Weather Shocks, Crime, and Agriculture:

Evidence from India[1]

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David S Blakeslee[2]

Ram Fishman[3]

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 the incidence of most types of crime increases with weather shocks that reduce agricultural output during the main agricultural growing season: low rainfall and high temperatures. 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 an income mechanism to be at work. High temperatures, however, have an effect on crime that is disproportionally high given their agricultural impacts, consistent with non-income related linkages found in industrialized countries. 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.

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[2] New York University – Abu Dhabi. Email: davidsblakeslee@nyu.edu
[3] George Washington University. Email: rfishman@gwu.edu

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. 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 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 societies, where incomes remain closely tied to annual weather patterns.[6] This approach has yielded a consistent and robust body of evidence on the effects of income shocks on civil

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[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.

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 and income 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; Rotton and Cohn, 2000).

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

[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.

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"), property 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). Corroboration of these results was provided in a recent working paper on the relationship between trade, consumption, and crime in India (Iyer and Topolova, 2014).[9]

Our results show that the effects of weather shocks on property crimes are larger, more uniform, and of greater statistical significance than for non-property crimes, consistent with the income mechanisms posited in economic models of crime. 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, since weather can have non-income related impacts, the exclusion restriction may fail to hold when using an instrumental variables approach, so that estimated IV coefficients would conflate income with effects operating through other channels. Instead, the approach we take in this paper is to compare the patterns relating

[9] Our own results were first presented in a working paper posted in January, 2013 (Blakeslee and Fishman, 2013).

weather and crime, and those relating weather and agricultural production.

We find that the effects of rainy season weather shocks on crime are closely paralleled by their effect on agricultural production: the same weather shocks that lead to increases in crime are shown to lead to sharp declines in agricultural output. Of course, the coincidence of these results is not unexpected in a setting where incomes are highly dependent on agricultural production, as is the case in India throughout the period covered in this study.[10] Nonetheless, the consistency of the correspondence between the crime and agriculture effects, using even highly disaggregated measures of weather events provides compelling evidence that agricultural income shocks are the primary mechanism at play.

An interesting qualification to these parallels is that the effects of high temperature are much larger than would be anticipated through their observed influence on agricultural production. The similar magnitude of rainfall and temperature effects occurs despite their very different effects on agricultural output, with negative rainfall proving more than four times as destructive to crops as positive temperature. Similarly, positive temperature shocks have an impact on crops comparable to that of negative temperature shocks, but about twice as large an impact on crime. This suggests that additional, non-economic mechanisms are also operative, with psychological responses to elevated temperatures being a particularly plausible candidate;[11] so that the estimated impact of positive

[10] 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.
[11] See Anderson (2000) and Hsiang *et al.* (2013) for a summary of this literature.

temperature shocks captures the combined effects of reduced opportunity costs and elevated aggression.

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 between the 1970s and 1980s, but has since remained stable at about 4%. We find no 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 reduced the magnitude of these impacts. We argue that these findings are consistent with the continuing presence of a highly vulnerable segment of rural society with no access to irrigation, which, though declining as a share of the total population, remains highly susceptible to weather-induced income shocks and prone to criminal adaptation.

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. 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 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.[12] The data provides a rich accounting of a wide variety of crimes. Among the crimes

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

included are burglary, robbery, banditry, theft, riots, murder, rape, kidnapping, cheating, counterfeiting, and homicide.[13]

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

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

districts from our sample when partitioning yields districts with few observations.[14] We consider this the appropriate approach, as the partitioning of districts is likely to yield significant changes in institutions and local governance.

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 indicate a general decline in the incidence of most property crimes, with substantial declines in burglary, banditry, thefts, and robbery.[15] 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

[14] 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.

[15] 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.

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 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.[16] 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

[16] 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.

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 between June-September (figure 3), 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 October-December, and term them the *Monsoon* and *Post-Monsoon* period (blue and green shades in figure 3).

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,[17] 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, which is well adapted to count-variable outcomes and handles the zero-value

[17] The one exception to this is banditry, for which zero values are encountered 7% of the time.

problem, but suffers from other limitations when a large number of fixed effects are included in the regression.[18] 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. In their research, only 8% of the sample took the zero value, mitigating the likelihood that this would bias their results. The linear specification has the advantages of more easily handling the inclusion of district fixed effects, and yielding coefficients of more transparent interpretation. For these reasons, we adopt the linear specification, with dummy variables to indicate zero-crime observations.

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, our temperature shock variables are specified as dummies equaling 1 when the

[18] 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.

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). 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.[19] Riots[20] are known to occur during times of economic duress, particularly in response to heightened food prices, and are often characterized by widespread looting.

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[19] 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.

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

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 in the post-monsoon season.

Using the full sample, we find that negative rainfall shocks during the monsoon are associated with a 3.6% increase in the incidence of crime, positive temperature shocks with a 5.2% increase, and negative temperature shocks with a 2.5% increase. There is also a 2.4% increase in crime with negative rainfall shocks in the post-monsoon period. Disaggregating the sample into property and non-property crimes, we see that effects of the shocks are generally larger for the former. Whereas negative rainfall shocks lead to a 4.2% increase in property crimes, they lead to a smaller 2.7% increase in non-property crimes; while the effects of positive temperature shocks are 6.6 and 2.9%, respectively, and those of negative temperature shocks 2.9 and 1.7%. These results are generally consistent with our thesis for the economic origins of the observed crime effects: as we will show 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 suffers from significant under-reporting.[21] 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 results for these two crimes with those obtained for the others will allow us to establish the reliability of the latter.

Table 3 shows the results for these regressions; Figure 4 summarizes the coefficients for monsoon period negative rain shocks and positive temperature shocks. As before, we estimate the effects with and without the post-monsoon weather shocks. Every crime but thefts shows a statistically significant increase with negative rainfall shocks. As was found in the pooled regressions, negative rainfall shocks consistently yield a larger increase in property crimes than non-property crimes: riots increase by a statistically significant 5.4%, burglaries by 5.5%, banditry by 4.6%, and robberies by 5.5%; whereas kidnapping is the only non-property crime that shows a statistically significant increase (2.8%). Positive temperature shocks are associated with large increase in crime, particularly property crimes, with banditry increasing by 10.5%, robbery by 8.9%, riots by 6.5%, and thefts by

[21] 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.

5.8%. Of the non-property crimes, murder shows a statistically significant increase of 3.7%, and rape a marginally significant 3.4% increase. Consistent with the argument above, we see no differential effect for robbery and murder against other types of crime, giving greater credibility to our results. The other weather shocks do not have as uniform an effect across crime categories.

The relationship between weather shocks and crime has been 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 with other channels of influence (e.g., psychological responses to elevated temperatures). These weather dummies may, however, 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 sd intervals; Figures 5 and 6 show the results. As can be seen, crime rises steadily with increasing negative rainfall deviations, while positive deviations have no effect for any interval. The relationship between crime and temperature shocks is far noisier: while crime increases steadily with positive temperature shocks up to the 1.25-1.75 sds interval, it thereafter drops precipitously, becoming indistinguishable from 0. There is also an evident increase in crime with cold shocks. Appendix table A1 gives the results for the corresponding regressions.[22]

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

The pattern of the temperature shocks would seem to indicate additional, non-economic mechanisms at work. For example, the fact that crime increases with temperatures up to 1.75 sds, but then falls to zero with higher temperatures, suggests that crime become less physiologically feasible where temperatures are too high, overcoming the income effect that would otherwise prevail. 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).

3.3 Alternative Rainfall Measures

As we have argued previously, because of the agricultural channel for the observed crime effects, it will be those weather fluctuations occurring during the pivotal monsoon season that will be most relevant for determining the patterns of crime. To test this thesis, we estimate specifications substituting *annual* weather shock variables for the monsoon variables employed in the previous analysis. The variables are specified as before, but with the relevant deviations being those from the annual levels of rainfall and temperature. The results from this specification are given in appendix table A2. Negative annual rainfall shocks yield crime increases of 2.8%, somewhat smaller than the monsoon coefficient of 3.6%. This is consistent with our earlier observation that it is monsoon rainfalls that largely determine agricultural yields; and that, because annual rainfall is, in a sense, a noisy measure of the relevant (monsoon) rainfall variable, it introduces classical measurement error into our regressions, thereby reducing the magnitude of the coefficient. The annual temperature shocks yield small and insignificant effects on crime, which is likely due to the same factor as that for rainfall. This provides strong evidence for the economic channel: it is only temperature shocks occurring during the monsoon season that increase crime, as this is the time when elevated temperatures most influence agricultural output.

4 Mechanisms

4.1 Agriculture and Weather Shocks

An important contribution of our paper is the ability to closely identify the economic correlates of the observed effects of weather shocks on crime. While the most obvious channel would be agricultural output, it is plausible that weather could operate through non-agricultural channels, such as disruptions to non-agricultural production, psychological responses, or perhaps even state capacity. To better understand the precise economic mechanism at work, we next turn to an analysis of the effect of weather shocks on agricultural production. Fishman (2012) has already explored this topic at some length; here we will provide a complementary analysis, investigating the effect of that vector of shocks analyzed above, and mapping the results to those obtained for crime. In doing so, we will show that the patterns are largely consistent, so that changes in agricultural production move in close tandem with crime rates in response to weather shocks.

Table 4 shows the effects of the weather shocks on agricultural production, with the outcome variable specified as the gross output[23] of the primary *Kharif* season crop in that district. For each district, we have defined the primary crop as that which occupies the largest portion of cultivated land in the greatest number of years. The primary crop may not necessarily be the most important in terms of overall gross value, but it is responsible for the income of the largest share of farmers residing in that district. Column (2) shows the results of a regression using log gross product as the outcome variable, and column (3) the results using non-log gross product. For the purpose of comparison, in column (1) we show again the results of the parallel crime regression using 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 22.6% decline in output, while negative and positive temperature shocks lead to a 4.8 and 6.1% decline, respectively. Shocks occurring during the post-monsoon period also affect crop production, with output falling by 11.3% with negative rainfall and 9.3% with positive temperatures, and increasing by 15.2% with positive temperatures. The non-log effects reflect these percentage changes, though the

[23] 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, 2010). Confirming this finding, when we estimate the impact of climate on prices in our sample, we find no effect.

difference between wet season negative rainfall shocks, on the one hand, and the positive and negative temperature shocks, on the other, is reduced. These patterns are largely consistent with previous empirical analyses of weather-agriculture relationship in India (Guiteras 2009, Fishman 2012).

As is readily apparent, the results are largely consistent with the crime results found earlier. Negative rainfall shocks and both types of temperature shocks during the monsoon period decrease crop production and increase crime rates, whereas positive rainfall shocks have no significant effect on neither crime nor production.[24] Negative rainfall shocks occurring during the post monsoon period also lead to reductions in agricultural output and increases in crime.[25] Interestingly, while the effect of temperature on crime is similar to that of rainfall, the effect of the latter on agriculture is more than twice the size of the former. Therefore, an appeal to pure income channels for the observed crime effects is contradicted by the disparity in magnitude of the economic impacts of rainfall and temperature shocks. However, if one posits in addition a psychological channel for temperature shocks, as has been demonstrated in a wide body of research (Anderson, 2001), then it may be the case that the temperature coefficients capture the combination of both income and psychological effects. This thesis receives additional support from the divergence in crime effects between negative and positive temperature effects. Whereas the two shocks have identical effects on agricultural output, positive shocks lead to an

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

[25] 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.

increase in crime nearly twice the size of negative shocks. This again makes sense if we suppose that elevated temperatures exert an additional effect through psychological channels, with negative temperatures perhaps leading to a symmetric decline in crime for psychological reasons. Finally, we would also note that as temperatures become very high (>2.25 sds), the crime effect falls to zero, despite the significant agriculture effect. This poses the interesting possibility that while high temperatures may lead to both economically and psychologically induced increases in crime, when temperatures become too elevated it may no longer be physiologically feasible to undertake criminal activities.[26]

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). High temperatures during this period have strong negative impacts on crop production, but do not seem to affect crime rates. We are not fully able to explain this disparity, but hypothesize the timing of shock realizations and farmers' decisions could play a role. After October, the realization of the principal shock affecting crops, i.e. rainfall, is fully known to farmers. Fishman (2012) shows that cropping decisions, for example, are mostly responsive to rainfall realizations in June and July. Farmers at that time may have a good sense of their predicted yields. In contrast, temperature shocks occurring later in the season may not have an effect

[26] Despite the plausibility of these psychological explanations, the possibility remains that other mechanisms were at work, such as reduced industrial output with temperature shocks due, for example, to power outages, or the death of livestock when temperatures are very high.

which is as clear to farmers before yields are actually realized at harvesting time, which may occur only in the following year. Crime responses may therefore not occur within the same calendar year which can explain the lack of a statistically significant response.

4.2 Interactions

4.2.1 Water Availability

There is immense variation in agro-climatic conditions across India. Two of the more salient features relevant to agricultural production, and therefore crime, are the mean climate conditions, and the availability of irrigation. 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 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. Areas of high irrigation may also be less responsive to weather shocks, as irrigation can buffer the effect of seasonal shocks on agricultural production.

Table 5 shows how weather shocks are mediated by prevailing climate conditions and water availability within the districts. In panel A, we regress crime rates on the climate 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 interaction term, therefore, tells us whether the effect of the weather shocks depends on more general climate conditions. There is no effect of mean temperature conditions on the effects of weather shocks: the un-interacted temperature shock variables show coefficients similar to those found before, and the interaction terms are small and 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 indicate that local adaptations are such that, regardless of the extremity or moderation of prevailing climate conditions, deviations from the district mean continue to have large effects on local crime rates.

In panel B we regress crime on interactions of the weather shocks and a dummy for high-irrigation districts, the dummy again identifying districts with irrigation levels above the mean. There is little evidence for a differential response to climate according to irrigation. This may seem surprising, given that irrigation has been found to mitigate the impact of some 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. More importantly, perhaps, for this study, we 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 workers 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.

5 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.[27]

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,

[27] 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.

during which time there were dramatic changes in agricultural production, 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 rising slightly to 4.2% in the 1990s. Table 6 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,[28] 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.

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

6 Conclusion

We provide some of the first evidence on the drivers of crime in developing countries, using a data set that spans over a billion people over 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 effects 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, which may be evidence for the presence of an additional, possibly psychological, mechanism. The disparity between the effect of negative and positive temperature shocks, with the latter leading to an increase in crime twice the size of the former, despite their similar effects on agricultural output, lends additional support to this thesis.

Despite higher incomes, greater access to income 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***	0.036***	0.042***	0.042***	0.028***	0.027***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.010)	(0.010)
pos rain	0.008	0.008	0.013	0.012	0.001	0.001
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
neg temp	0.024**	0.025***	0.028**	0.029**	0.017	0.017
	(0.010)	(0.009)	(0.012)	(0.011)	(0.011)	(0.011)
pos temp	0.053***	0.052***	0.066***	0.066***	0.031***	0.029**
	(0.012)	(0.013)	(0.015)	(0.015)	(0.012)	(0.013)
post-monsoon						
neg rain		0.024**		0.022		0.024**
		(0.012)		(0.014)		(0.012)
pos rain		0.005		0.007		0.002
		(0.007)		(0.009)		(0.008)
neg temp		0.003		-0.001		0.011
		(0.010)		(0.013)		(0.011)
pos temp		0.008		0.005		0.013
		(0.009)		(0.011)		(0.010)
R-squared	0.920	0.920	0.922	0.922	0.838	0.838
N	74970	74970	46811	46811	28159	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 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 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	0.055***	0.043*	0.012	0.045**	0.054***	0.028*	0.028	0.018
	(0.016)	(0.023)	(0.015)	(0.021)	(0.018)	(0.017)	(0.017)	(0.011)
pos rainfall	0.009	0.035*	0.013	0.005	0.005	-0.001	-0.001	0.001
	(0.012)	(0.018)	(0.011)	(0.017)	(0.017)	(0.014)	(0.016)	(0.010)
neg temp	0.015	0.038	0.022**	0.048**	0.010	0.024	0.021	0.004
	(0.013)	(0.024)	(0.011)	(0.019)	(0.019)	(0.017)	(0.019)	(0.011)
pos temp	0.024	0.105***	0.058***	0.089***	0.065***	0.021	0.034*	0.037***
	(0.019)	(0.026)	(0.016)	(0.024)	(0.020)	(0.019)	(0.019)	(0.014)
post-monsoon								
neg rainfall	0.001	0.017	0.012	0.024	0.049**	0.040**	-0.004	0.035***
	(0.015)	(0.023)	(0.014)	(0.025)	(0.022)	(0.020)	(0.020)	(0.011)
pos rainfall	-0.000	-0.018	0.025***	0.013	0.014	0.023*	0.000	-0.018**
	(0.012)	(0.019)	(0.009)	(0.017)	(0.015)	(0.014)	(0.014)	(0.008)
neg temp	0.017	0.022	-0.007	-0.004	-0.033*	-0.013	0.002	0.035***
	(0.016)	(0.025)	(0.013)	(0.022)	(0.017)	(0.018)	(0.019)	(0.013)
pos temp	-0.002	-0.015	-0.015	0.025	0.026	0.009	0.008	0.014
	(0.014)	(0.024)	(0.012)	(0.019)	(0.017)	(0.016)	(0.018)	(0.011)
R-squared	0.831	0.768	0.822	0.765	0.810	0.745	0.782	0.760
N	9391	9321	9346	9381	9372	9391	9395	9373

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 and Agriculture

	log	gross product	
	crime	log	non-log
	(1)	(2)	(3)
monsoon			
neg rainfall	0.036***	-0.226***	-21.275***
	(0.010)	(0.034)	(3.286)
pos rainfall	0.008	-0.013	-3.108
	(0.009)	(0.019)	(2.578)
neg temp	0.025***	-0.048**	-9.379***
	(0.009)	(0.023)	(2.877)
pos temp	0.052***	-0.061**	-10.924***
	(0.013)	(0.030)	(3.533)
post-monsoon			
neg rainfall	0.024**	-0.113***	-15.126***
	(0.012)	(0.024)	(4.849)
pos rainfall	0.005	-0.018	-0.900
	(0.007)	(0.026)	(2.760)
neg temp	0.003	0.152***	13.269***
	(0.010)	(0.025)	(3.161)
pos temp	0.008	-0.093***	-6.731**
	(0.009)	(0.029)	(2.945)
R-squared	0.920	0.862	0.826
N	74970	7357	7357

The outcome variable is output of primary monsoon crops. In column (2) these are logs, in columns (3) in non-logs. The weather shocks are defined as rainfall/temperature 1 standard deviation from the mean. Dummies are included for the district. Year fixed effects are included, as well as state-year quadratic time tends. Error terms are clustered at the district level.

Table 5: Water Interactions

	all crimes		property crime		non-property crime	
	neg rain	pos temp	neg rain	pos temp	neg rain	pos temp
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Climate Interactions						
weather shock	0.044***	0.034**	0.054***	0.042**	0.027**	0.02
	(0.013)	(0.016)	(0.016)	(0.019)	(0.013)	(0.015)
shock X high rain/temp	-0.024	0.018	-0.036*	0.016	-0.004	0.021
	(0.018)	(0.017)	(0.022)	(0.020)	(0.019)	(0.018)
Panel B: Irrigation Interactions						
weather shock	0.021	0.050***	0.019	0.053***	0.024	0.045***
	(0.013)	(0.012)	(0.016)	(0.014)	(0.015)	(0.015)
shock X high irrigation	0.016	-0.006	0.025	0.006	0	-0.023
	(0.019)	(0.016)	(0.023)	(0.018)	(0.021)	(0.019)

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. Interaction terms are included of the weather shocks with the indicated variables. 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 6: 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: Annual Shocks and Pooled Crimes

	all crimes		property crimes		violent crimes	
	neg	pos	neg	pos	neg	pos
	(1)	(2)	(3)	(4)	(5)	(6)
rainfall shocks	0.036***	0.006	0.038**	0.01	0.033***	0
	(0.013)	(0.009)	(0.016)	(0.011)	(0.011)	(0.009)
temperature shocks	0.016	0.004	0.009	0.004	0.028*	0.004
	(0.017)	(0.019)	(0.021)	(0.023)	(0.015)	(0.017)

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 *annual* 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 time tends. Error terms are clustered at the district level.

Table A3: 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.

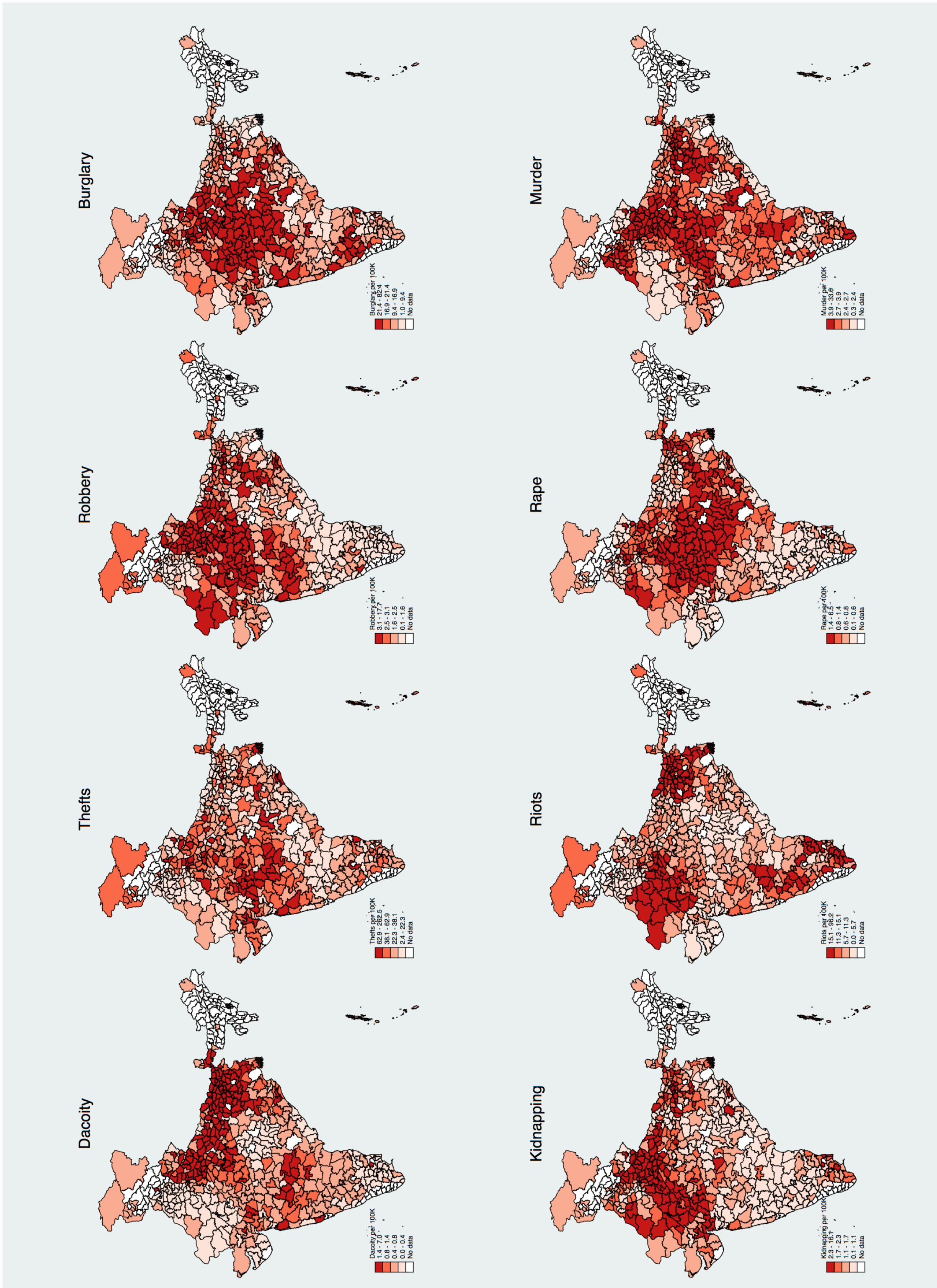

Figure 1: The spatial distribution of average 1971-2000 crime rates (crimes committed per 100,000 population).

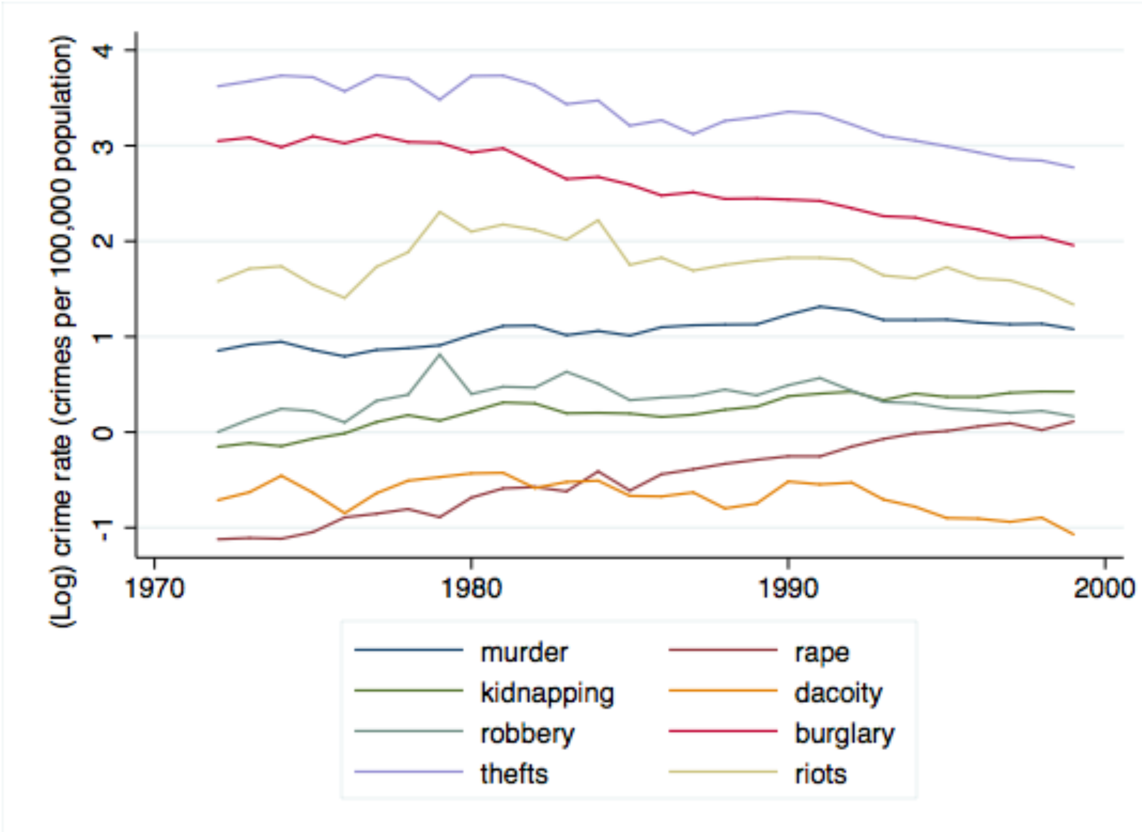

Figure 2: Plots of the (logarithm) of India-wide average crime incidence (per 100,000 population) over time.

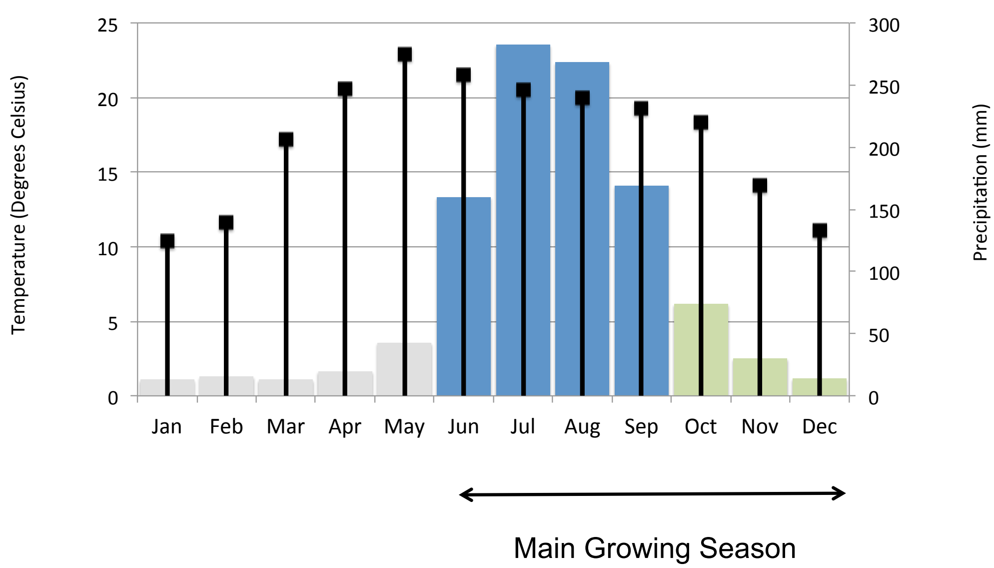

Figure 3: Average climate in India. Monthly average temperature (black drop lines) and precipitation (bars). Monsoon crops are usually sown around June-August and harvested between October and December. The blue and green shades represent the breakup of weather indicators used in the empirical analysis.

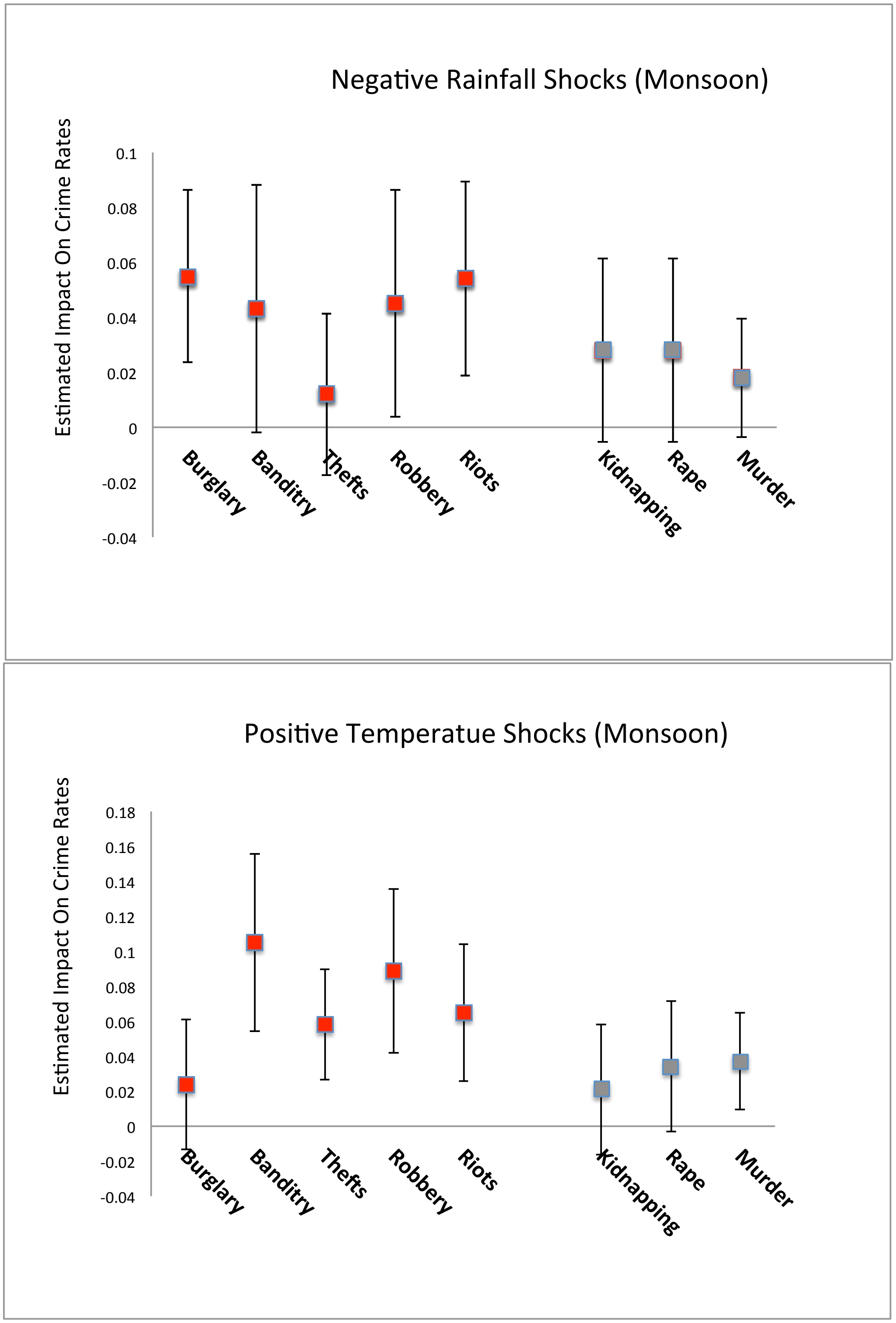

Figure 4: Estimated coefficients from regressions of disaggregated crime rates on negative monsoon rainfall shocks (top) and positive monsoon temperature shocks (bottom). Property crimes coefficients are indicated by red markers, and violent crime coefficients are indicated by grey markers.

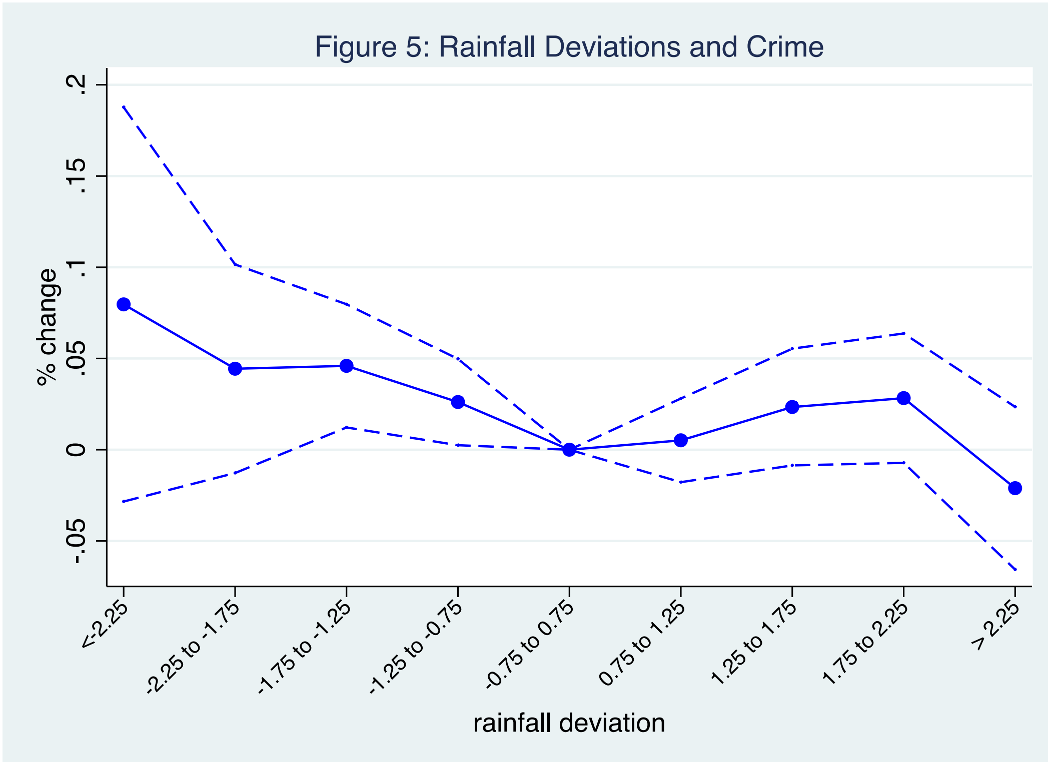

Figure 5: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bin.

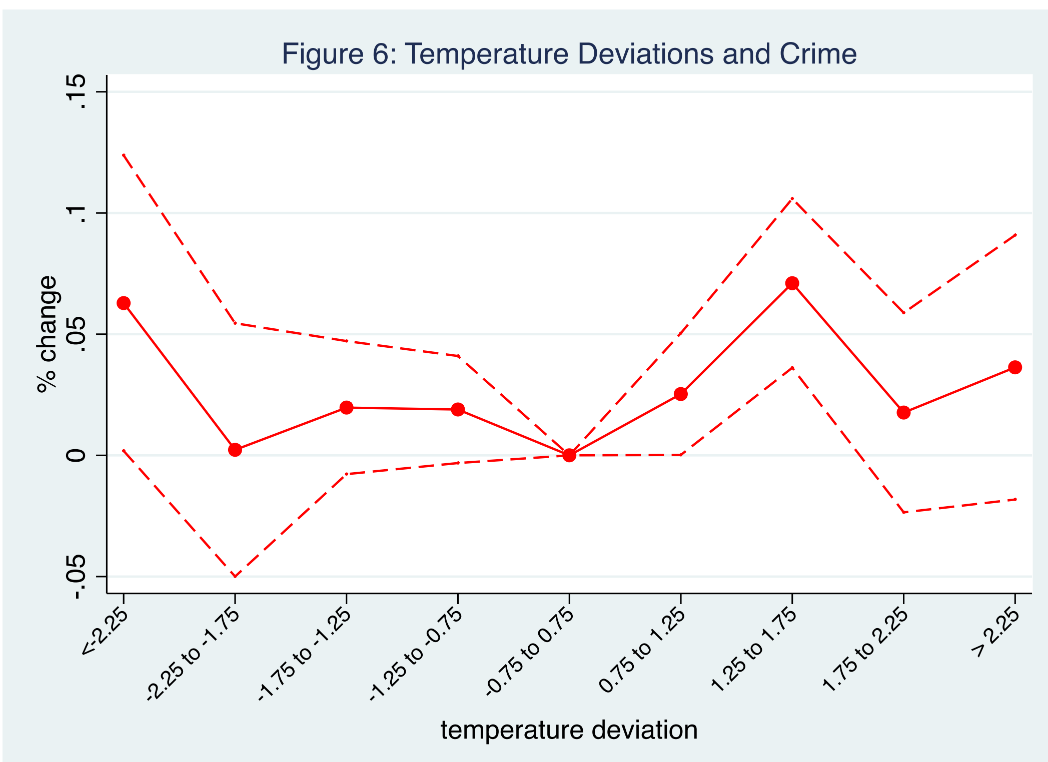

Figure 6: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bin.

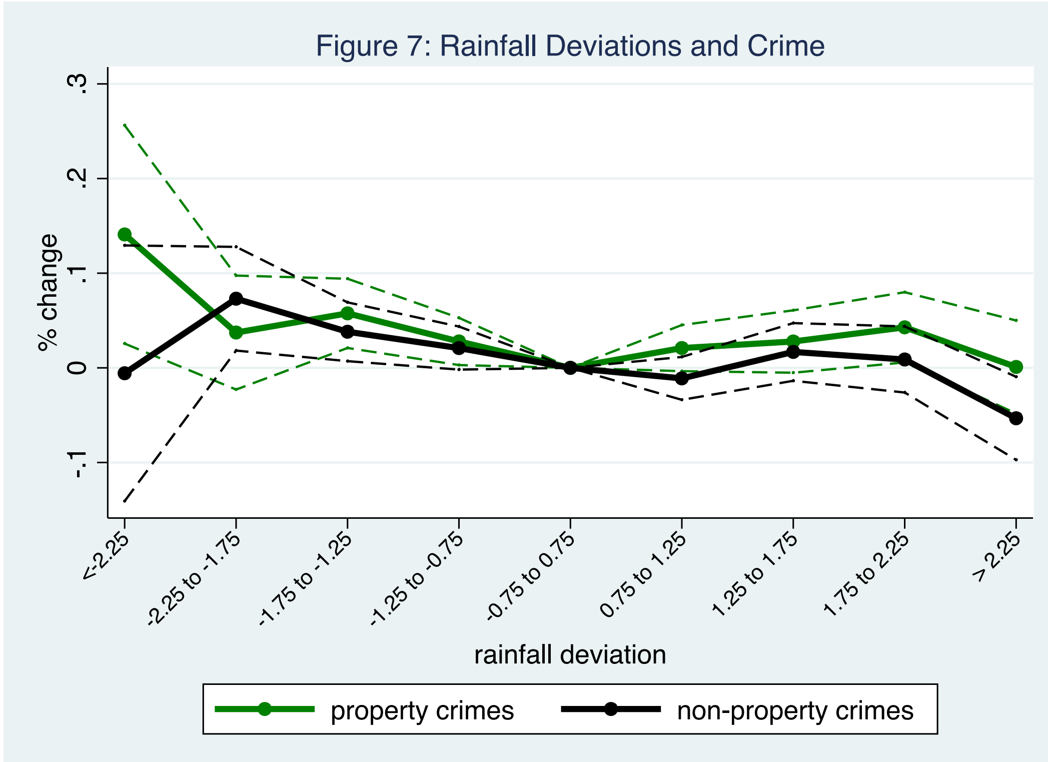

Figure 7: Coefficients from a regression of crime on monsoons rainfall in the indicated standard deviation bins. Crime is disaggregated into present and non-property crimes.

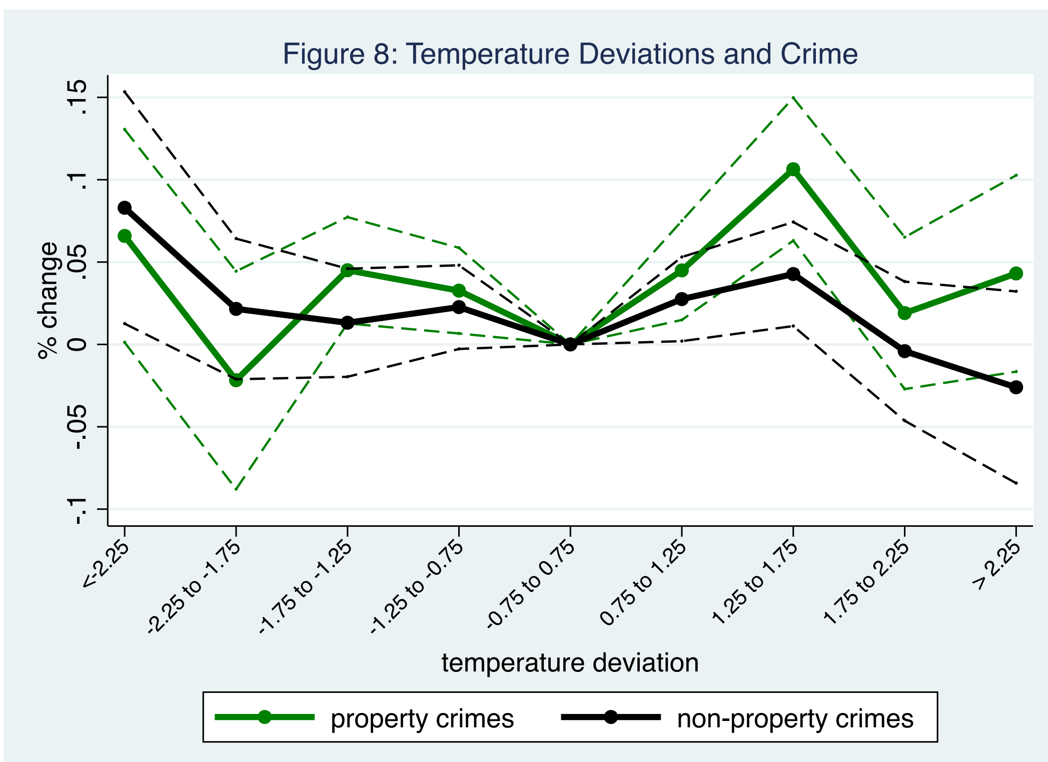

Figure 8: Coefficients from a regression of crime on monsoon degree days in the indicated standard deviation bins. Crime is disaggregated into property and non-property crimes.

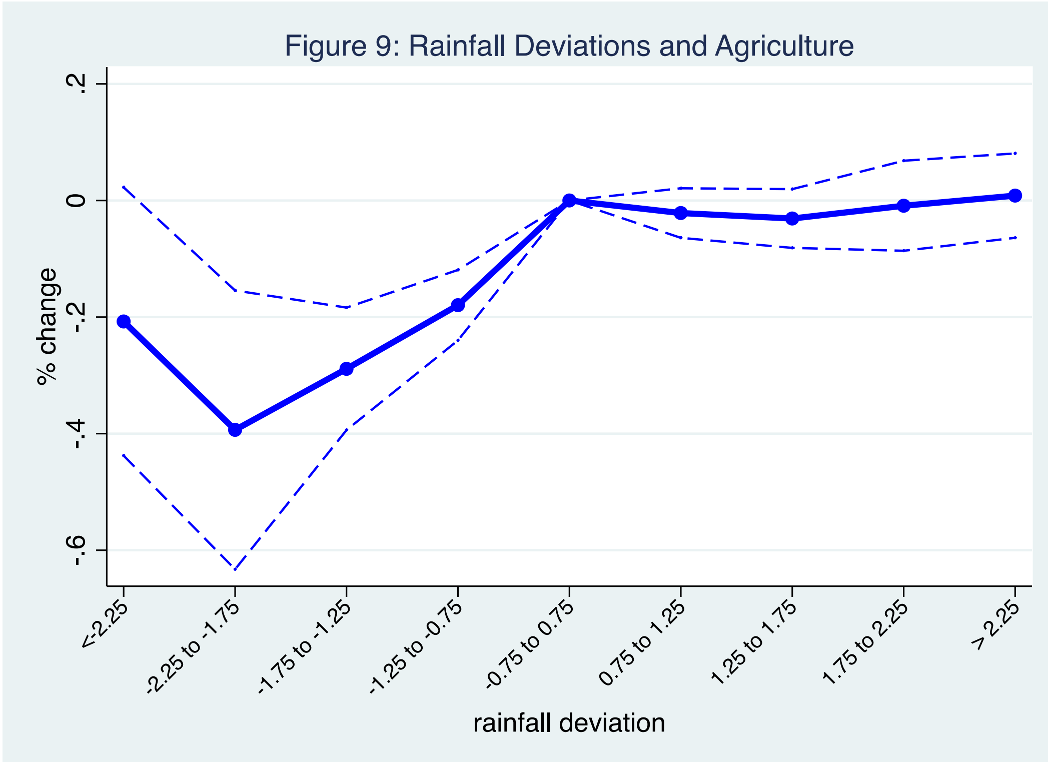

Figure 9: Coefficients from a regression of the primary monsoon crop on monsoon rainfall in the indicated standard deviation bins.

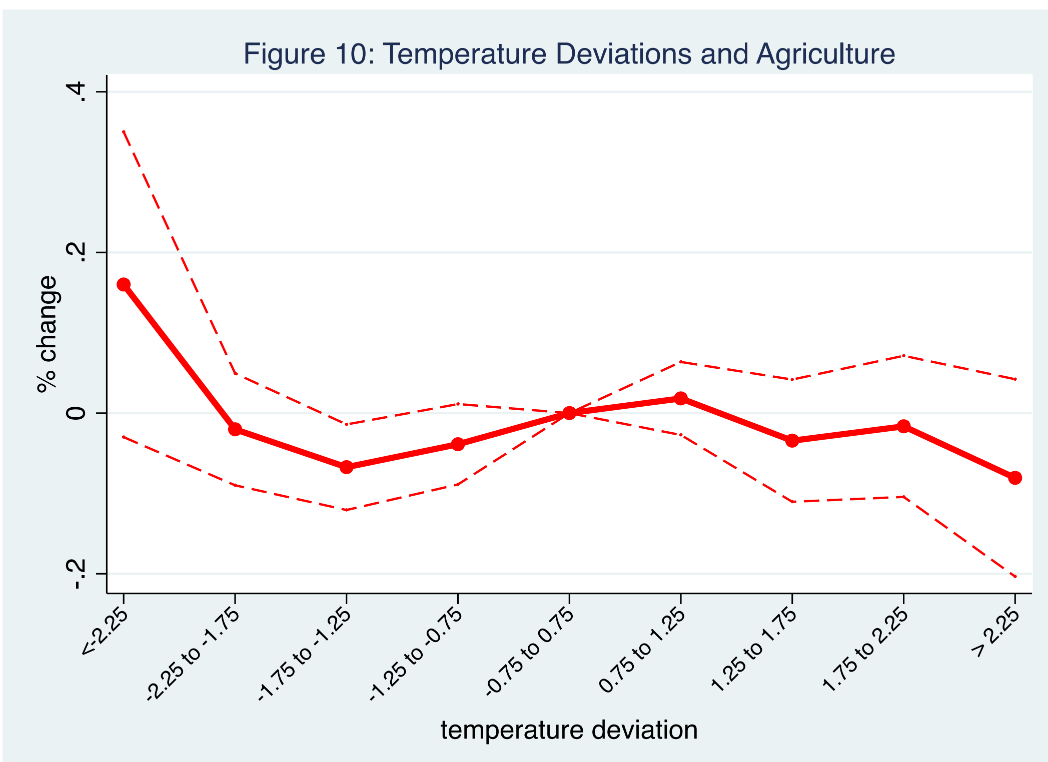

Figure 10: Coefficients from a regression of the primary monsoon crop on monsoon degree days in the indicated standard deviation bins.

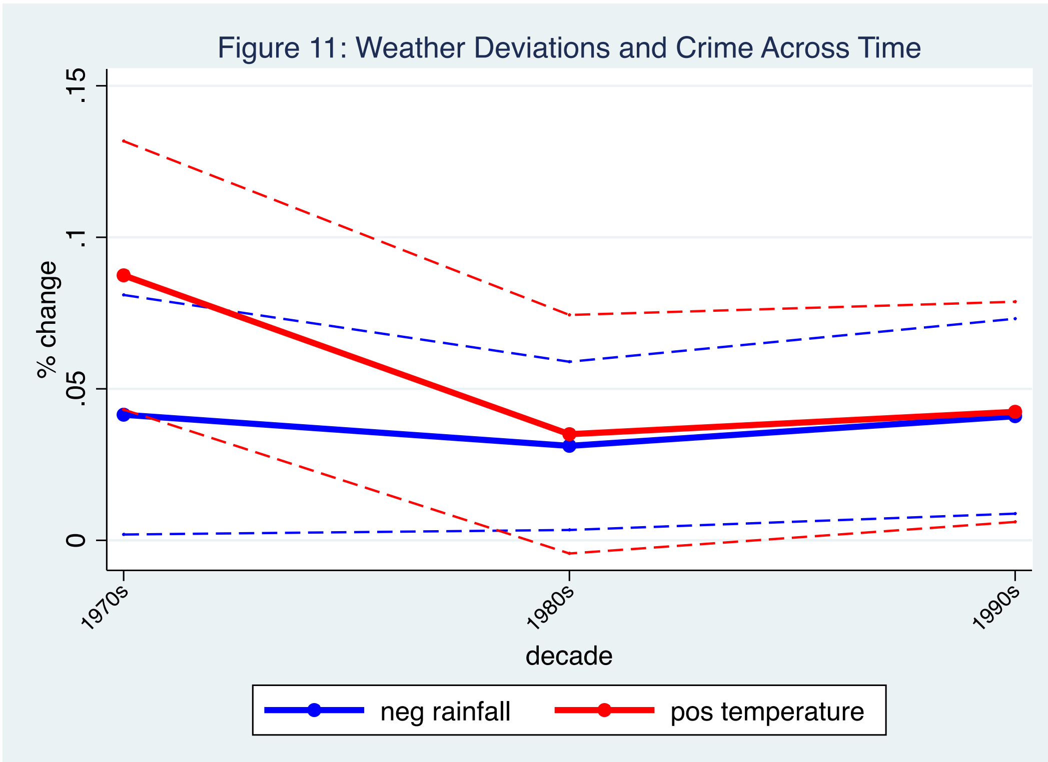

Figure 11: Coefficients from a regression of crime on monsoon rainfall and degree days across the indicated decades, with separate climate dummies used for each decade.