-invariant unobservables. The most common approach is to fix the districts on a certain date, and then aggregate later partitions of the district into the original. In our analysis, we approach this issue as conservatively as possible, maintaining as independent districts the districts resulting from partitions. This has the advantage, at times, of increasing the sample size, but the disadvantage of effectively removing some districts from our sample when partitioning yields districts with few observations.[19] We consider this the appropriate approach, as the partitioning of districts is likely to

[19] For example, it is not uncommon for sub-districts to have only a few years of data, so that the fixed effects will absorb much of the relevant variation.

yield significant changes in institutions and local governance, which would only partially be captured with the use of constant district fixed effects.

Our crime variables are measured as the number of incidents per 100,000 people. Figure 1 presents the average geographical distribution of the rates of the different crime categories in our data. Figure 2 presents plots of India-wide average crime rates over time and table 1 presents some summary statistics. The three columns tabulate the incidence of the indicated crime across the three decades spanning 1971-2000, and show a general decline in the incidence of most property crimes, with substantial declines in burglary, banditry, thefts, and robbery.[20] Kidnapping was relatively stable across this period, and riots declined slightly. Murder and rape increased somewhat during this period. Agricultural production improved considerably during this interval due to the widespread adoption of HYVs with the green revolution. Yields per hectare for both rice and wheat nearly double, and gross product shows an increase of a similar magnitude.

3 Results

3.1 Empirical Strategy

There are two principal specifications used in this analysis: in the first, we pool together all crimes in a single regression; in the second we estimate the same specification separately for each crime, with fixed effects and time effects adjusted

[20] Robbery is distinguished from theft in that it includes violence in the commission of the crime. Banditry is distinguished from robbery by its involving 5 or more individuals in the commission of the crime.

accordingly. The empirical specification is the linear model with the outcome given as log crime:

$$\ln(y_{cist}) = \alpha + \beta \cdot P_{it}^{+} + \gamma \cdot P_{it}^{-} + \mu \cdot T_{it}^{+} + \nu \cdot T_{it}^{-} + \kappa_{c,t} + \delta_{c,i} + \kappa_{c,s} \times f(year_t) + \varepsilon_i.$$

The natural log of the incidence of crime *c* (per 100k people) in district *i*, state *s*, and year *t* is regressed on dummy variables for positive and negative precipitation (P^+, P^-) and temperature (T^+, T^-) shocks in year t, in district i in state s. The positive-shock dummy takes a value of 1 for rainfall (temperature) movements 1 standard deviation or greater above the mean and zero otherwise, and the negative-shock dummy taking a value of 1 for rainfall (temperature) movements 1 standard deviation or more below the mean.[21] District-crime fixed effects and year-crime fixed effects are also included ($\delta_{c,i}$ and $\kappa_{c,t}$, respectively), as well as quadratic state-crime time trends. For the individual crime regressions, the crime dummies and their interactions with time variables and district fixed effects are removed.

The main agricultural growing season in India, called the *Kharif*, occurs between June and December (the exact period depends on the specific crop), when rain-fed cultivation is possible; for the poor especially, who lack access to irrigation, this season is the primary source of agricultural income. Almost all rainfall occurs

[21] There is some debate on whether the appropriate measure of weather shocks is year-on-year changes or levels (Miguel and Satyanath, 2011; Ciccone, 2011). The approach adopted here is more akin to the latter, with shocks defined by deviations of rainfall and temperature from their long-run means.

between June-September (figure 3),[22] though some crops remain in the field and are harvested as late as December, when temperatures have declined. We therefore disaggregate our weather indicators into the two periods of June-September and the remaining months of the year, and term them the *monsoon* and *non-monsoon* period (the former being shaded blue in figure 3). Later, we decompose the non-monsoon shocks into pre- and post-monsoon, to more fully explore the correspondence of crime and agricultural effects of weather shocks.

In our regressions, we cluster error terms at the district level. This follows the approach adopted by Sekhri and Storeygard (2010) and Burgess *et al.* (2013). The latter justify this clustering by noting that measurement errors are likely to be correlated within districts across time. An alternative approach would be to cluster error terms at the state-year level, which would make sense if we were concerned about state-level unobservables that vary across time, such as levels of expenditures on law enforcement. Therefore, though we adopt district clustering as our preferred specification, we test whether the results obtained are robust to the use of state-year clustering.

A small number of observations in our sample report zero crime rates. These observations occur at a frequency of less than 2% for most crimes,[23] but result in undefined values for our independent variable, the logarithm of crime rates. In dealing with similar issues, some authors have adopted a Poisson specification,

[22] There is some regional variation in the timing of the monsoon, with some areas continuing to receive significant rainfall through October.
[23] The one exception to this is banditry, for which zero values are encountered 7% of the time.

which is well adapted to count-variable outcomes and handles the zero-value problem, but suffers from other limitations when a large number of fixed effects are included in the regression, as is the case in this paper.[24] An alternative approach, adopted by Pakes and Griliches (1980), is to replace the outcome variable with zero where the crime incidence is zero, and then to include a dummy indicating the transformation. We note that the incidence of zero values in our sample (around 2%) is substantially lower than in Pakes and Griliches's (1980) sample (around 8%). This specification has the advantages of more easily handling the inclusion of district fixed effects, and yielding coefficients of more transparent interpretation, and we adopt it here.

The temperature measure from which we generate our temperature shock variable is the summation of degree days during a given interval. Degree days are a measure intended to capture the temperature variation relevant to agricultural growth (Schlenker *et al.*, 2006), and are measured as

$$DDS = \sum_{d} D\left(T_{avg,d}\right)$$

$$D(T) = \begin{cases} 0 & \text{if } T \leq 8^{\circ}C \\ T - 8 & \text{if } 8^{\circ}C < T \leq 32^{\circ}C \\ 24, & \text{if } T > 32^{\circ}C. \end{cases}$$

Fishman (2012) gives a detailed account of the relevance of this measure for agricultural production in India. The degree days measure having been constructed,

[24] Hausman et al. (1984) is an example of this approach. Sekhri and Storeygard (2012) also use this approach in their study of the effect of rainfall shocks on dowry deaths in India. The latter paper, it should be noted, dealt with a crime for which zero-outcomes occurred, according to our calculations, in approximately 16% of the sample.

our temperature shock variables are specified as dummies equaling 1 when the number of degree days is more than one standard deviation above (below) the district mean. The rainfall measure is more straightforward, and is based simply upon the cumulative millimeters rainfall in the district during the indicated interval.

An important element of our analysis is the distinction between property and non-property crimes. Economic models of crime make strong predictions for the former, but less clear-cut predictions for the latter, except insofar as some non-property crimes may occur during the commission of a property crime (e.g., murder during the course of a robbery) (Bourguignon, 1999).[25] Therefore, in most regressions we will disaggregate our sample according to the economic content of the crime, exploring whether there exist differential effects of climate shocks across the two categories. Of the crimes included in the data, we classify burglary, banditry, theft, robbery, and riots as property crimes, and murder, rape, and kidnapping as non-property crimes. Of these, kidnapping and rioting would seem to occupy an ambiguous place; however, closer scrutiny justifies our classification. Kidnapping, for example, is disproportionately targeted against women, for reasons not entirely, or even principally, economic.[26] Riots[27] are known to occur during times of

[25] Despite the ambiguous predictions for non-property crimes, most research finds even non-property crimes increasing with negative income shocks, implying the presence of additional mechanisms beyond economic incentive.

[26] The data indicates that the 74 % of kidnappings are targeted against women, though this disaggregation is only reported after 1987. Though others have classified this as an economic crime, such a classification overlooks this important non-economic component.

[27] Note that these are not the Hindu-Muslim riots analyzed by Bohlken and Sergenti (2010).

economic duress, particularly in response to heightened food prices, and are often characterized by widespread looting.

Reporting-related measurement errors in crime variables are discussed in detail in the results section below.

3.2 Rainfall and Temperature Shocks

Coefficients for rainfall and temperature shocks using the pooled crime regressions are reported in Table 2. Columns (1)-(2) give the estimated effects when including all types of crime; columns (3)-(4) include only property crimes; and columns (5)-(6) only non-property crimes. For each sample, we estimate specifications with and without weather shocks occurring outside the monsoon season ("non-monsoon").

Using the full sample, we find that negative rainfall shocks during the monsoon are associated with a 3.7% increase in the incidence of crime, positive temperature shocks with a 5.3% increase, and negative temperature shocks with a 2.5% increase, although the latter is not robust to alternative clustering of errors by state-year. Weather shocks occurring outside the monsoon season have no significant effect on crime. Disaggregating the sample into property and non-property crimes, we see that effects of weather shocks on property crimes tend to have generally larger point estimates. Whereas positive temperature shocks lead to a 6.5% increase in property crimes, they lead to a smaller 3.1% increase in non-property crimes, and the difference is statistically significant at the 1% level. Similarly, while negative rainfall shocks lead to a 4.3% increase in property crimes, they lead to a smaller 2.7% increase in non-property crimes, though our sample size only allows us to establish this difference with relatively low confidence (p=0.16).

The distinction between the effects of monsoon versus non-monsoon shocks is more definitive: it is only weather shocks occurring during the agriculturally important monsoon season that influence the patterns of crime, whereas those occurring during the other eight months of the year have no significant effect. As we will see later, negative rainfall shocks lead to large reductions in agricultural output, while negative and positive temperature shocks lead to smaller, but still substantial, declines in agricultural output.

We next estimate the effects of weather shocks for each crime individually. In addition to the inherent intrigue of the effects for individual crimes, this specification is important for two reasons. First, it allows us to assess whether the differential effects for property versus non-property crimes is sensitive to the classification adopted for kidnapping and riots, which, as noted in the introduction, are of somewhat ambiguous economic content. Second, as discussed in a number of studies, crime data can suffer from significant under-reporting.[28] Some researchers have addressed this issue by focusing on murder and robbery, which are considered to be less susceptible to biased reporting due to the conspicuous violence involved in each (Fajnzylber *et al.*, 1998). Therefore, a comparison of the estimated impacts of these two types of crimes with those of the other types will provide some indication on the presence of bias resulting from under-reporting.

[28] This under-reporting will not be a problem for our identification strategy, so long as the bias is not correlated with the weather shock variables. It is not implausible that local authorities would in fact increase the level of under-reporting at precisely those times when crime is most increasing, as after an adverse weather shock. However, such behavior would, if anything, bias our results downwards.

Table 3 reports full individual crime regression estimates and figure 4 displays the estimated coefficients for monsoon period negative rain and positive temperature shocks. While every property crime but thefts shows a statistically significant increase with negative rainfall shocks, amongst non-property crimes it is only murder that shows a statistically significant increase (though the other coefficients are only marginally insignificant). As was found in the pooled regressions, negative rainfall shocks generally yield a larger increase in property crimes than non-property crimes: riots and burglaries increase by a statistically significant 5.6%, banditry by 4.4%, and robberies by 4.7%; whereas murder is the only non-property crime that shows a statistically significant increase (2.1%). Positive temperature shocks are associated with large increase in crime, particularly property crimes, with banditry increasing by 10.5%, robbery by 9.0%, riots by 6.5%, and thefts by 5.1%. Amongst the non-property crimes, murder shows a statistically significant increase of 3.9%, and rape a marginally significant 3.2% increase.

No differential effect is found for robbery and murder compared to other types of crime, indicating that under-reporting of crime is unlikely to be systematically biasing our results. We also note the larger coefficients found for robbery, a property crime, compared to murder, a non-property crime, though the difference between rainfall coefficients is again marginally insignificant (p=0.19).

The relationship between weather shocks and crime was estimated non-parametrically, due both to the demonstrated non-linear relationship between agricultural production and weather (see below), as well as non-linearities which would likely be present in other channels of influence (e.g., psychological responses to elevated temperatures). The weather dummies we used above may collapse together distinct phenomena if, for example, abundant rainfall leads to bountiful harvests, but excessive rainfall to floods and destruction. We therefore estimate the relationship between weather shocks and crime using more disaggregated z-score intervals; Figures 5 and 6 show the results of these semi-parametric regressions. As can be seen, crime rises steadily with larger negative rainfall deviations, while positive deviations have no effect at any deviation. The relationship between crime and temperature shocks is far noisier: while crime increases steadily with positive temperature shocks up to z-scores of 1.25-1.75, it drops precipitously thereafter, to become indistinguishable from zero. There is also an evident increase in crime with severe cold shocks. Appendix table A1 tabulates the full results of the corresponding regressions.[29] The patterns with respect to rainfall shocks are relatively similar across property and non-property crimes, as seen in Figure 7. The exception to this is the large increase in property crimes when rainfall shocks are more than 2.25 sds below the mean, in contrast to the slight decline for non-property crimes. This is unsurprising, given that it is with the most extreme negative rainfall shocks that there is the greatest economic disruption, and therefore incentive to engage in economically motivated crimes. In addition, property crimes increase slightly with positive rainfall shocks, consistent with what we saw earlier for the effects on banditry and thefts. Property crimes show a consistently larger increase for positive temperature shocks at all intervals (Figure 8).

[29] The particular form of this regression is suggested by Sekhri and Storeygard (2013), who find that larger negative rainfall shocks yield larger increases in dowry deaths.

4 Mechanisms

4.1 Agriculture and Weather Shocks

A central element of our analysis is an examination of the role agricultural productivity shocks may be driving the observed weather-crime relationship. Weather shocks could also potentially operate through non-agricultural channels, such as disruptions to manufacturing, non-agricultural wages, psychological responses, or declines in state capacity. To examine the role of agriculture, we first turn to an analysis of the effect of weather shocks on agricultural production. Ideally, one would want to observe a distribution of annual income across a gradient of wealth. However, such data is, to the best of our knowledge, unavailable at the required spatio-temporal resolution. Despite this limitation, previous studies have shown that agricultural output generally moves in tandem with agricultural wages and employment (Jayachandran, 2005; Kaur, 2012), suggesting that it proxies for income shocks to both landowners as well as landless laborers.

Various studies have already explored the relationship between weather and agricultural yields at some length (Guiteras, 2009; Fishman, 2012); here we provide a complementary analysis, by estimating the effects of the same vector of shocks whose impacts on crime were discussed above, and analyzing the correspondence of the two sets of impacts. If agricultural shocks play a significant role in the observed effect of weather on crime, one would expect those weather shocks that reduce agricultural output to increase crime, and those that do not affect agriculture to have a relatively smaller impact on crime (though the presence of other, non-agricultural mechanisms may still result in non-zero coefficients). The pattern we observe concurs with these predictions.

Table 4 reports the effects of the weather shocks on agricultural production, with the outcome variable specified as the gross output[30] of the primary crop in that district. For each district, we have defined the primary crop as that which occupies the largest portion of cultivated land across the all years. We use the production of the primary crop as a proxy for agricultural income in a district in order to avoid reliance on a particular crop that may be little cultivated in some areas. Below, we test the robustness of the results by using the yields of specific crops.

The regressions reported in the previous section separated the annual cycle into the monsoon and non-monsoon periods. However, since the non-monsoon period consists of sub-periods that differ in their average temperature, and play different role in the agricultural calendar, this aggregation may hide variation in impacts occurring at different points of the non-monsoon period. In the regressions reported below, we therefore disaggregate non-monsoon temperature shocks into those occurring during the months of March-May, and those that occur during October-December (no such decomposition is required for precipitation as rainfall is extremely scarce outside the monsoon season).[31] Column (2) reports the results of a regression that uses log yield as the outcome variable, and column (3) and (4)

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[30] We do not show the effect of climate on prices. This is because, with the advent of the railroad and the integration of agricultural markets, there is little within year price variability across districts (Donaldson, 2012). Confirming this finding, when we estimate the impact of climate on prices in our sample, we find no effect.

[31] Though a few states in the south continue to receive some rainfall during October as well.

reports results of regressions that use the log and level of gross product as the outcome variables. For the purpose of comparison, in column (1) we show again the results of a parallel regression of crime rates that uses the same explanatory variables.

Weather shocks are seen to have a large impact on crop production, particularly those shocks occurring during the monsoon period. Negative rainfall shocks lead to a 14.1% decline in yields and 21.3% decline in output, while positive temperature shocks lead to a 3.9 and 11.8% decline in yields and product, respectively. Negative temperature shocks during the post-monsoon period lead to an increase in log yield and product (6.8 and 16.3%, respectively), while positive temperature shocks lead to a 4.5% decline in yields, but no decline in product. Negative temperature shocks during the pre-monsoon hot months (March-May) lead to an increase in agricultural output (yield and product), while positive temperature shocks also lead to an increase in product. These patterns are largely consistent with previous empirical analyses of weather-agriculture relationship in India (Guiteras, 2009; Fishman, 2012).

As is apparent, the results are largely consistent with the crime results found earlier. Negative rainfall shocks and positive temperature shocks during the monsoon period decrease crop production and increase crime rates. Negative temperature shocks during the monsoon also lead to an increase in crime, but the agriculture effect is ambiguous, with declines in level terms, but no in percentage terms.[32] Positive rainfall shocks also have somewhat ambiguous effects, leading to declines in agricultural production, but no change in crime.[33] Finally, while positive post-monsoon temperature shocks lead to some decline in yields, there is no effect on product or crime.[34]

Interestingly, while the effect of temperature on crime is slightly higher than that of rainfall, the effect of the latter on agriculture is considerably larger. Therefore, an appeal to purely agricultural channels for the observed crime effects is contradicted by the disparity in magnitude of the economic impacts of rainfall and temperature shocks. This apparent contradiction may be reconciled by noting that positive temperature shocks have also been found to lead to reductions in industrial output, including manufacturing (Hsiang, 2010; Jones and Olken, 2010; Dell *et al*., 2012),[35] with one study showing this effect specifically for India (Sudarshan and Tewari, 2013), so that the income shock from elevated temperatures occur across both the agricultural and manufacturing sectors. Potentially re-enforcing the effect of these economic channels are the psychological effects of elevated temperatures, which have been found in a wide body or research to be associated with elevated aggression (Anderson, 2001).

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32 This is because the decline in output is happening in areas with high mean levels of production, which is offset by increases in areas with low mean levels of output.

33 Banditry is the main exception, an effect discussed in detail in a previous draft of this study.

34 As noted before, weather patterns during the months of October-December continue to influence the production of monsoon crops in many areas, particularly those where crops are harvested later in December.

35 See Dell *et al*. (2014) for a review of this literature.

One qualification should be appended to the previous analysis. While the patterns of crime and agricultural output generally align quite closely, we see that there exist discrepancies for the shocks occurring in the post-monsoon period (October-December). In table A2, we show the effect of weather shocks on specific crops. As can be seen, the patterns of rice production closely correspond to crime effects, whereas other crops match only imperfectly. This is unsurprising, as rice is by far the most important crop in India, being cultivated on the largest share of land, and being one of the most labor-intensive crops.

4.2 Instrumental Variables Estimation

As noted previously, weather shocks likely fail the exclusion restriction, and therefore cannot be used as instruments to estimate the effect of agricultural output on the incidence of crime. We have therefore argued for the importance of the agricultural channel by appealing to the close correspondence of the crime and agriculture effects of the various weather shocks. The violation of the exclusion restriction is most likely for temperature shocks, which have been shown elsewhere to affect crime directly through psychological channels, and to also have income effects through manufacturing output. Rainfall shocks, in contrast, have been shown to have no effect on industrial production (Hsiang, 2010; Dell *et al.*, 2012) and are unlikely to have important psychological effects; and are therefore more likely to satisfy the exclusion restriction as instruments in a regression of crime on agricultural output. Noting the possibility that rainfall may affect crime through other channels, we will here briefly relax our vigilance against this possibility to see what precise estimates of the elasticity of crime with respect to agricultural output might be identified through an IV approach. This liberty is further justified by noting the similar monotonicity in the response of crime and agricultural output to negative rainfall deviations in figures 5 and 9, respectively.

In table A4, we regress the log crime variable on the log output of the primary crop grown in the district. Because positive shocks enter the agricultural production function differently than negative shocks (cf. figure 9), we instrument for agricultural output using the negative rainfall shock alone (with positive rainfall included as a control), and a linear rainfall variable. The results are robust to both instrumental approaches. In column (1), we estimate an OLS specification; in column (2) we regress log agricultural output (product and yield) on negative rainfall shocks; in column (3) we regress log crime on negative rainfall shocks; and in column (4) we estimate the IV specification. As can be seen, the elasticity of crime with respect to agricultural product is 0.14, and with respect to yield is 0.22.

4.3 Interactions

4.3.1 Economic Characteristics

To better understand the mechanisms by which weather shocks affect the incidence of crime, we next explore heterogeneities in the effects of weather shocks across a variety of relevant socio-economic characteristics. The variables selected for analysis are urbanization, literacy, irrigation, inequality, agricultural labor force, the population of young men, and the size of the manufacturing workforce.[37] The specification estimated is as before, though we now limit the weather shocks to only those occurring during the monsoon season, and we include interactions of the weather shocks with district fixed effects. The latter feature has the virtue of allowing us to identify the interactive effects of each variable using within district variation; this is important, as each of these variables are likely to be correlated with unobservables that one might expect to be important for the estimated effects.

Table 5 gives the results for these specifications. Our specifications include only shocks occurring during the monsoons season. In columns (1), (3), and (5) are given the level effects of the socio-economic variables; and in columns (2), (4), and (6) the indicated interaction terms. Before discussing the interaction terms, it is worth noting the level effects of changes in the socio-economic variables. Indeed, a large literature has sought to estimate the effects of precisely these variables on crime rates, but been hampered by brief panels with small levels of variation; the length and resolution of our own data, in contrast, allows for a more precise estimate of these effects than was possible in earlier research. Higher levels of irrigation are associated with significant declines in the crime rate, consistent with the rising incomes generated by through irrigated agriculture, and the concomitant rise in the

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[37] The variables are defined as follows: urbanization is the share of the population living in cities; literacy is the share of the population aged 15-34 who are literate; irrigation is the percentage of the cultivated land that is irrigated, as estimated from a regression of irrigated land on a quadratic time trend; inequality is measured as the rural gini coefficient; agricultural labor force is the percentage of farmers who are engaged in agricultural labor; young men is the share of the population composed of men between the ages of 15 and 34; and the manufacturing workforce is the percentage of working adults engaged in manufacturing, whether in the formal or informal sectors.

opportunity cost of engaging in crime. Higher levels of rural inequality are associated with increases in crime. In addition, the share of the rural labor force working as agricultural labor is positively correlated with crime rates; as we have already controlled for rural inequality, this may have to do with agricultural wage laborers' being more vulnerable to economic shocks than are independent farmers, consistent with Jayachandran's (2006) finding that wage earners bear the brunt of adjustments to weather induced agricultural shocks. Of more uncertain import is the finding that higher literacy rates are associated with *increases* in crime, and the higher young-man shares of the population being associated with *decreases* in crime. While Fajnzylber *et al.* (1998) argue that higher levels of education may lead to increases in crime due education's being an input in the crime production function, we suspect that there is some omitted variable driving the result. The fact that young men are associated with declining crime rates is probably due to their both being caused by an omitted variable, presumably economic opportunity, which could have the effect of both attracting young men and reducing the incidence of crime.

Turning next to the interaction effects, it should first be noted that none of the rainfall interaction terms is statistically significant. At first blush, this is quite surprising, as one would anticipate, for example, that irrigation and urbanization would make districts less sensitive to negative rainfall shocks. Two plausible explanations suggest themselves for this finding. First, virtually every district has a high share of its population engaged in agriculture-related production, so that there may be insufficient relevant variation in agriculture dependence across districts.

This high level of agriculture dependence may imply large general equilibrium effects for the overall economy, so that even non-agricultural sectors are buffeted by shocks to aggregate demand and factor markets arising from weather-induced agricultural shocks. A second plausible explanation lies in the possibility that crime may be due to a small segment of the population that is highly vulnerable, with this group being characterized by a relatively constant vulnerability across time. In this event, even were the share of this population to decline over time, shocks to their income could lead to similar *percentage* changes in crime.

The null effect of the irrigation interaction terms requires further explanation, as irrigation is crucial to agricultural production, and has been found in a number of studies to mitigate the impact of weather shocks on agricultural output (Duflo and Pande, 2007; Fishman, 2012; see also Sarsons, 2011). In these papers, however, the focus was the effect of irrigation in mediating *per hectare yields*; in results not shown, we find that irrigation plays a smaller role in buffering the impact of weather shocks on *gross output*, as declining yields are partially offset by changes in the total area being cultivated. Moreover, we would note that irrigation is disproportionately used by more affluent farmers, whereas poorer farmers largely depend on seasonal rain for crop production. Because it is the poorer farmers in the agricultural sector that are most prone to turn to crime during economic distress, the presence of irrigation in a district is unlikely to buffer crop production for the population most relevant to the incidence of crime.

More interesting are the temperature interactions, which yield results consistent with the non-agricultural mechanisms discussed earlier. For example, a larger manufacturing workforce is associated with a larger increase in crime with positive temperature shocks, and a smaller increase with negative temperature shocks. This result is consistent with Sudarshan and Tewari's (2013) finding that manufacturing output falls with elevated temperatures. We also find that the effect of positive temperature shocks is amplified where a larger share of the population consists of young men, which may be due to psychological factors. Finally, we also find that higher literacy rates mute the effect of positive temperature shocks, and higher inequality amplifies it. Inequality, it seems, both increases mean crime rates, and also renders the society more prone to criminal responses to adverse economic shocks. The fact that this result holds for positive temperature shocks but not negative rainfall may indicate the operating mechanism to be as much social tensions as economic duress. While (marginally) insignificant, urbanization too is associated with an amplification of the effect of elevated temperatures, presumably due to a combination of economic and psychological factors.

4.3.2 Heterogeneity In Impacts by Average Climate

The weather shock dummies used in our regressions are based on standardized deviations (z-scores) from district means, and therefore represent the average treatment effect (ATE) across a wide diversity of agro-climatic environments. One might, however, expect there to be significant heterogeneities according to prevailing climatic conditions; it is not clear, for example, that declines in rainfall will have the same impact on crime where mean rainfall levels are high as they would in areas with lower mean rainfall, where negative deviations may tip the district into drought.

Table 6 shows how weather shocks are mediated by prevailing climate conditions within the district. We regress crime rates on the weather variables, as well as their interaction with a dummy indicating whether the district was characterized by mean climate conditions above the national average, with separate dummies for temperature and rainfall conditions; the rainfall shock variables are interacted with the mean temperature dummy, and the temperature shocks likewise interaction with the mean temperature dummy. The interaction terms, therefore, tells us whether the effects of weather shocks depend on more general climate conditions. There is little effect of mean temperature conditions on the effects of temperature shocks: the un-interacted positive temperature shock variables show coefficients similar to those found before, and the interaction term is small and insignificant; negative temperature shocks, however, have a larger effect in warmer areas, though the coefficient is insignificant. There is some evidence that the effect of negative rainfall shocks is mitigated by higher mean rainfall levels, particularly for property crimes, with the coefficient for high-rainfall districts being roughly half the size of that for low-rainfall districts. These results give some evidence that low-rainfall regions are more likely to see a spike in crime with negative rainfall shocks, and low-temperature regions with negative temperature shocks, but the results are imprecisely estimated.

5 Discussion

The results presented here, showing that declines in agricultural output play an important role in increasing crime rates, constitute a significant contribution to the empirical evidence for the economic theory of crime. Using seasonally disaggregated weather and agricultural shocks, we find compelling evidence that changes in agricultural production are the principal mechanism whereby weather shocks lead to increases in crime, though with suggestive evidence that high temperatures may be affecting crime through other channels as well.

Though we have established a close connection between declines in agricultural output and increases in crime rates, data limitations prevent us from establishing the precise mechanism driving the relationship. Agricultural production shocks can affect the incomes of both land-owning farmers operating their own plots of land, as well as of landless casual wage laborers; and may also affect non-farming incomes through spillover to other sectors. Importantly, these income shocks are likely to most adversely affect the poorest farmers due to their lacking access to credit or other means of buffering themselves against adversity (Jayachandran, 2006); and it is precisely these individuals who, due to already low opportunity costs, are predicted to be most likely to adapt to negative income shocks through illicit income generation. Agricultural output shocks can also potentially increase crime through increases in food prices, which would reduce the real incomes of non-farming households; through spillovers to other sectors; or through reductions in state capacity, among others. We believe that the direct income channel is the most plausible, however, as India's agricultural markets have become increasingly integrated over the course of our study period, so that local agriculture shocks would not significantly affect prices, and agricultural output is only a marginal source of tax revenue for local governments, and therefore relatively unimportant for state capacity.

A comparison of the responses of crime and agricultural production to the various weather shocks gives compelling evidence for the important role played by agricultural income in mediating the effect of weather shocks on crime. As noted previously, however, disparities in the magnitude of temperature effects would seem to indicate the presence of alternative mechanisms at play as well. In table 5 we found evidence for both the rival explanations, with manufacturing production amplifying the effect of positive temperature shocks, and muting the effect of negative shocks; and the share of the population composed of young men increasing the effect of positive temperature shocks, which we have argued to have a psychological explanation.

Despite the economic mechanisms underlying the relationship between weather shocks and crime, the fact that the relationship obtains even for crimes with less clear economic content suggests that there may be more a general social breakdown engendered by economic adversity not entirely captured by cost benefit analysis. This result is consistent across a number of countries and time periods, indicating that such non-economic mechanisms are widely prevalent. In our own results, we found that the expected differential effect for positive temperature shocks across property versus non-property crimes was positive and significant, but that the differential effect for rainfall was marginally insignificant. Though the differential effect of rainfall shocks according to the economic content of the crime is ambiguous, less uncertain is the importance of the economic environment itself: it is those shocks leading to declines in agriculture that increase the incidence of crime, whereas those shocks leaving agriculture unchanged, or even increasing agricultural output, have no effect.

6 Climate Change and the Evolution of Crime Responsiveness

We finally turn to an analysis of whether there have been changes over time in the effects of weather shocks on crime. The continuing build-up of atmospheric green house gases will increase India's temperatures in coming years, and significantly alter the timing of precipitation. Given our findings, there is the troubling possibility that these changes, in addition to their attendant economic disruptions, will also lead to increases in crime. Crime, in turn, entails both direct disruptions to human welfare, and possibly further reductions of income (Bourguignon, 1999). As we suggested earlier, however, there exist countervailing forces that may mitigate these effects; for, as countries undergo economic transformation, production becomes less dependent on agriculture, and agriculture itself becomes (potentially) less vulnerable to extreme weather, which should lower the responsiveness of crime to weather shocks.[38]

To explore this issue further, we examine how the responsiveness of crime has changed over the years of our data set. Because our data covers three decades, during which time there were dramatic changes in agricultural production,

[38] Additional salutary effects can come with economic development, as shown in Barreca *et al.* (2012), who find that mortality rates in the US have become less responsive to high temperatures due to the expansion of air conditioning.

increasing urbanization, and significant economic growth, we can assess the effects of economic modernization on the observed relationship between weather and crime. This represents a significant contribution to the existing literature on climate and conflict, as most previous research has focused on economically static countries, so that it was not possible to identify how the estimated effects might change with economic and human development. Whether the remarkably consistent effects of climate on conflict found across a broad literature might be qualified by economic development is a question of considerable import (Hsiang *et al.*, 2013).

Figure 11 shows the relationship between crime and weather shocks across the three intervals: 1971-1980; 1981-1990; and 1991-2000. The effect of negative rainfall shocks is remarkably stable across time, remaining around 4% across these decades, with a slight dip in the 1980s. In contrast, the effect of temperature shocks drop from 9% in the 1970s, down to 3.4% in the 1980s, then rise slightly to 4.2% in the 1990s. Table 7 gives the effects disaggregated by economic content. The stability of the rainfall effect masks a slight increase for property crimes, and a decrease for non-property crimes. The decline of the temperature effect is also found across both types of crime; however, with non-property crimes showing a 5.1% response with temperature shocks in the 1970s, the declining effect had by the 1990s resulted in non-property crimes showing no statistically significant relationship with positive temperature shocks.

In appendix table A3, we disaggregate the decadal regressions across all types of crime. Burglary, robbery, riots, and kidnapping all continue to be highly responsive to negative rainfall shocks through the 1990s. The only crimes that clearly become less responsive to negative rainfall shocks are banditry and rape, though the latter is statistically insignificant in all decades, and subject to considerable reporting bias. Theft and riots show a marked decline in their responsiveness to temperature shocks across time, with the effect disappearing entirely in the 1990s. Banditry, thefts, riots, and rape become less responsive to positive temperature shocks, while robbery and kidnapping become more responsive. Robbery and thefts seem to move in opposite directions, raising the possibility that there has either been a change in reporting conventions, with thefts being re-classified as robbery,[39] or a true change in the nature of property crime, with violence more likely to be deployed in the expropriation of property.

However, because the mean level of each crime was changing over time, the significance of these coefficients will vary. For example, though the temperature effects for murders drops from 5.7% in the 1970s to 4.5% in the 1990s, because the mean murder rate increased between these periods from 3.3 per 100k to 4.1, the increase in murders per 100k with positive temperature shocks actually increased slightly. Robbery and kidnapping responses to positive temperature shocks show similar increases across these years. This finding is troubling, and would indicate that some of the most pernicious crimes may become more common as climate change intensifies, a danger of which policy makers must be cognizant.

[39] Recall that the only difference between the two crimes is that robbery is a theft in which force is used.

7 Conclusion

We provide some of the first evidence on the drivers of crime in developing countries, using a data set covering nearly a billion people, and spanning three decades of economic and social transformation. Variation in temperature and rainfall are found to play a large role in driving changes in the incidence of crime. These results obtain for both property and non-property crimes, though the effects are larger, more robust and remarkably uniform for the former. This fact, and the alignment of these effects with the responses of agricultural production to the same weather shocks provide strong evidence for the presence of an income mechanism, whereby falling agricultural output leads to increases in crime, due to the decline in opportunity costs associated with criminal activity.

However, we also find that the effect of elevated temperatures is higher than expected based on their effect on agricultural output, for which we provide evidence that both non-agricultural income and psychological mechanisms are operative. The effects of income shocks on crime are highly non-symmetric: while negative agriculture shocks consistently lead to increases in crime, positive agriculture shocks do no lead to a decline. Secular increases in rural income, however, due to the expansion of irrigation, are associated with significant reductions in crime, highlighting the importance of distinguishing between long-term and short-term income changes in empirical and theoretical research on the economic determinants of crime. We have also found that higher rates of inequality are associated with increases in mean levels of crime, as well as a higher responsiveness of crime to positive temperature shocks.

Despite higher incomes, greater access to consumption smoothing instruments, and reduced susceptibility of agriculture to climatic variability that accompany economic growth, there is little evidence that crime has become less responsive to extreme weather than it was prior to these improvements. This may be taken as evidence that, despite India's remarkable gains in human and economic development, the poorest members of society, being those most likely to resort to crime during times of economic adversity, continue to remain highly vulnerable to aggregate economic shocks. This observation adds to existing concerns about the equity of India's remarkable economic growth. In sum, the evidence indicates that policy makers will have to be vigilant against rising crime rates as India's climate is increasingly buffeted by the global accumulation of atmospheric greenhouse gases.

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Table 1: Summary Statistics By Decade

	1970-2000	1970s	1980s	1990s
	(1)	(2)	(3)	(4)
Crimes (per 100k)				
burglary	20.5	33.8	19.7	12.9
banditry	1.4	2.09	1.5	0.9
thefts	42.2	66.8	41.7	27.5
robbery	3.2	4.2	3.3	2.4
riots	11.4	12.0	12.5	10.2
kidnapping	2.0	2.0	1.9	2.1
rape	1.2	0.7	1.1	1.6
murder	3.8	3.3	3.6	4.1
Agriculture				
irrigation	0.571	0.512	0.575	0.604
wheat product	146.2	93.7	146.2	183.0
yield	1.64	1.22	1.562	2.001
area	72.9	68.5	76.3	73.1
rice product	169.8	130.2	164.0	213.2
yield	1.661	1.194	1.729	2.032
area	106.6	109.8	103.3	107.0

Table 1 gives the summary statistics for crime and agriculture. Crime is given as incidents per 100k population. Irrigation is defined as the percentage of cultivated land which is irrigated. Product is thousands of kgs, and yield is kgs per hectare.

Table 2: Weather Shocks and Property Crimes

	all crimes		property crimes		non-property crimes	
	(1)	(2)	(3)	(4)	(5)	(6)
monsoon						
neg rain	0.037***	0.037***	0.043***	0.043***	0.027***	0.027***
	(0.010)	(0.010)	(0.013)	(0.012)	(0.010)	(0.010)
pos rain	0.008	0.008	0.012	0.012	0.001	0.001
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
neg temp	0.024**	0.025***	0.029**	0.029**	0.018	0.018
	(0.010)	(0.010)	(0.012)	(0.010)	(0.011)	(0.011)
pos temp	0.053***	0.053***	0.066***	0.065***	0.032***	0.031**
	(0.012)	(0.013)	(0.015)	(0.015)	(0.012)	(0.012)
non-monsoon						
neg rain		0.001		0.002		-0.001
		(0.008)		(0.009)		(0.009)
pos rain		-0.004		-0.006		-0.003
		(0.011)		(0.012)		(0.011)
neg temp		0.007		0.006		0.010
		(0.009)		(0.011)		(0.010)
pos temp		0.010		0.007		0.016
		(0.010)		(0.012)		(0.011)
R-squared	0.920	0.920	0.921	0.921	0.837	0.837
N	74978	74978	46816	46816	28162	28162

The outcome variable is crimes per 100k. In columns (1)-(2), all crimes are included; while in columns (3)-(4) only property crimes, and columns (5)-(6) non-property crimes. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year-crime quadratic time tends. Error terms are clustered at the district level.

Table 3: Weather and Disaggregated Crimes

	property crimes					non-property crimes		
	burglary	banditry	thefts	robbery	riots	kidnapping	rape	murder
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
monsoon								
neg rainfall	0.056***	0.044*	0.014	0.050**	0.056***	0.026	0.027	0.022**
	(0.016)	(0.023)	(0.014)	(0.021)	(0.018)	(0.017)	(0.017)	(0.011)
pos rainfall	0.008	0.034*	0.012	0.005	0.005	-0.000	-0.001	0.000
	(0.012)	(0.018)	(0.011)	(0.016)	(0.017)	(0.014)	(0.016)	(0.010)
neg temp	0.017	0.043*	0.025**	0.046**	0.010	0.022	0.022	0.006
	(0.013)	(0.024)	(0.011)	(0.019)	(0.019)	(0.017)	(0.019)	(0.011)
pos temp	0.026	0.102***	0.048***	0.087***	0.064***	0.021	0.030	0.037***
	(0.019)	(0.026)	(0.016)	(0.024)	(0.021)	(0.019)	(0.019)	(0.014)
non-monsoon								
neg rainfall	-0.021	-0.001	-0.001	-0.004	-0.005	-0.002	-0.009	0.006
	(0.015)	(0.021)	(0.013)	(0.021)	(0.018)	(0.017)	(0.016)	(0.012)
pos rainfall	0.010	-0.002	0.016	-0.013	0.000	0.008	-0.007	-0.003
	(0.012)	(0.018)	(0.011)	(0.017)	(0.014)	(0.014)	(0.015)	(0.009)
neg temp	0.068***	0.024	0.002	-0.029	-0.030*	0.019	-0.011	0.040***
	(0.015)	(0.025)	(0.013)	(0.024)	(0.017)	(0.018)	(0.018)	(0.012)
pos temp	0.006	-0.005	0.012	0.004	0.009	-0.007	0.027	0.010
	(0.012)	(0.023)	(0.013)	(0.019)	(0.017)	(0.015)	(0.017)	(0.010)
R-squared	0.832	0.766	0.820	0.765	0.808	0.740	0.779	0.766
N	9378	9322	9322	9377	9373	9390	9396	9374

The outcome variable is crimes per 100k. Regressions are estimated separately for each type of crime. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year time tends. Error terms are clustered at the district level.

Table 4: Weather Shocks, Agriculture and Crime

	log crime	primary crop: log yield	primary crop: product, log	primary crop: product, level
	(1)	(2)	(3)	(4)
monsoon				
neg rainfall	0.038***	-0.141***	-0.213***	-18.274***
	(0.010)	(0.015)	(0.033)	(3.312)
pos rainfall	0.007	0.003	-0.045**	-5.190*
	(0.009)	(0.010)	(0.020)	(2.655)
neg temp	0.027***	-0.007	-0.029	-7.526**
	(0.010)	(0.011)	(0.022)	(2.942)
pos temp	0.049***	-0.039**	-0.118***	-11.551***
	(0.013)	(0.016)	(0.029)	(3.670)
pre monsoon				
neg temp	0.016	0.037***	0.051**	5.927*
	(0.010)	(0.011)	(0.023)	(3.178)
pos temp	0.011	0.009	0.046**	6.269***
	(0.008)	(0.011)	(0.019)	(2.395)
post monsoon				
neg temp	0.006	0.068***	0.163***	14.649***
	(0.011)	(0.012)	(0.025)	(3.273)
post temp	0.009	-0.045***	-0.026	-3.193
	(0.009)	(0.013)	(0.031)	(2.997)
R-squared	0.920	0.829	0.926	0.834
N	74932	6759	6815	6815

The outcome variable in column (1) is log crime; in columns (2)-(4) it is agricultural output. In column (2) it is log yield, in column (3) in log product, and in column (4) level product. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district-crime. Year-crime fixed effects are included, as well as state-crime-year quadratic time tends. Error terms are clustered at the district level.

Table 5: Heterogeneous Weather Effects

outcome variable: log crime per 100k	level	interaction		level	interaction		level	interaction
	(1)	(2)		(3)	(4)		(5)	(6)
urbanization			inequality			young men		
X neg rain	0.036	0.011	X neg rain	1.815***	0.432	X neg rain	-0.280	-0.322
	(0.042)	(0.088)		(0.550)	(0.653)		(0.848)	(3.647)
X pos rain		-0.073	X pos rain		0.566	X pos rain		2.557
		(0.048)			(0.546)			(2.728)
X neg dds		0.036	X neg dds		-0.003	X neg dds		-0.322
		(0.090)			(0.618)			(3.644)
X pos dds		0.094	X pos dds		1.369**	X pos dds		9.577***
		(0.064)			(0.636)			(3.147)
literacy rate			agricultural labor			manufacturing		
X neg rain	0.695*	-0.026	X neg rain	0.098***	0.015	X neg rain	-0.280	0.524
	(0.361)	(0.308)		(0.034)	(0.058)		(0.848)	(0.805)
X pos rain		0.299	X pos rain		0.010	X pos rain		0.134
		(0.237)			(0.060)			(0.788)
X neg dds		-0.082	X neg dds		-0.065	X neg dds		-3.787**
		(0.369)			(0.073)			(1.788)
X pos dds		-0.720**	X pos dds		-0.045	X pos dds		1.871**
		(0.286)			(0.068)			(0.832)
irrigation								
X neg rain	-0.197***	-0.051						
	(0.069)	(0.099)						
X pos rain		0.069						
		(0.099)						
X neg dds		0.127						
		(0.134)						
X pos dds		0.103						
		(0.069)						

The outcome variable is crimes per 100k. In columns (1), (3), and (5) are given the uninteracted coefficients for the indicated socio-economic variables; in columns (2), (4), and (6) are given the interaction terms. The climate shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district-crime. Year-crime fixed effects are included, as well as state-year-crime time tends. Interaction terms are included of the weather shock and district fixed effects. Error terms are clustered at the district level.

Table 6: Climate Interactions

	all crimes		property crime		non-property crime	
	shock	shock X climate	shock	shock X climate	shock	shock X climate
	(1)	(2)	(3)	(4)	(5)	(6)
monsoon shocks						
neg rain	0.046***	-0.019	0.058***	-0.033	0.025**	0.004
	(0.013)	(0.019)	(0.016)	(0.023)	(0.013)	(0.019)
pos rain	0.013	-0.014	0.022	-0.026	-0.002	0.007
	(0.012)	(0.016)	(0.014)	(0.018)	(0.013)	(0.018)
neg dds	0.016	0.017	0.015	0.028	0.016	0.001
	(0.013)	(0.019)	(0.016)	(0.025)	(0.014)	(0.019)
pos dds	0.048***	0.004	0.066***	-0.005	0.018	0.02
	(0.018)	(0.018)	(0.022)	(0.022)	(0.015)	(0.018)

The outcome variable is crimes per 100k. In columns (1)-(2), all crimes are included; while in columns (3)-(4) only propety crimes, and columns (5)-(6) non-property crimes. The climate shocks are defined as rainfall/temperature 1 standard deviation from the mean. Interaction terms are included of the climate shocks with the mean climate conditions: for temperature shocks, the interaction term is for mean temperature conditions; for rainfall shocks, the interaction term is for mean rainfall conditions. Dummies are included for the district-crime. Year-crime fixed effects are included, as well as state-year-crime quadratic time tends. Error terms are clustered at the district level.

Table 7: Weather Effects by Decade

	all crime		property crime		non-property crime	
	neg rain	pos temp	neg rain	pos temp	neg rain	pos temp
	(1)	(2)	(3)	(4)	(5)	(6)
decade						
1970s	0.039**	0.090***	0.040*	0.112***	0.040**	0.051**
	(0.020)	(0.022)	(0.024)	(0.026)	(0.020)	(0.023)
1980s	0.031**	0.034*	0.038**	0.048**	0.016	0.013
	(0.014)	(0.020)	(0.017)	(0.024)	(0.016)	(0.023)
1990s	0.041**	0.042**	0.048**	0.051**	0.029*	0.029
	(0.016)	(0.019)	(0.019)	(0.021)	(0.017)	(0.018)
R-squared	0.92		0.922		0.838	
N	74970		46811		28159	

The outcome variable is crimes per 100k. In columns (1)-(2), all crimes are included; while in columns (3)-(4) only property crimes, and columns (5)-(6) non-property crimes. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean; dummies are included separately for shocks occurring in each decade. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year-crime time tends. Error terms are clustered at the district level.

Table A1: Disaggregated Weather Shocks and Pooled Crimes

	all		property		non-property	
	neg	pos	neg	pos	neg	pos
	(1)	(2)	(3)	(4)	(5)	(6)
rainfall						
25 to 75	0.002	0.008	-0.004	0.014	0.011	-0.004
	(0.009)	(0.009)	(0.011)	(0.011)	(0.010)	(0.010)
75 to 125	0.026**	0.009	0.028**	0.021*	0.021*	-0.011
	(0.011)	(0.011)	(0.013)	(0.012)	(0.012)	(0.012)
125 to 175	0.051***	0.024*	0.058***	0.028*	0.038**	0.017
	(0.015)	(0.015)	(0.019)	(0.017)	(0.016)	(0.016)
175 to 225	0.051**	0.031*	0.037	0.043**	0.073***	0.009
	(0.026)	(0.016)	(0.031)	(0.019)	(0.028)	(0.018)
225 up	0.086	-0.019	0.141**	0.001	-0.006	-0.053**
	(0.054)	(0.020)	(0.059)	(0.025)	(0.069)	(0.022)
temperature						
25 to 75	0.005	0.005	0.011	0.01	-0.005	-0.004
	(0.010)	(0.009)	(0.011)	(0.011)	(0.012)	(0.010)
75 to 125	0.029**	0.039***	0.033**	0.045***	0.023*	0.028**
	(0.012)	(0.013)	(0.013)	(0.015)	(0.013)	(0.013)
125 to 175	0.033**	0.083***	0.045***	0.106***	0.013	0.043***
	(0.014)	(0.018)	(0.016)	(0.022)	(0.017)	(0.016)
175 to 225	-0.005	0.011	-0.022	0.019	0.022	-0.004
	(0.025)	(0.020)	(0.034)	(0.024)	(0.022)	(0.022)
225 up	0.073***	0.018	0.066**	0.043	0.083**	-0.026
	(0.028)	(0.026)	(0.033)	(0.030)	(0.036)	(0.030)

The outcome variable is crimes per 100k. In columns (1)-(2), all crimes are included; while in columns (3)-(4) only property crimes, and columns (5)-(6) non-property crimes. The weather shocks are defined as rainfall/temperature falling in the given sd intervals from the mean. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year-crime time tends. Error terms are clustered at the district level.

Table A2: Weather, Agriculture, and Crime

		rice			arhar			jowar		
	log	log yield	product		log yield	product		log yield	product	
	crime		log	level		log	level		log	level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
monsoon										
neg rainfall	0.038***	-0.165***	-0.261***	-16.965***	-0.111***	-0.212***	-1.455***	-0.103***	-0.218***	-4.274***
	(0.010)	(0.017)	(0.030)	(3.065)	(0.017)	(0.030)	(0.279)	(0.020)	(0.041)	(1.035)
pos rainfall	0.007	0.011	0.012	-3.247	-0.012	-0.010	-0.017	-0.063***	-0.107***	-3.862***
	(0.009)	(0.010)	(0.017)	(2.391)	(0.013)	(0.023)	(0.178)	(0.017)	(0.033)	(0.900)
neg temp	0.027***	0.024**	0.039*	-6.229**	0.056***	0.067***	0.141	-0.009	0.029	-0.950
	(0.010)	(0.011)	(0.021)	(2.539)	(0.015)	(0.026)	(0.175)	(0.016)	(0.038)	(0.905)
pos temp	0.049***	-0.029**	-0.106***	-6.923**	-0.013	-0.033	0.230	0.019	-0.136***	-3.857***
	(0.013)	(0.014)	(0.027)	(3.463)	(0.016)	(0.028)	(0.214)	(0.021)	(0.047)	(1.143)
pre monsoon										
neg temp	0.016	0.029**	0.091***	4.868*	-0.003	0.037	0.066	0.083***	0.098***	2.474**
	(0.010)	(0.012)	(0.026)	(2.848)	(0.014)	(0.025)	(0.205)	(0.017)	(0.034)	(0.996)
pos temp	0.011	0.026***	0.025	4.619**	0.013	0.028	-0.532**	0.031*	0.059*	2.533**
	(0.008)	(0.010)	(0.019)	(2.208)	(0.014)	(0.025)	(0.260)	(0.016)	(0.031)	(1.113)
post monsoon										
neg temp	0.006	0.067***	0.130***	11.901***	0.022	0.037	0.416*	0.092***	0.173***	2.579***
	(0.011)	(0.012)	(0.022)	(2.950)	(0.017)	(0.031)	(0.225)	(0.016)	(0.044)	(0.881)
post temp	0.009	0.007	-0.003	-3.614	-0.085***	-0.110***	-1.167***	-0.109***	-0.075*	0.845
	(0.009)	(0.012)	(0.024)	(2.634)	(0.017)	(0.028)	(0.284)	(0.020)	(0.039)	(1.151)
R-squared	0.920	0.794	0.946	0.845	0.652	0.887	0.808	0.677	0.916	0.855
N	74932	7290	7130	7130	7918	7889	7889	5447	5392	5392

The outcome variable is agricultural output, given in log yields, log product, and level product. In columns (2)-(3), the crop is rice; in columns (4)-(6) it is arhar; and in columns (8)-(10) it is jowar. Column (1) gives the estimates from the crime regression for comparison. The climate shocks are defined as rainfall/temperature falling in the given sd intervals from the mean. District fixed effects are included, as are year fixed effects and state-year quadratic time trends. Error terms are clustered at the district level.

Table A3: Agricultural Output and Crime: IV Specifications

	OLS log crime	log crop prod/yield	log crime	IV log crime
	(1)	(2)	(3)	(4)
Panel A				
primary crop	-0.008***			-0.141***
log product	(0.001)			(0.032)
monsoon		-0.248***	0.035***	
neg rainfall		(0.064)	(0.007)	
R-squared	0.916	0.318	0.916	0.895
N	50736	6306	50240	50240
Panel B				
primary crop	-0.023***			-0.224***
log yield	(0.005)			(0.056)
monsoon		-0.138***	0.034***	
neg rainfall		(0.019)	(0.007)	
R-squared	0.916	0.604	0.915	0.912
N	50298	6251	49802	49802

The outcome variables are log crime and log agricultural output. In column (1) is given the OLS from a regression of crime on agricultural output. In columns (2) and (3) are given the results from a regression of crime and agricultural output on negative rainfall shocks; and in column (4) is given the results for the IV regression of crime on agricultural output, using negative rainfall as the instrument. In panel A the agriculture variable is defined as log primary crop product, and in panel A it is defined as log primary crop yield. Controls are included for positive monsoon rainfall shocks, and temperature shocks in three different seasons. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year-crime quadratic time tends. Error terms are clustered at the district level.

Table A4: Crime and Weather Across Decades

	property crimes					non-property crimes		
	buglary	banditry	thefts	robbery	riots	kidnapping	rape	murder
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
negative rainfall								
1970s	0.053	0.101**	-0.028	0.100**	0.099***	0.041	0.042	0.038*
	(0.036)	(0.043)	(0.033)	(0.046)	(0.030)	(0.031)	(0.033)	(0.020)
1980s	0.061***	0.006	0.059***	0.029	0.046	0.014	0.041	0.041**
	(0.019)	(0.033)	(0.020)	(0.031)	(0.028)	(0.025)	(0.028)	(0.016)
1990s	0.085***	0.031	0.040*	0.078**	0.050*	0.072***	0.016	0.036*
	(0.025)	(0.039)	(0.020)	(0.034)	(0.030)	(0.028)	(0.031)	(0.021)
positive temperature								
1970s	0.04	0.235***	0.119***	0.014	0.139***	0.009	0.092**	0.053**
	(0.038)	(0.047)	(0.032)	(0.051)	(0.039)	(0.037)	(0.041)	(0.021)
1980s	0.01	0.04	0.027	0.094*	0.072*	-0.041	0.070*	0.003
	(0.031)	(0.046)	(0.028)	(0.055)	(0.041)	(0.039)	(0.038)	(0.020)
1990s	0.013	0.088**	0.033	0.108***	0.033	0.051*	-0.021	0.053**
	(0.028)	(0.038)	(0.024)	(0.030)	(0.030)	(0.026)	(0.026)	(0.023)

The outcome variable is crimes per 100k. Regressions are estimated separately for each type of crime. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean; dummies are included separately for shocks occurring in each decade. Dummies are included for the district-crime. Year fixed effects are included, as well as state-year-crime time tends. Error terms are clustered at the district level.

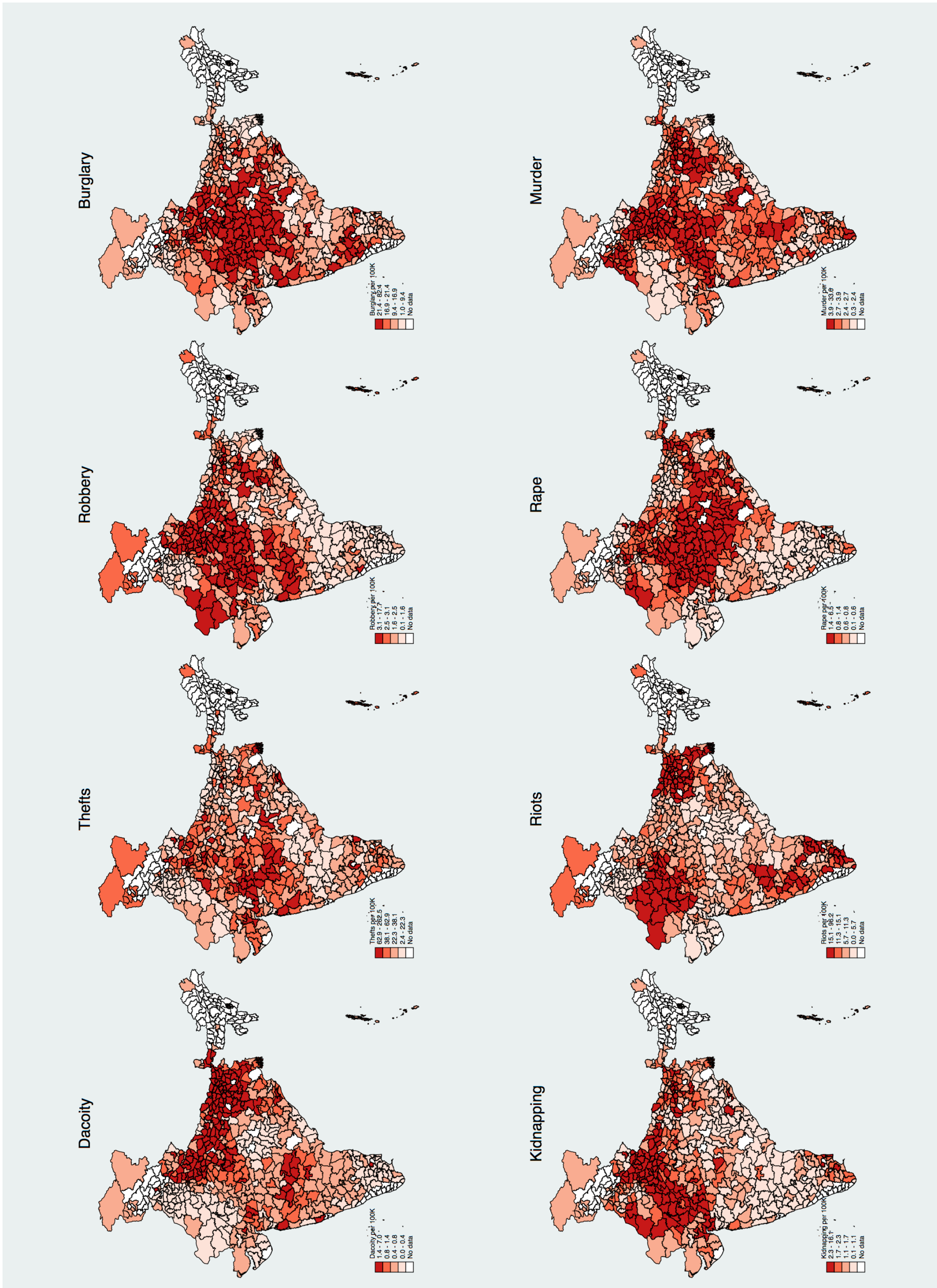

Figure 1: The spatial distribution of average 1971-2000 crime rates (crimes committed per 100,000 population).

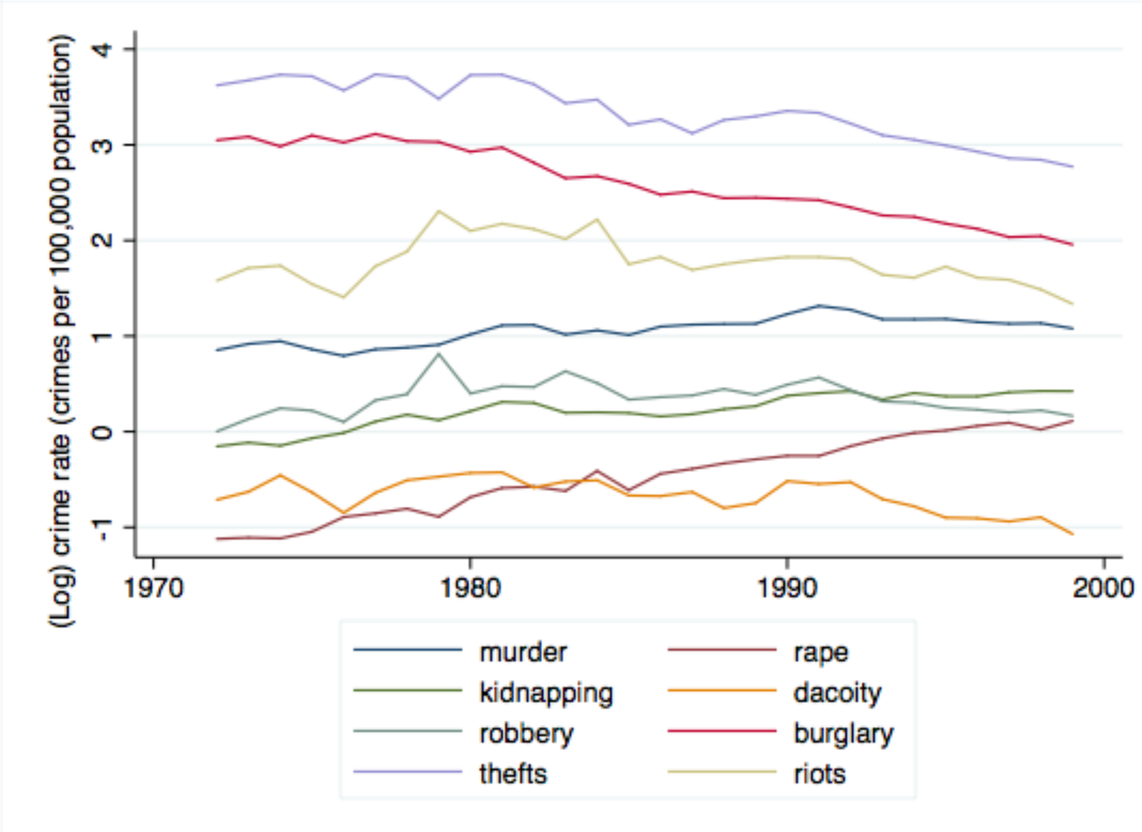

Figure 2: Plots of the (logarithm) of India-wide average crime incidence (per 100,000 population) over time.

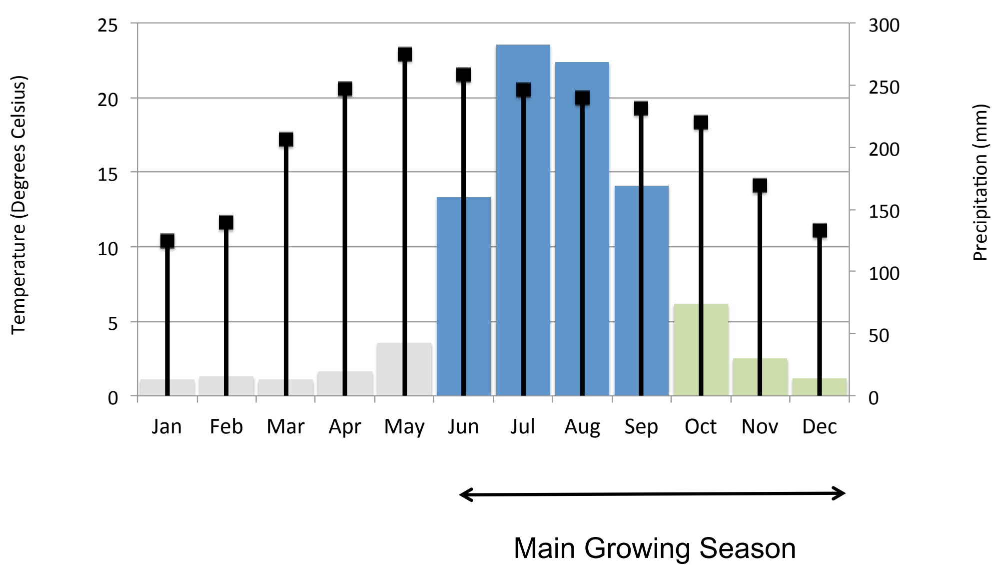

Figure 3: Average climate in India. Monthly average temperature (black drop lines) and precipitation (bars). Monsoon crops are usually sown around June-September and harvested between October and December. The blue and green shades represent the breakup of weather indicators used in the empirical analysis.

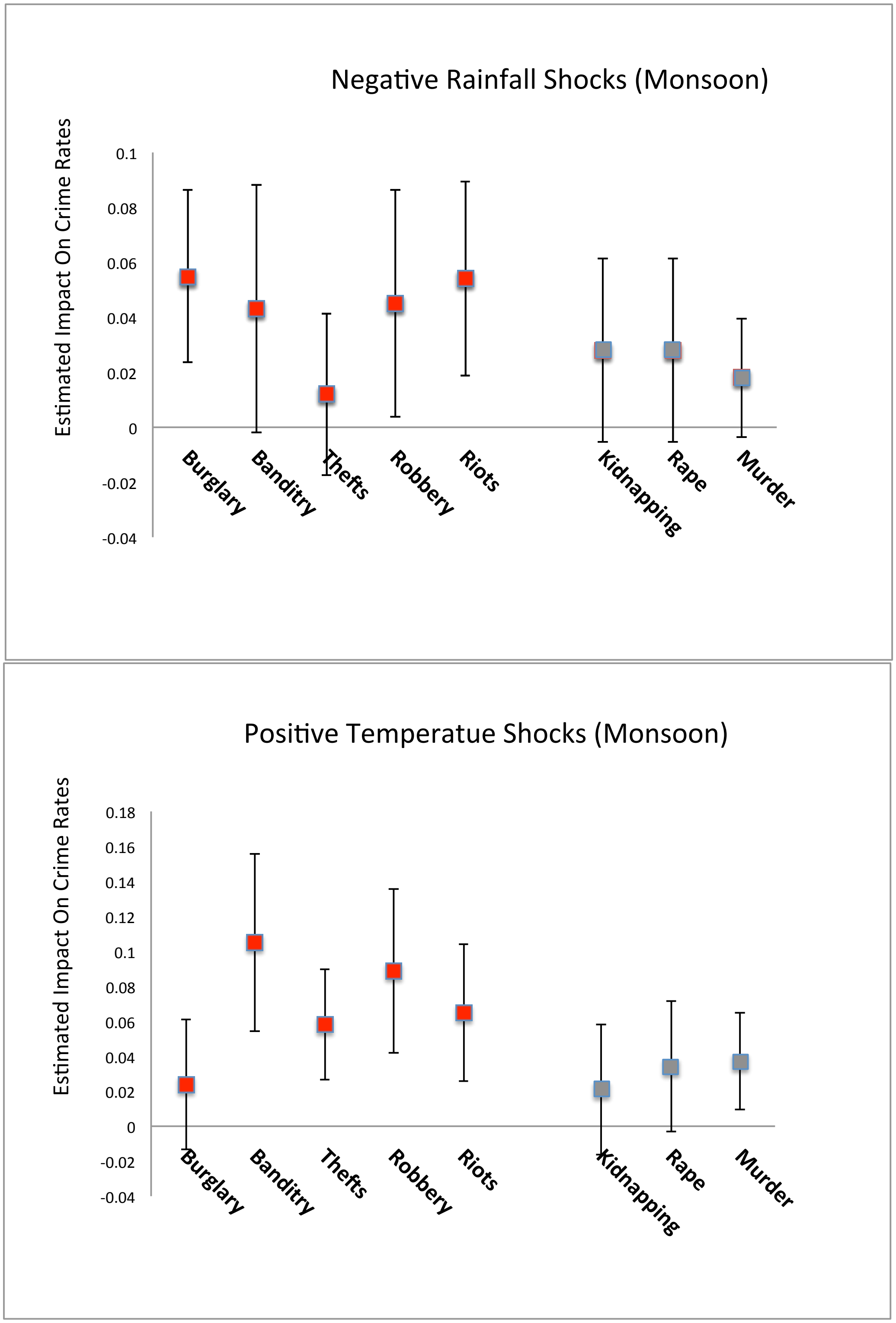

Figure 4: Estimated coefficients from regressions of disaggregated crime rates on negative monsoon rainfall shocks (top) and positive monsoon temperature shocks (bottom). Property crimes coefficients are indicated by red markers, and violent crime coefficients are indicated by grey markers.

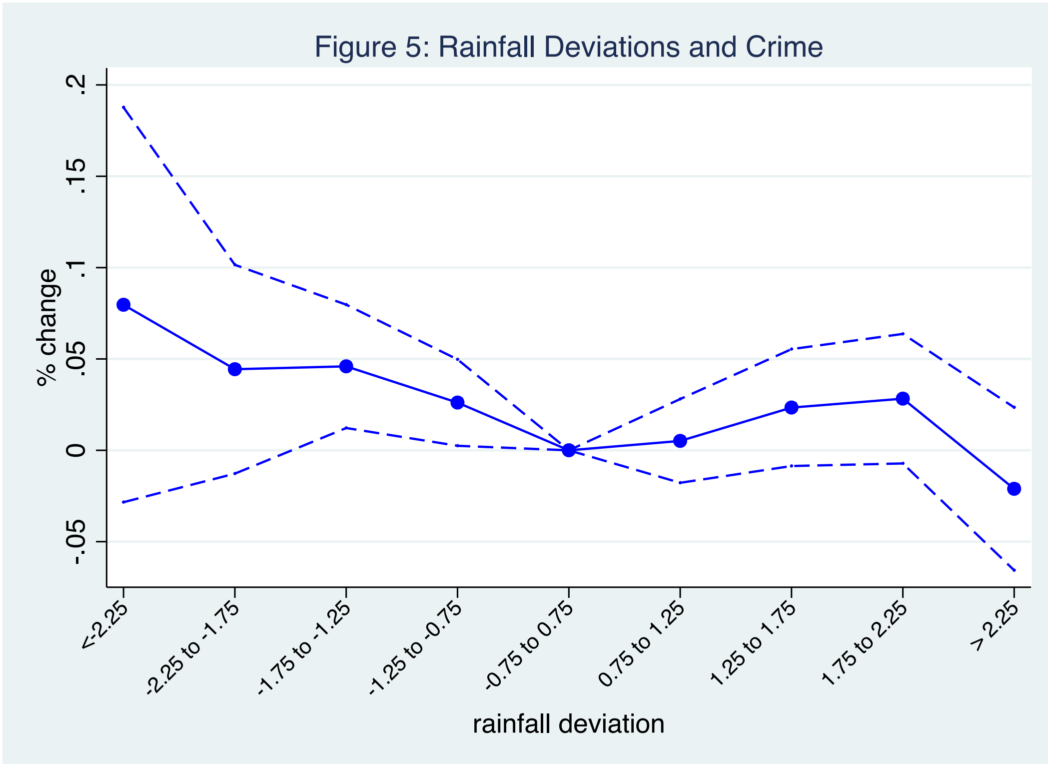

Figure 5: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bin.

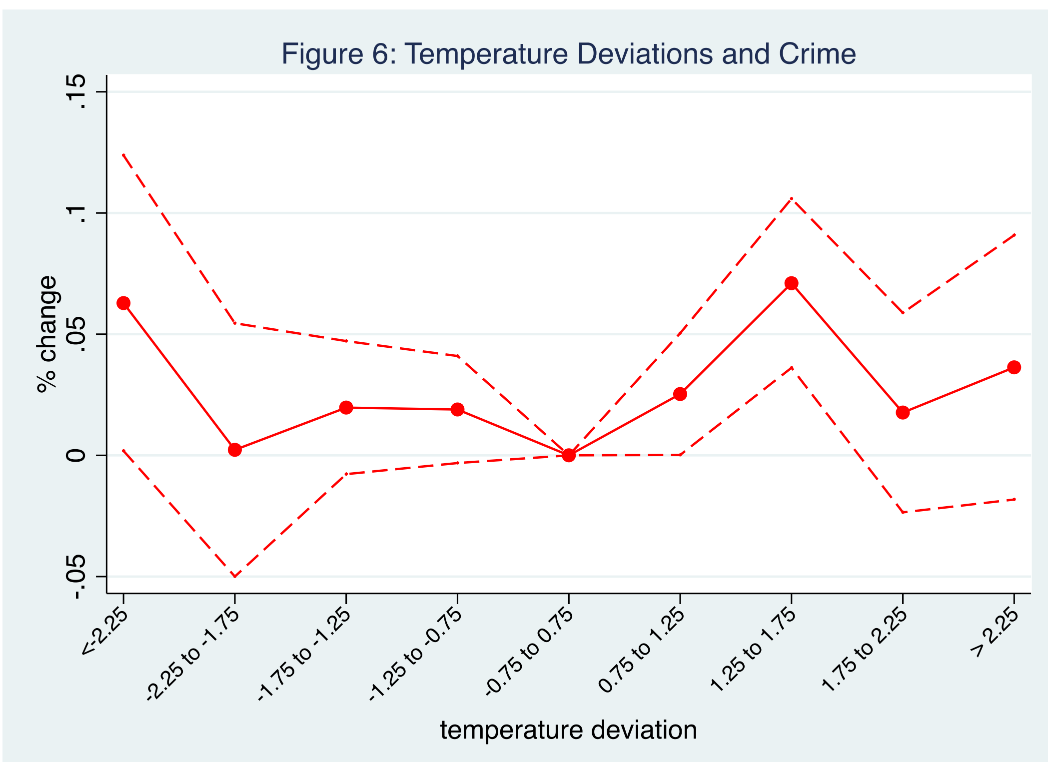

Figure 6: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bin.

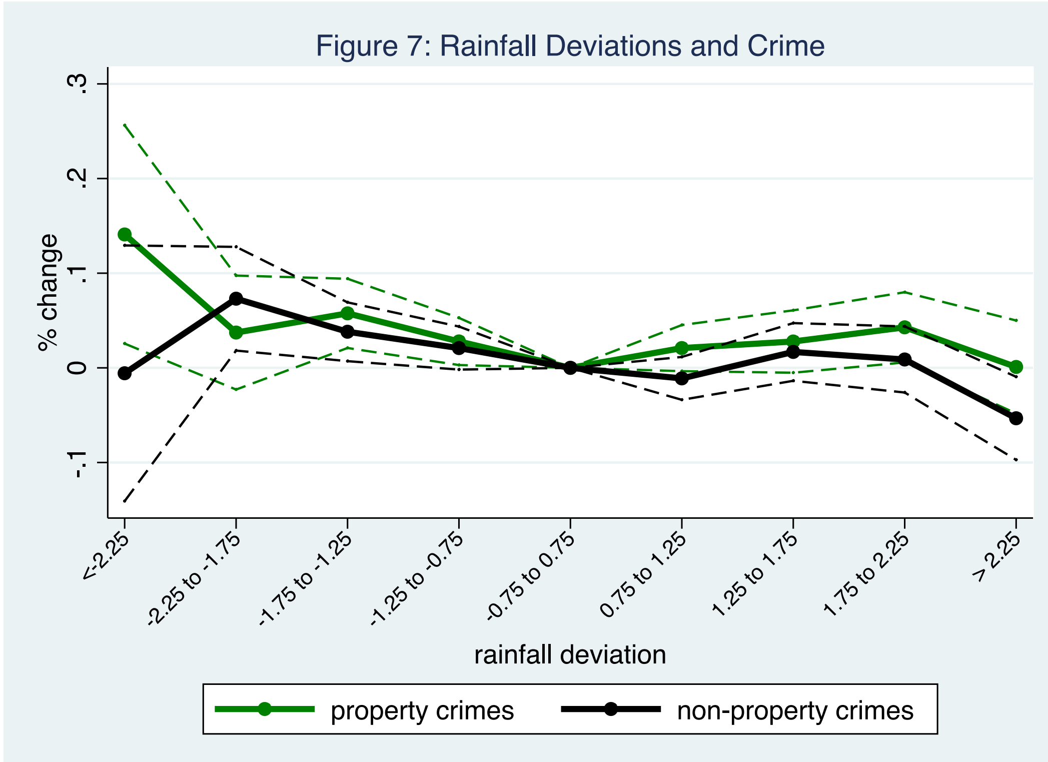

Figure 7: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bins. Crime is disaggregated into present and non-property crimes.

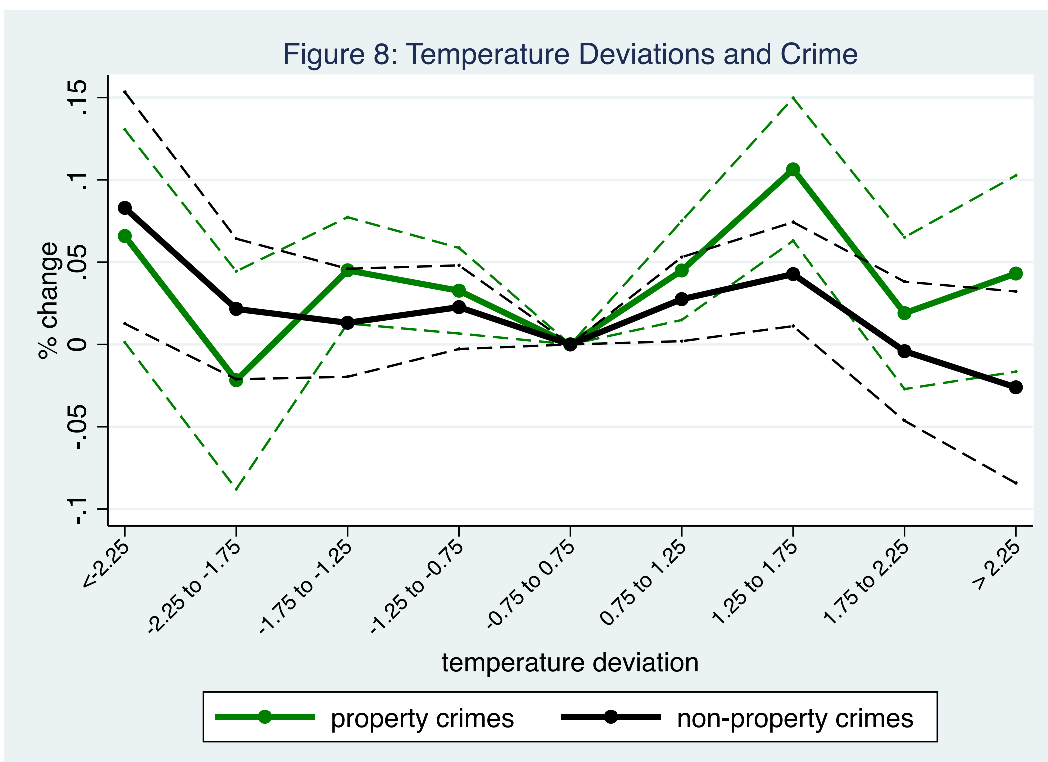

Figure 8: Coefficients from a regression of crime on monsoon degree days in the indicated standard deviation bins. Crime is disaggregated into property and non-property crimes.

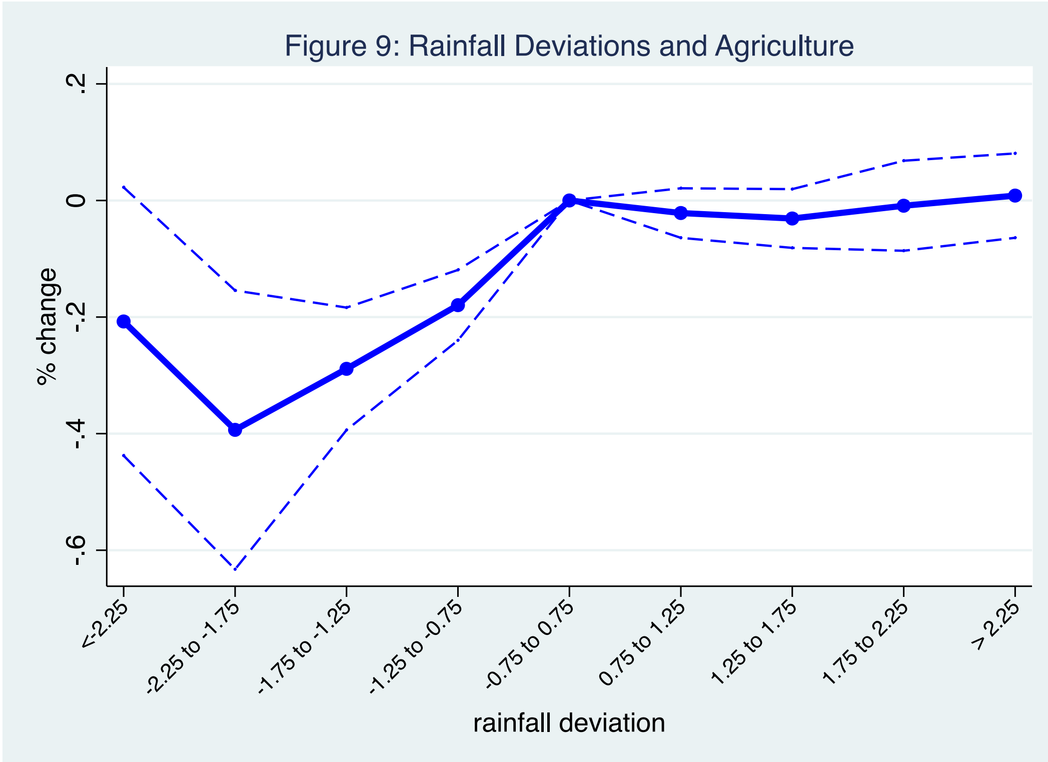

Figure 9: Coefficients from a regression of the primary monsoon crop on monsoon rainfall in the indicated standard deviation bins.

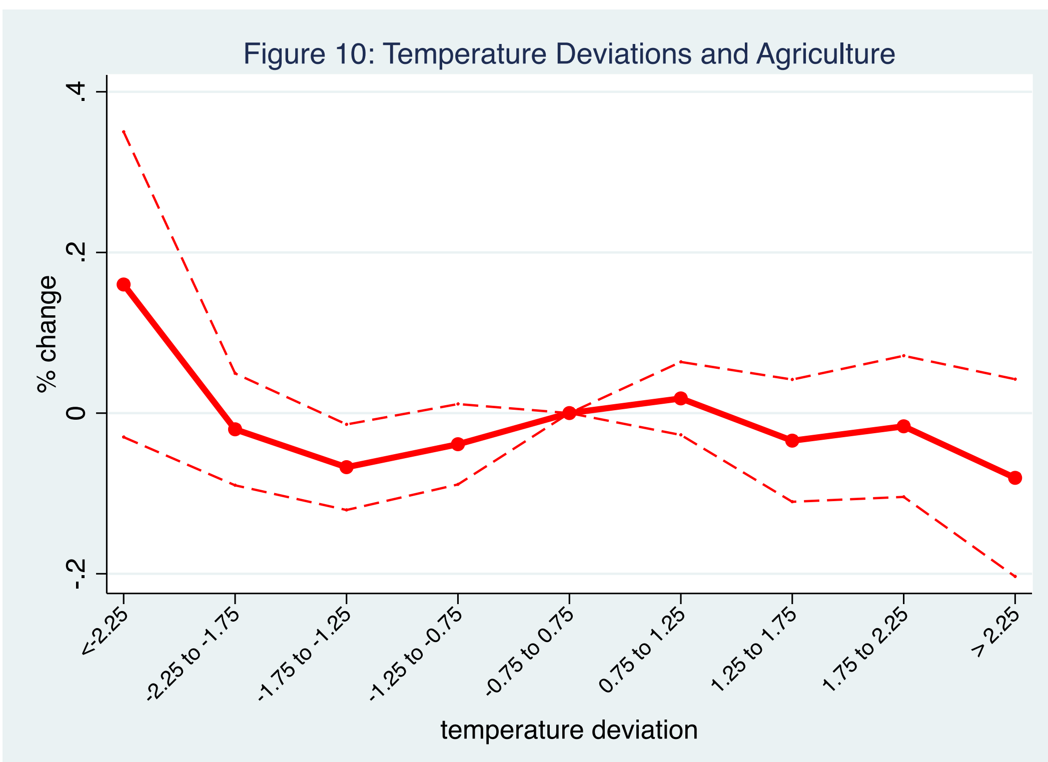

Figure 10: Coefficients from a regression of the primary monsoon crop on monsoon degree days in the indicated standard deviation bins.

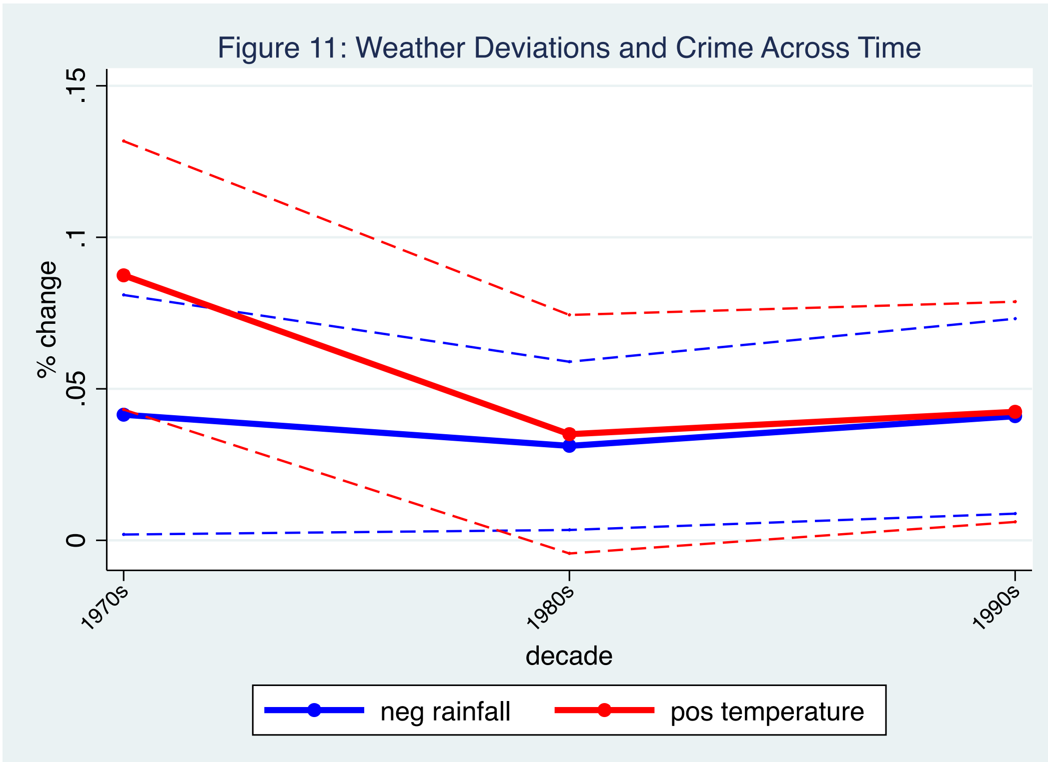

Figure 11: Coefficients from a regression of crime on monsoon rainfall and degree days across the indicated decades, with separate climate dummies used for each decade.