Poverty and Crime: Evidence from Rainfall and Trade Shocks in India*

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Abstract

Does poverty lead to crime? We shed light on this question using two independent and exogenous shocks to household income in rural India: the dramatic reduction in import tariffs in the early 1990s and rainfall variations. We find that trade shocks, previously shown to raise relative poverty, also increased the incidence of violent crimes and property crimes. The relationship between trade shocks and crime is similar to the observed relationship between rainfall shocks and crime. Our results thus identify a causal effect of poverty on crime. They also lend credence to a large literature on the effects of weather shocks on crime and conflict, which has usually assumed that the income channel is the most relevant one.

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1. Introduction

The recent interest in climate change has spurred a large body of literature examining how climate influences human behavior, particularly human conflict. Synthesizing this rapidly growing literature, Hsiang, Burke and Miguel (2013) establish that across all major world regions, and time periods extending from 10,000 BCE to the present day, rainfall and temperature patterns have a significant influence on the risk of human conflict. Deviations from normal in precipitation and air temperature raise the likelihood of violent crimes (such as murders), intergroup conflict (such as riots and rebellions), political violence, civil war onset, and even institutional breakdowns.

While the link between climate and human conflict is well established, we still do not fully understand the mechanisms that underlie the observed association. As discussed by Hsiang, Burke and Miguel (2013), the most commonly hypothesized channel is the income channel. In agrarian economies, precipitation is one of the most important determinants of household wellbeing (see Dell et. al., 2014, for example). Severe rainfall shortages cause economic productivity to decline, and the resulting decline in income could increase the value of criminal activities as an alternative source of income. Alternatively, the economic decline could undermine the ability of government institutions to monitor and curtail criminal activity, or reduce the ability of people to protect themselves against crime. This line of thought, which has permeated the large body of literature that uses weather shocks as an instrument for income,[1]

[1] See the seminal paper by Miguel, Satyanath and Sergenti (2004), and subsequently Miguel (2005), Mehlum et. al., (2006), Bohlken and Sergenti (2010) and Ciccone (2011). Brückner and Ciccone (2011) and Chaney (2013) examine the effects of weather shocks on political institutions. A related recent body of literature examines the effects of commodity price shocks on conflict and political institutions (see, among others, Angrist and Kugler, 2008, Brückner and Ciccone, 2010, Brückner et. al., 2012, Dube and Vargas, 2013, Bazzi and Blattman, 2013).

explicitly assumes that rainfall's only influence on crime or conflict is through its effect on average income and poverty. However, this may not be the case.

Several psychological studies have documented a direct link between temperature changes and aggressive or violent behavior, without any changes to income.[2] Analysis of U.S. data at the monthly level also shows a strong link between rising temperatures and increases in crime (Ranson, 2014). Alternatively, large climatic events could also lead to the dislocation of the population or faster urbanization of certain areas, which could in turn exacerbate frictions and conflict over existing resources. Rogall and Guariso (2013) find that heavy rainfall reduces conflict by hindering the movement of armed forces.

In this paper, we shed light on the mechanisms underlying the observed relationship between rainfall and crime. Using four decades of district level data from India, we first establish a robust effect of rainfall shocks on different types of crime, with the strongest effects on violent crimes (including murder) and property crimes.[3] We then go beyond previous studies, which simply document the link between weather variations and human conflict, and examine to what extent poverty is the main causal pathway between rainfall shocks and crime.[4]

To this end, we identify an additional source of exogenous income shocks for households in rural India that is completely independent of the amount of rainfall, namely trade liberalization. Starting in 1991, India enacted a series of dramatic trade reforms following a balance of payments crisis and a subsequent IMF bailout package. Previous studies (Topalova, 2007, 2010) have established that these trade reforms had a significant impact on regional economic outcomes.

[2] See, among others, Anderson (2001), Anderson et al (2000) and Cohn and Rotton (2000).

[3] Our results on the effects of rainfall shocks on property crimes and violent crimes are similar to those of Blakeslee and Fishman (2013). Contrary to Sekhri and Storeygard (2013), we see no effect of precipitation on crimes against women, including dowry deaths.

[4] Harari and La Ferrara (2013) make some progress in this direction by showing that the link between weather shocks and conflict in sub-Saharan Africa are primarily driven by weather shocks during the growing season of the main crop in a given region.

Districts that were more exposed to trade liberalization through their pre-reform employment mix experienced slower progress in poverty reduction and slower economic growth. We examine whether these districts differed in the incidence of various types of crime as a result of the trade reform.

We find that violent crimes and property crimes, the types of criminal activities that are most sensitive to rainfall shocks, indeed respond to trade shocks. The larger the loss in trade protection a district experienced, the higher is the incidence of these crimes. And just as in the case with rainfall shocks, trade shocks do not seem to affect crimes against public order or crimes against women. The similarity in patterns of how criminal behavior responds to two very different sources of variation in poverty and income suggests that the income channel is the most relevant mechanism behind the observed rainfall-crime relationship.

We compute the implied elasticity of crime to poverty and income shocks using both of these determinants of rural well-being. If the income channel is the primary mechanism through which weather and trade shocks affect crime, we expect to see similar estimated elasticities regardless of whether we use trade shocks or rainfall shocks as an instrument for income. We instead find that the estimated elasticities depend on the proxies used for measuring income. When we use per capita consumption as the measure of income, the estimated income-crime relationship is larger when using the rainfall instrument. When we use poverty (head count ratio or poverty gap) as the measure of income, the estimated income-crime relationship is larger when using the trade shocks instrument. This can be explained by the fact that rainfall shocks affect consumption throughout the income distribution, while trade shocks predominantly affect the consumption of households in the lower deciles of income, a pattern we verify empirically.

Finally, we examine whether policy measures to weaken the rainfall-income relationship also attenuate the rainfall-crime relationship. We focus on two such policy measures in the Indian context. The first is India's biggest social insurance scheme: the nationwide workfare program created by the National Rural Employment Guarantee Act (NREGA), which guarantees a hundred days of minimum-wage employment to every rural household. The program was rolled out in three phases over 2006-2008, enabling us to examine whether the rainfall-crime relationship is weaker after the implementation of this program. We do not find any such attenuation of the rainfall-crime relationship, possibly because the program may not have been able to offset the sensitivity of consumption to weather patterns.[5]

The second policy measure we examine is the construction of dams. While the presence of dams upstream from a district has been shown to insulate agricultural productivity from the vagaries of the weather, there is no statistically significant impact on the rainfall-poverty relationship (Duflo and Pande, 2007). Consistent with this, we also do not find any attenuation of the rainfall-crime relationship in places with or without upstream dams.

Our study thus makes three key contributions to the literature on the economic determinants of crime and conflict. We provide empirical evidence of the causal impact of trade or globalization on crime and conflict, on which there is little previous work.[6] Second, we provide evidence that income indeed is one of the main channels underlying the observed relationship between rainfall shocks and crime, lending credence to a vast literature that has so far assumed this must be the main channel. We also provide evidence on the causal effects of income

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[5] See, among others, Zimmermann (2013), Imbert and Papp (2013) and Niehaus and Sukhtankar (2013) for analyses of the NREGA's effect on employment, rural wages and corruption. However, the lack of district-level annual data on per capita consumption or poverty rates makes it difficult to assess whether the program made a significant difference to the rainfall-poverty relationship.

[6] Chua (2002) hypothesizes that a greater role of market forces in a democratic setting may sometimes result in ethnic or class conflict; Bezemer and Jong-a-pin (2013) provide cross-country empirical evidence in support of this argument. Prasad (2012), on the other hand, argues that the dismantling of controls and protection accompanying economic liberalization would reduce the incentives for illegal trade which is often associated with violent crime. Using aggregate and state-level data for India, he finds that homicides fell in the post-reform period.

shocks on crime, which is relatively rare for developing countries.[7] Third, while we are not the first paper to examine the relationship between weather shocks and crime in the case of India, compared to previous studies, we use a longer time series on crime, analyze a much wider range of crime categories, and are the first to consider the effects of temperature variation. We also use a newly assembled data set on Hindu-Muslim riots to analyze the relationship between weather and religious violence.[8]

The remainder of the paper is organized as follows. Section 2 describes our data sources and the construction of variables used in the analysis, and Section 3 lays out the empirical strategy. Section 4 presents our empirical findings, and Section 5 concludes.

2. Weather, Trade and Crime in India: Data and Variable Construction

2.1 Crime

We obtained district level data on crime from India's National Crime Records Bureau (NCRB) for the period 1971-2010. These are data for the number of crimes reported in each district annually, and are provided for many different crime categories. We combined individual crime categories into five broad categories: violent interpersonal crimes (murder, culpable homicide, attempted murder, assault, kidnapping), property crimes (armed robbery, robbery, burglary, theft), economic crimes (breach of trust, cheating, counterfeiting), crimes against public order (riots, arson) and crimes against women (rape, sexual harassment, dowry deaths, kidnapping of women, cruelty by husband or relatives). Our

[7] Many papers which examine the income-crime relationship do not use exogenous determinants of income, and the results can therefore be subject to issues of omitted variables bias or reverse causality (see, for example, Dreze and Khera, 2000). In a developing country setting, using exogenous variation in income that stems from sources other than rainfall or commodity price shocks is very rare. Fafchamps and Minten (2006) is a notable exception in this regard.

[8] Previous work that focuses on religious violence in India, such as Mitra and Ray (2013). Bohlken and Sergenti (2010) and Sarsons (2011), use the Varshney and Wilkinson (2004) data set, which contains data until 1995. Our paper uses an updated data set with data until 2010.

preferred measures of crime intensity are computed as the log of the number of crimes per capita. NCRB provides the data at the level of the police district.

We aggregate our crime variables to the level of the administrative district, and further adjust for splits in administrative districts over time. [9] We restrict our analysis to the 16 major states.[11] In this paper, we abstract from issues of differential crime reporting over time, on the assumption that weather or trade shocks do not affect the incentives of crime victims to report crime or the incentives of police officials to record victim complaints.[12] We also use information on the occurrence of Hindu-Muslim riots (religious violence), from the Kaysser et. al. (2014) updated version of the Varshney and Wilkinson (2004) database.

2.2 Weather Shocks

[9] Indian districts are periodically reorganized, typically by splitting one district into two. When we analyze the relationship between weather shocks and crime, we map all the district level information to the district boundaries as of 1971, since 1971 is the earliest year for which we have both rainfall and crime information. When we analyze the relationship between trade shocks and crime, our unit of analysis is the district as defined in 1987, the earliest year for which we have tariff information.

[11] The included states are Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal, accounting for 96% of total population and 94% of total crimes reported in 2001. Three new states—Chhattisgarh, Jharkhand and Uttarakhand—were carved out in 2001, from Madhya Pradesh, Bihar and Uttar Pradesh respectively.

[12] Soares (2002) finds that crime reporting rates are strongly correlated with economic development. If this pattern exists in the case of India, and negative income shocks cause households to underreport crime, our estimates would underestimate the true causal impact of poverty on crime. Iyer et. al. (2012) show that political empowerment of women leads to greater reporting of crimes against women.

Data on rainfall and temperature were obtained from the University of Delaware website,[13] and matched to the centroids of the 2001 administrative district boundaries following Cole et. al. (2012).[14] Our main measure of rainfall is simply the logarithm of the total annual rainfall in a district, measured in millimeters as in Brückner and Ciccone (2011). Since there are many ways to parameterize rainfall, we also examine a non-linear specification. For this, we define a "negative rainfall shock" as a dummy which takes the value of 1 when annual rainfall in a district is one standard deviation below the long-run mean rainfall level, and a "positive rainfall shock" as the occurrence of rainfall one standard deviation above the long-run mean. This is similar to the measure used in Cole et. al. (2012). While excessively high rainfall might result in floods and thereby also decrease agricultural productivity or incomes, in the Indian context more rainfall appears to be only beneficial, a relationship also established by Duflo and Pande (2007).

Several recent papers have focused on the impact of temperature changes on economic production in a cross-country setting (Dell et. al., 2012, 2014). The effect of temperature shocks has not been previously examined in the Indian context. Consistent with the specification in Dell et. al. (2012), we use the average annual temperature as our main measure of temperature shocks. Since this may not capture potentially non-linear effects of temperature variation, we also construct a second measure based on monthly temperature data collected from the same source. Based on agronomic relationships estimated primarily from US data (Schlenker et. al., 2006), and shown to be relevant in the Indian context (Guiteras, 2009; Fishman, 2012), we calculate our measure of "harmful" degree-months as

[13] "Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950 - 2010)", Version 3.02, Cort J. Willmott and Kenji Matsuura Center for Climatic Research, University of Delaware.
[14] In particular, the centroid for each district is calculated using a 2001 GIS map. The district's rainfall and temperature pattern is defined by the grid point that is closest to the centroid.

follows: each month with mean temperatures above $32^{o}C$ is assigned the difference between that month's mean temperature and $32^{o}C$. These harmful degree-months are then summed over the year for each district. Our results are robust to changing this threshold to $33^{o}C$ or $35^{o}C$.[15]

2.3 Trade Shocks[16]

After attaining political independence in 1947, the Indian economy enjoyed a high degree of protection from foreign competition with high tariff and non-tariff barriers, and a complex import licensing system. While there was some gradual easing in the trading regime in the late 1980s, the average tariff remained greater than 90 percent and only 12 percent of manufacturing goods could be imported without a special import license. The 1991 balance-of-payments crisis, and the economic reforms that ensued as part of an IMF structural adjustment program, ushered in a radical change in India's trading regime. Import tariffs were cut dramatically, with the average tariff falling from 80 percent in 1990 to 37 percent in 1996. The share of goods subject to quantitative restrictions fell from 87 percent to 45 percent between 1987 and 1994. Tariff reduction paths were quite different for different goods as one of the goals of the trade reforms was to reduce the dispersion of protection across industries. Consequently, districts in India were subject to varying degrees of exposure to these trade shocks, based on their

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[15] Many papers on the U.S. have emphasized the use of daily temperature data (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2008). Papers which have used daily temperature data for India (Guiteras, 2009; Burgess et. al., 2013) rely on a gridded data set obtained by interpolation along the lines of Ngo-Duc et.al. (2005). As of this draft, we did not have access to this interpolated data. Alternative sources of daily temperature data have only limited coverage of the Indian subcontinent. In the NCEP/NCAR source (Kalnay et.al., 1996), only 36% of Indian districts had a weather station within a 100 km distance, while the Daily Global Historical Climatology Network (GHCN)has daily temperature from only 124 out of 3805 weather stations in India.

[16] This section draws on Topalova (2007) and Topalova and Khandelwal (2011). For a fuller discussion of the Indian trade reforms and the effect of trade liberalization on poverty, see Topalova (2010).

initial employment composition. Prior work has demonstrated that districts which experienced larger reduction in trade protection had substantially slower income growth, poverty decline, and schooling increases (Topalova 2007, Topalova, 2010, Edmonds et. al., 2010). These differential exposures to tariff reductions can be considered exogenous shocks to per capita income or poverty levels at the district level, and can be exploited to see if they also result in changes in crime rates.[17]

Similar to Topalova (2010), we use data on import tariffs from 1987-2010 and compute a measure of tariff exposure for each district *d* and year *t* ($Tariff_{dt}$) as the nominal, national, ad-valorem tariffs for each industry, weighted by the district's employment composition in 1991, i.e. prior to the trade reforms:

$$Tariff_{dt} = \left(\Sigma_i \, Worker_{d,i,1991} \, Tariff_{i,t}\right) / \, TotalWorker_{d,1991}$$

where *i* indexes a specific industry. The above measure takes into account employment in traded and non-traded industries such as services, trade, transportation, construction and growing of cereals and oilseeds within a district.[18] Non-traded industries are assigned zero tariffs in all years. Therefore a large part of the variation in this measure of district tariffs is driven by the variation in the share of the non-traded sector across districts. To capture purely the policy-driven

[17] In treating the district as the relevant unit of analysis, we are following convention in the micro empirical literature on India (see Banerjee and Iyer, 2005, Cole et. al., 2012, Duflo and Pande, 2007 and Jayachandran, 2006 among others). Using district level data, rather than state level, enables us to compute local level shocks to economic activity. The non-availability of crime data below district level prevents us from a further disaggregated analysis.

[18] Topalova (2010) argues that the latter two categories should be treated as non-traded because all product lines within cereals and oilseeds were canalized (i.e. imports were allowed only by the state trading monopoly) and the tariffs on all product lines under the growing of cereals are zero until 2000. In the 2000s, the non-tariff barriers for these products were slowly reduced, while the tariffs were raised. This change in policies was not accompanied by a change in the actual imports of these goods. For consistency with the earlier period, we continue to treat these products as non-traded.

change in tariffs, we instrument $Tariff_{dt}$ by a measure of tariffs only in the traded sectors $TrTariff_{dt}$ defined as

$$TrTariff_{dt} = \left(\Sigma_i\, Worker_{d,i,1991}\, Tariff_{i,t}\right) / \Sigma_i\, Worker_{d,i,1991}$$

Further, since sectors with higher initial tariffs in 1991 experienced greater tariff reductions over the next decade in line with the guidelines of the tariff reform spelled out in the IMF conditions, we use the initial tariff in 1991 as an additional instrument for $Tariff_{dt.}$ Our baseline specification relies on these two instruments.[19]

The most dramatic period of trade reform was during the Eighth Plan (1992-97); this is also a period in which there appears to be no systematic pattern between tariff changes and pre-reform industry characteristics, such as productivity or industry size (Topalova, 2007). India remained committed to further trade liberalization after 1997 as well, and import tariffs continued to decline. However, at the time the government announced the export-import policy in the Ninth Plan (1997-2002), the pressure for further reforms from external sources (like the IMF) had abated. Since variation in tariffs in this later period may reflect various political economy factors (see Topalova and Khandelwal, 2011), our primary period for analysis is 1988-1997, over which tariff reductions can be considered exogenous. We also show results for the full time period for which we can construct district-level employment weighted tariffs (1988-2010), though these results may be subject to a greater degree of endogeneity in the tariff measure. Similarly, when we examine the effect of rainfall and temperature on crime, we will show results for the 1988-1997 period to match the period of

[19] Our OLS estimates, presented in Table A.3, are very similar to the IV estimates.

exogenous trade reforms, as well as the full period for which weather and crime data are available, 1970-2010.

We should note that trade shocks and rainfall shocks are very weakly correlated in our data. The observed correlation of rainfall and tariff levels for the 1988-1997 period was 0.24; the correlation of rainfall and the more policy-driven traded tariff levels was only -0.03.

2.4 Income and Poverty

Data on per capita income, poverty or GDP are scarce at the district level in India.[20] We use the National Sample Surveys from 1983, 1987-88, 1993-94 and 1999-00 to compute district level estimates of per capita consumption and poverty in the rural sector.[21] We construct two measures of poverty. The head count ratio, defined as the fraction of the population whose annual consumption is below the poverty line, captures the incidence of poverty, and the poverty gap, defined as the average distance of the poor from the poverty line, captures the depth of poverty. When we examine the links between weather and income/poverty, we use all years for which outcome data are available. However, when we present evidence on the effects of trade liberalization on income/poverty, we focus only on the long difference, i.e. the data from 1987 and 1999 NSS rounds, since 1993 is right in the middle of the trade reforms.

[20] Data on per capita GDP at the district level for 1999-2006 were collected by the Planning Commission of India. However, since these data do not cover the period during which trade shocks can be viewed as exogenous, we do not use them in our paper.

[21] We correct consumption data from the 1999-2000 round for the change in the survey design following Deaton (2003a) and use the poverty lines and price indices proposed by Deaton (2003b) to compute real expenditure and poverty incidence. See Topalova (2007) for more detail. Given the NSS sampling methodology in urban areas, it is not possible to create representative aggregates at the district level in urban India. In 2001, 71.5% of India's population lived in rural areas.

2.5 Income Shock Mitigators

In 2005, the government of India passed the National Rural Employment Guarantee Act (NREGA) to "provide for the enhancement of livelihood security of the households in rural areas of the country by providing at least one hundred days of guaranteed wage employment in every financial year to every household whose adult members volunteer to do unskilled manual work" (Government of India, 2005). This large workfare program accounted for 5% of the government's budget in the fiscal year 2012-13 and 0.3% of GDP. The program was rolled out in three phases over 2006-2008, with the 200 most backward districts obtaining access to the program in February 2006, a further 130 districts getting access in April 2007 and the remaining 283 districts in April 2008. Previous research has documented that NREGA provided alternative sources of employment during periods of poor rainfall (Zimmermann, 2013), and led to a significant rise in rural wages (Imbert and Papp, 2013), despite the existence of considerable corruption and leakage in its administration (Niehaus and Sukhtankar, 2012). This suggests that the implementation of this program is likely to weaken the relationship between rainfall and poverty. If the rainfall-crime relationship is primarily driven by the income channel, we might expect this program to also attenuate the rainfall-crime relationship. We obtained the year the NREGA program was rolled out in each district from the Planning Commission of India.

In a similar vein, the presence of dams upstream from a district has been shown to reduce the impact of rainfall on agricultural productivity (Duflo and Pande, 2007). We can therefore check if the presence of upstream dams also reduces the link between rainfall shocks and crime, using data on the presence of dams in each district from Duflo and Pande (2007), for the period 1970-2000.

2.6 Other Variables

We obtain census data on demographic variables such as literacy rates, sex ratios, urbanization, the fraction of Scheduled Castes and Scheduled Tribes,[22] and the fraction of the population working in agriculture from the Maryland Indian District Database,[23] extended with the 2001 and 2011 Indian Census. These are interpolated for the inter-censal years and used as control variables in our regressions.

3. Empirical Strategy

Our analysis exploits the detailed district panel data that we have constructed on the incidence of various types of crime, rainfall and temperature for the 1970-2010 period, trade shocks for the 1987-2010 period, and poverty and consumption for 1983, 1987, 1993-94 and 1999-2000. Our goal is to examine the link between income shocks and crime, by focusing on two very different sources of exogenous variation in household income in rural India: weather shocks and trade shocks. We first establish that these shocks do indeed significantly affect measured poverty rates and per capita expenditures, using the sparse household consumption data available. We then examine the reduced form relationship between the two types of shocks and criminal activity. If income is the main driving force behind the link between rainfall shortfalls and trade liberalization and crime, we should expect to see the implied elasticity of crime to poverty and consumption to be roughly similar when using these two disparate sources of income fluctuations.

To that purpose, we first establish the causal effect of weather shocks and trade shocks on per capita consumption and poverty levels. Our regression

[22] The Scheduled Castes are communities that have historically been at the bottom of the Hindu caste hierarchy. Scheduled Tribes include communities traditionally outside the Hindu caste system.
[23] Available at http://www.vanneman.umd.edu/districts/index.html.

specification for this "first stage" relationship between poverty and weather is as follows:

$$(1) \qquad Y_{dst} = \alpha_{ds} + \beta_t + \gamma_1 \, Rain_{dst} + \gamma_2 \, Temp_{dst} + \delta X_{dst} + u_{dst}$$

where Y_{dst} is per capita consumption or poverty in district d of state s and year t, $Rain_{dst}$ is the log of total annual rainfall, $Temp_{dst}$ is the average annual temperature, α_{ds} is a district fixed effect which would control for all time-invariant district characteristics that affect the average income or general weather patterns in a district and β_t is a year fixed effect which would control for year-specific shocks which are common across all districts (such as an overall shortfall in monsoon rainfall or the occurrence of an election or changes in nationwide macroeconomic policy). X_{dst} is a vector for other time-varying characteristics. In most of our regressions, this will include time-varying demographic variables such as literacy rates, gender ratios and the share of Scheduled Castes and Scheduled Tribes in the population.

We examine the effect of trade shocks on poverty levels, using a very similar specification to (1) above, following Topalova (2010):

$$(2) \qquad Y_{dst} = \alpha_{ds} + \beta_t + \phi \, Tariff_{dst} + \delta^* \beta_t \, X_{ds0} + u_{dst}$$

where $Tariff_{dst}$ is the employment-weighted district tariff instrumented by $TrTariff_{dst}$ (the employment-weighted district traded tariff) and the initial level of tariffs interacted with a post-reform indicator. Unlike the weather, variations in which can be safely deemed as exogenous, an important concern with specification (2) is that changes in district trade protection, as captured by $Tariff_{dst}$ and $TrTariff_{dst}$ may be systematically correlated with unobserved time-varying district-specific factors that also have a bearing on the district's poverty and consumption. As discussed in Topalova (2010), one way to address this concern is to allow the initial sectoral composition and other pre-reform district characteristics that may affect its future growth to have a time varying effect. Hence, X_{ds0} includes the district's employment composition at a more aggregate level than the one used in the construction of the $Tariff_{dst}$ (namely the share of workers in agriculture, manufacturing, mining, trade, transport and services), the literacy rate, and the population share of Scheduled Castes and Scheduled Tribes prior to the reforms. These characteristics are interacted with a post-liberalization indicator (which in this two period framework is equivalent to the year fixed effects, β_t).

We examine the "reduced form" impact of weather and trade shocks on crime using the same regression specifications as above, namely:

$$(3) \qquad Crime_{dst} = a_{ds} + b_t + c_1 Rain_{dst} + c_2 Temp_{dst} + dX_{dst} + e_{dst}$$

$$(4) \qquad Crime_{dst} = a_{ds} + b_t + fTariff_{dt} + d^* \beta_t {}^* X_{ds0} + e_{dst}$$

where $Crime_{dst}$ is measured as the log of the number of crimes per capita for each crime category. Unlike the "first stage" regressions, which rely on poverty and consumption data available only at five-year intervals, regressions (3) and (4) are based on annual data for the period 1971-2010 in the case of weather shocks and 1987-2010 in the case of trade shocks. As discussed above, due to the nature of the Indian trade liberalization, which was largely unexpected and externally driven in its initial stages, we will focus primarily on the 1988-1997 period when the variation in trade protection across districts and over time could be deemed exogenous and the estimated effects of trade shocks on income (and crime) could be safely given a causal interpretation. For the crime regressions listed above, we include differential linear time trends across states. We cluster the standard errors at the district level to account for potential serial correlation or any other type of covariance in the residuals within a district (Bertrand, Duflo and Mullainathan, 2004).

4. Empirical Results

4.1 Rainfall Shocks, Trade Shocks and Income

Consistent with many previous cross-country and India-specific studies, we find that rainfall is a significant determinant of per capita income and poverty. A one standard deviation increase in log rainfall (0.54) is associated with 1.24% higher per capita consumption, a 4.5 percentage point reduction in the head count ratio and 1.6 percentage point reduction in the poverty gap (Table 2, panel A, columns 1-3). In contrast to cross-country studies, we find that higher temperatures have no significant effect on per capita consumption or poverty measures. Consistent with this insignificant effect of temperature, the effects of rainfall on consumption and poverty remain very similar if we exclude temperature from our regressions (Table 2, panel A, columns 4-6).

Despite the possibility that high rainfall might have detrimental effects due to flooding or destruction of crops, we find that positive rainfall shocks are associated with higher consumption and lower poverty in the Indian context, while negative rainfall shocks are associated with lower consumption and higher poverty (Table A.1, Panel A). In other words, we do not find any evidence of a non-linear relationship between rainfall and poverty, providing support for our use of rainfall levels as the main measure of rainfall variation. As before, temperature does not significantly predict consumption or poverty. There is also no non-linear effect on temperature when using the “harmful” degree-months measure of temperature variations (Table A.1, Panel B).

As documented in Topalova (2007), trade shocks, measured by the district-specific employment-weighted tariffs, also have an impact on per capita consumption and poverty (Table 2, panel B). Districts with a greater concentration of production sectors exposed to trade liberalization experienced slower declines in poverty and lower consumption growth. A one standard deviation (0.06) reduction in the district specific tariff is associated with 3.1% lower income per capita, a 2.7 percentage point decrease in the head count ratio and a 0.76 percentage point decrease in the poverty gap (Table 2, panel B, columns 1-3). These IV estimates of the impact of trade liberalization on consumption and poverty are very similar to those obtained with OLS estimation (Table 2, panel B, columns 4-6).

4.2 Rainfall Shocks and Crime

We find that higher rainfall is associated with significantly lower levels of crime (Table 3, panel A). A one standard deviation increase in log rainfall is associated with 3.6% lower total crimes per capita. This decrease is primarily driven by decreases in violent interpersonal crimes (4.2% decline), property crimes (2.2% decline) and economic crimes (3.8% decline). We do not find significant effects of higher rainfall on crimes against public order or crimes against women. The impact of rainfall on violent crimes and property crimes remains statistically significant when our estimation sample is extended to the longer time period of 1970-2010, though the magnitude of the coefficients falls (Table 3, panel B). In a robustness check, we verify that the effects of rainfall on crime categories remain very similar if we exclude temperature from our regressions (Table A.2, panels A and B).

Examining individual crime categories, we find that higher rainfall is associated with lower rates of murder and rape (Table 4, panels A and B). The impact on theft is statistically significant only in the restricted sample (Table 4, panel A). The impact on riots is variable: we observe higher rainfall associated with lower incidence of riots in the 1988-1997 sample but not in the 1970-2010 sample, while the results for inter-religious violence (Hindu-Muslim riots) shows the opposite pattern (Table 4, panels A and B). Nevertheless, the broad pattern of higher rainfall being associated with lower crimes, in several different crime categories, is present.

While the effects of rainfall are consistent with the income hypothesis, two pieces of evidence suggest that other factors may also be at work. First, higher average temperatures are associated with higher crimes against public order and crimes against women, particularly rape, in the longer sample period (Tables 3 and 4, panel B), even though temperature variations are not predictive of variations in consumption or poverty. Second, property crimes display a non-linear relationship with rainfall, even though consumption and poverty do not. Property crimes are significantly higher when rainfall is both one standard deviation lower *and* one standard deviation higher than the long-run average (Table A.2, panel C, column 3).

4.3 Trade Shocks and Crime

The relationship between trade shocks and crime rates is very similar to that between rainfall shocks and crime. Districts which were not as exposed to the reduction in trade protection because of their initial employment mix, and hence experienced relatively faster reduction in poverty, have lower levels of crime. A one standard deviation increase in average district tariffs results in 2.4% lower total crimes per capita (Table 5, panel A). Very similar to the pattern with rainfall shocks, this decline is driven primarily by a decline in violent interpersonal crimes (2.7% decline), property crimes (3.1% decline) and economic crimes (6.1% decline), and there is no statistically significant impact on crimes against public order or crimes against women. The impact of trade shocks on violent crimes and property crimes remains large and statistically significant when we extend the sample to the longer period 1988-2010, while the impact on economic crimes is statistically insignificant (Table 5, panel B). Again, this is very similar to the pattern observed with rainfall shocks. However, we do not estimate statistically significant effects of trade shocks on individual crime categories, except for burglary in the 1988-1997 period and theft in the longer 1988-2010 period (Table 6). As a robustness check, we also show that the results are not dependent on instrumenting for tariff levels with initial tariffs and traded tariff levels. The relationship between tariff levels and crime rates is very similar in the OLS specification as well (Table A.3).

4.4 Comparing the Effects of Rainfall and Trade Exposure on Crime

While trade shocks and rainfall shocks appear to influence crime rates in a similar direction (Tables 3 and 5), are the magnitudes of these effects comparable? This is important in assessing whether the mechanism through which these effects operate is predominantly shocks to income or poverty. As described earlier, the lack of annual panel data on income or poverty rates at the district level prevents us from directly computing instrumental variable estimates using these different sets of exogenous shocks to income and comparing the resulting magnitudes. However, we can compute the "implied" instrumental variable estimate by dividing the estimated effects of rainfall and trade on crime rates (the "reduced form") by the estimated effects of rainfall and trade on consumption and poverty (the "first stage").

If income or poverty is the main mechanism of influence, we should find similar "implied IV" effects, regardless of whether we use rainfall shocks or trade shocks as the instrumental variable. Given that trade shocks are of a more permanent nature than rainfall shocks, we might also find that the effects on crime using trade shocks are larger than using income shocks. Table 7 instead shows that the implied effects of average consumption on crime rates are much higher when we use rainfall as the instrument than when we use the trade shocks as the instrument. Conversely, the impact of poverty (head count ratio or poverty gap) on crime is much higher with the trade shocks instrument than with the rainfall shock instrument.

How can these differential patterns be reconciled? One possibility is that rainfall and trade shocks affect people in different parts of the income distribution. The poverty measures capture the impact only on the lower end of the income distribution, which might be quite different than the impact on average consumption. If trade shocks primarily affect people at the lower end of the income distribution while rainfall shocks affect people over the entire range, then we would indeed see larger effects of average consumption on crime when using the rainfall instrument (simply because many more people experience a change in their income).

This is indeed the case. As documented in Topalova (2010), the estimated effect of tariff cuts on per capita consumption is largest for the households in the bottom tenth and twentieth percentile of the consumption distribution. As one moves up the income distribution, the effect decreases in magnitude and becomes statistically insignificant (Figure 1, panel A). A one standard deviation increase in tariffs increases consumption by 4.2% at the 10th percentile of the income distribution, but this effect is halved to 2.1% at the 40th percentile, and stays low thereafter. Possible explanations for this pattern could be the difference in employment sectors of people along the income distribution, or a greater geographic or occupational mobility at higher levels of income. Higher rainfall, on the other hand, increases average consumption across the full range of the income distribution. A one standard deviation in log rainfall increases per capita consumption by 4.9% at the 10th percentile of the income distribution and by 4.7% at the 90th percentile (Figure 1, panel B).

In sum, comparing the magnitude of the impact of rainfall and trade shocks on crime provides further evidence that the primary channel of influence is through changes in consumption or poverty. The differential patterns when using average consumption versus poverty levels are explained by the differential effects of rainfall shocks and trade shocks on different parts of the income distribution.

4.5 Mitigating the Effect of Rainfall on Income

A further way to corroborate the role of poverty is to examine two features of the institutional landscape which might help in mitigating the impact of rainfall shocks on consumption—the implementation of the social safety net in the form of the NREGA workfare program, and the building of dams. We extend our regression specification to include interaction terms as follows:

$$(5)\quad Crime_{dst} = a_{ds} + b_t + mPostNREGA_{dst} + m_1 PostNREGA_{dst} * Rain_{dst} + c_1 Rain_{dst} + e_{dst}$$

$$(6)\quad Crime_{dst} = a_{ds} + b_t + gDamUpstream_{dst} + g_1 DamUpstream_{dst} * Rain_{dst} + c_1 Rain_{dst} + e_{dst}$$

If the observed rainfall-crime relationship is due to the income channel, and if NREGA implementation helps to attenuate the impact of rainfall shocks on income, then we expect to see $m_1 > 0$ in the regressions above. Similarly, if the presence of a dam in the upstream district dampens the effect of rainfall on income or poverty, we expect to see $g_1 > 0$ when estimating equation (6). Since neither of these interventions are expected to affect the relationship between temperature and crime (if any), we do not include temperature in these regressions. Specifications with temperature included are shown in the appendix.

We find that neither of these policy-driven interventions appears to have a strong moderating effect on the relationship between rainfall shocks and crime. When estimating specification (5), we find no significant differences between the effects of rainfall shocks before and after NREGA is implemented (Table 8, panel A). In fact, the estimated interaction coefficient m_1 is consistently negative (though insignificant) for all crime categories, suggesting no mitigating effect of this policy intervention.[24]

The presence of dams also does not mitigate the effects of rainfall shocks on crime. Previous work has demonstrated that the presence of dams in an upstream district dampens the effect of rainfall shocks on productivity (Duflo and Pande 2007). However, it appears that crime in districts downstream of dams is just as likely to respond to rainfall shocks as crime in districts that do not benefit from the presence of dam.[25] The estimated interaction coefficients g_1 are mostly negative in sign though statistically indistinguishable from zero (Table 8, panel B).

One possible explanation for why these policy measures do not dampen the rainfall-crime relationship could be because they do not have a large impact on the rainfall-poverty or rainfall-consumption relationship. Indeed, when we examine whether income and poverty are as sensitive to rainfall in districts that are downstream to dams, we do not find strong evidence that income and poverty are insulated from variations in weather in these areas. As demonstrated in Table A.5, the coefficients on the interaction of rainfall levels and an indicator for the presence of a dam in an upstream district are negative, but not statistically

[24] Our results on crime are in contrast to the findings of Fetzer (2013), who finds a mitigating effect of NREGA implementation on violence in insurgency-affected areas.

[25] Sarsons (2011) finds a similar pattern when examining the role of rainfall shocks on religious violence. However, Hindu-Muslim riots in India are predominantly an urban phenomenon (Varshney, 2002), while dams are more likely to act as an income-smoothing device in rural areas, suggesting that the Sarsons (2011) analysis may not be particularly relevant to test the income channel for this specific crime category.

significant.[26] Our results on the non-impact of the NREGA program is somewhat surprising in light of other studies which document that NREGA presence completely offsets the rainfall dependence of agricultural wages (Fetzer, 2013) or reduces the impact of droughts on child stunting by three-quarters (Dasgupta, 2013). In related regressions, we have also verified that the effect of rainfall shocks on crime rates does not vary significantly across districts with more or fewer people employed in farming (results not shown).

5. Conclusions

Using variation in per capita consumption and poverty generated by differential exposure of different regions in India to the trade liberalization process of the 1990s, we examine whether the income channel is the primary driver of the observed relationship between rainfall shocks and crime. We analyze a wide range of crime categories over a period of several decades. Our evidence provides strong support for the income channel. Violent crimes and property crimes rise during periods of low rainfall and/or higher exposure to foreign competition, while other crime categories such as crimes against women do not show a strong relationship with either of these exogenous income shifters. Our results are novel in providing evidence for the income mechanism behind the observed rainfall-crime relationship, which has mostly been assumed in the prior literature.

We also find several other interesting results which are important in understanding the relationship between economic shocks, climate variation and crime. Trade liberalization affects the consumption of households at the lower deciles of the income distribution, while rainfall shocks affect consumption over

[26] This finding is in line with Duflo and Pande (2007) who document that having a dam upstream mitigates the effects of rainfall on agricultural productivity and wages, though not the effect of rainfall on income and poverty.

the whole range. Temperature variations have a significant effect on some types of crime, including crimes against women, even though per capita consumption or poverty is not much affected by temperature. Policies such as dam construction or workfare programs do not appear to smooth consumption in the face of weather shocks to a large enough extent to have an impact on crime. These findings are important to keep in mind when designing appropriate policy responses for income support or crime prevention.

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Table 1
Summary Statistics

Weather, trade, income and crime, 1988-1997	N	Mean	SD	Min	Max
Log rainfall	3000	6.90	0.54	4.23	8.54
Average temperature	3000	25.35	3.01	-5.45	30.31
Negative rainfall shock	3000	0.11	0.31	0	1
Positive rainfall shock	3000	0.15	0.36	0	1
Tariff	3410	0.06	0.06	0.00	0.69
Log Mean Consumption	1487	1.60	0.16	1.21	1.87
Head Count Ratio	1487	0.37	0.18	0	0.86
Poverty Gap	1487	0.12	0.10	0	0.40
Total crimes	2994	0.50	0.54	-1.89	2.18
Violent interpersonal crimes	2995	-2.10	0.84	-4.50	0.63
Property crimes	2995	-0.86	0.61	-4.50	1.16
Crimes against public order	2961	-2.55	1.02	-8.08	-0.22
Economic crimes	2987	-3.29	0.78	-8.33	-0.77
Crimes against women	2991	-3.32	1.00	-7.41	-0.64
Murder	2995	-3.32	0.54	-6.42	-0.96
Riots	2937	-2.58	0.99	-8.08	-0.22
Rape	2986	-4.50	0.87	-8.36	-2.30
Burglary	2994	-2.13	0.80	-6.63	-0.29
Theft	2994	-1.37	0.69	-4.30	0.86
Hindu-Muslim riots (number)	3001	0.11	0.50	0.00	8.00
Weather, trade and crime, 1970-2010	N	Mean	SD	Min	Max
Log rainfall	12000	6.88	0.58	3.24	8.60
Average temperature	12000	25.46	2.98	-5.54	30.63
Negative rainfall shock	12000	0.15	0.36	0	1
Positive rainfall shock	12000	0.16	0.37	0	1
Tariff (1988-2010)	7843	0.04	0.06	0.00	0.69
Total crimes	11869	0.48	0.57	-2.02	3.58
Violent interpersonal crimes	11869	-2.21	1.05	-6.60	0.69
Property crimes	11872	-0.81	0.79	-4.50	2.71
Crimes against public order	11796	-2.67	1.09	-8.08	2.03
Economic crimes	11858	-3.16	0.76	-8.33	0.24
Crimes against women	11690	-3.66	1.59	-8.59	-0.43
Murder	11845	-3.49	0.57	-7.99	0.38
Riots	11635	-2.71	1.09	-8.22	2.03
Rape	11680	-4.69	0.98	-8.59	-1.63
Burglary	11867	-2.07	1.00	-8.12	1.93
Theft	11868	-1.32	0.84	-7.11	2.25
Hindu-Muslim riots (number)	12305	0.09	0.68	0.00	45.00

Note: All summary statistics are from India's 16 major states. Crime variables are measured as the log of number of crimes per capita. Rain is the precipitation in a district in units of 100 mn per year. Temperature is the average air temperature in degrees Celsius. Tariff is the employment weighted district tariff as in Topalova (2007, 2010). Negative rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation below the historical averge district rainfall. Positive rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation above the historical average district rainfall.

Table 2
The Impact of Weather Shocks and Trade Shocks on Income and Poverty

Panel A: Weather Shocks

	Log Mean Consumption	Head Count Ratio	Poverty Gap	Log Mean Consumption	Head Count Ratio	Poverty Gap
	(1)	(2)	(3)	(4)	(5)	(6)
Log Rain	0.023 ***	-0.084 ***	-0.029 ***	0.022 ***	-0.083 ***	-0.031 ***
	[0.004]	[0.015]	[0.005]	[0.003]	[0.014]	[0.005]
Average Temperature	0.003	-0.001	0.003			
	[0.003]	[0.011]	[0.004]			
R-squared	0.98	0.74	0.87	0.98	0.74	0.87
N	1487	1487	1487	1487	1487	1487

Panel B: Trade Shocks

	Log Mean Consumption	Head Count Ratio	Poverty Gap	Log Mean Consumption	Head Count Ratio	Poverty Gap
	(1)	(2)	(3)	(4)	(5)	(6)
		IV			OLS	
Tariff	0.514 **	-0.452 **	-0.127 **	0.531 **	-0.461 **	-0.132 **
	[0.241]	[0.206]	[0.055]	[0.264]	[0.206]	[0.055]
R-squared	0.96	0.85	0.81	0.96	0.85	0.81
N	680	680	680	680	680	680

Notes: All specifications use district-level data from India's 16 major states and include district and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. Panel A includes the years 1973, 1983, 1987, 1993 and 1999. Panel B includes the year 1987 and 1999. Rain is the precipitation in a district in units of 100 mm per year. Temperature is the average air temperature in degrees Celsius. Tariff is the employment weighted district output tariff as defined in Topalova (2010). In Panel B, columns (1), (2) and (3), the tariff is instrumented by traded employment weight-tariffs and the initial tariff interacted with a post-reform indicator. Regressions in panel A control for percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers. Regressions in panel B control for the initial literacy rate, percent of Scheduled Caste and Scheduled Tribe population and initial district industrial structure interacted with a post-reform indicator, and are weighted by the number of households in the district as in Topalova (2007, 2010).

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table 3
The Impact of Weather Shocks on Crime: Broad Crime Categories

	Total crimes	Violent crimes	Property crimes	Crimes against public order	Economic crimes	Crimes against women
	(1)	(2)	(3)	(4)	(5)	(6)
				Panel A: 1988-1997		
Log Rain	-0.067 ***	-0.078 *	-0.041 **	-0.047	-0.071 *	-0.009
	[0.016]	[0.048]	[0.020]	[0.040]	[0.039]	[0.048]
Average Temperature	-0.013	0.067 **	-0.030	0.009	0.012	0.009
	[0.016]	[0.029]	[0.019]	[0.036]	[0.031]	[0.028]
R-squared	0.92	0.84	0.90	0.90	0.81	0.88
N	2994	2995	2995	2961	2987	2991
				Panel B: 1970-2010		
Log Rain	-0.036 ***	-0.028 *	-0.029 **	-0.025	-0.019	-0.025
	[0.013]	[0.017]	[0.013]	[0.026]	[0.018]	[0.022]
Average Temperature	-0.003	0.021	0.003	0.049 **	0.010	0.061 ***
	[0.013]	[0.020]	[0.014]	[0.024]	[0.019]	[0.023]
R-squared	0.82	0.85	0.86	0.78	0.70	0.92
N	11869	11869	11872	11796	11858	11690

Notes: All specifications use district-level data from India's 16 major states and include district, and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as the log of number of crimes per capita. Rain is the precipitation in a district in units of 100 mm per year. Temperature is the average air temperature in degrees Celsius. All regressions control for state-specific time trends, percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table 4
The Impact of Weather Shocks on Crime: Specific Crime Categories

	Murder	Riots	Rape	Burglary	Theft	Hindu-Muslim Riots
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1988-1997			
Log Rain	-0.080 ***	-0.066 *	-0.108 ***	-0.023	-0.054 **	-0.053
	[0.024]	[0.038]	[0.041]	[0.028]	[0.021]	[0.054]
Average Temperature	0.000	0.017	0.009	-0.023	-0.040 *	-0.014
	[0.022]	[0.034]	[0.033]	[0.023]	[0.020]	[0.026]
R-squared	0.86	0.90	0.86	0.92	0.92	0.31
N	2995	2937	2986	2994	2994	3000
			Panel B: 1970-2010			
Log Rain	-0.028 **	0.003	-0.054 **	-0.030 *	-0.021	-0.157 **
	[0.013]	[0.028]	[0.022]	[0.016]	[0.016]	[0.075]
Average Temperature	-0.006	0.040	0.040 *	-0.018	0.036 **	-0.009
	[0.014]	[0.027]	[0.021]	[0.018]	[0.017]	[0.018]
R-squared	0.73	0.76	0.78	0.86	0.84	0.19
N	11845	11635	11680	11867	11868	12000

Notes: All specifications use district-level data from India's 16 major states and include district, and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as the log of number of crimes per capita. Rain is the precipitation in a district in units of 100 mm per year. Temperature is the average air temperature in degrees Celsius. All regressions control for state-specific time trends, percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table 5
The Impact of Trade Shocks on Crime: Broad Crime Categories

	Total crimes		Violent crimes		Property crimes		Crimes against public order	Economic crimes		Crimes against women
	(1)		(2)		(3)		(4)	(5)		(6)
Panel A: 1988-1997										
Tariffs	-0.392	**	-0.446	*	-0.513	**	0.230	-1.018	**	-0.171
	[0.165]		[0.267]		[0.240]		[0.338]	[0.425]		[0.376]
R-squared	0.19		0.76		0.36		0.14	0.10		0.77
N	3403		3405		3405		3363	3392		3401
Panel B: 1988-2010										
Tariffs	-0.168		-1.732	***	-0.530	**	0.369	0.065		-0.125
	[0.172]		[0.466]		[0.241]		[0.325]	[0.415]		[0.362]
R-squared	0.33		0.71		0.59		0.53	0.24		0.82
N	7834		7836		7836		7788	7816		7832

Notes: All specifications use district-level data from India's 16 major states and include district, and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as the log of number of crimes per capita. Tariff is the employment weighted district tariff instrumented by traded employment weight-tariffs and the initial tariff interacted with the year indicators. All regressions control for state-specific time trends, and the initial literacy rate, percent of Scheduled Caste and Scheduled Tribe population and initial district industrial structure interacted with a post reform indicator.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table 6
The Impact of Trade Shocks on Crime: Specific Crime Categories

	Murder	Riots	Rape	Burglary	Theft	Hindu-Muslim Riots
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 1988-1997			
Tariffs	-0.013	0.158	-0.303	-0.340 **	-0.442	-0.183
	[0.206]	[0.344]	[0.336]	[0.171]	[0.297]	[0.246]
R-squared	0.23	0.20	0.18	0.33	0.43	0.06
N	3405	3333	3395	3401	3403	3410
			Panel B: 1988-2010			
Tariffs	-0.366 **	0.259	0.361	-0.054	-0.624 **	-0.051
	[0.172]	[0.366]	[0.258]	[0.251]	[0.277]	[0.150]
R-squared	0.43	0.56	0.29	0.63	0.56	0.03
N	7835	7599	7820	7831	7834	7843

Notes: All specifications use district-level data from India's 16 major states and include district, and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as the log of number of crimes per capita. Tariff is the employment weighted district tariff instrumented by traded employment weight-tariffs and the initial tariff interacted with the year indicators. All regressions control for state-specific time trends, and the initial literacy rate, percent of Scheduled Caste and Scheduled Tribe population and initial district industrial structure interacted with a post reform indicator.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table 7
Comparing the Effect of Weather and Trade Shocks on Crime Rates

	(1)	(2)	(3)	(4)
Panel A: Impact of Rainfall and Tariffs on Consumption/Poverty (First Stage)				
	Log Mean Consumption	Head Count Ratio	Poverty Gap	
Impact of rainfall	0.023	-0.084	-0.029	
Impact of tariff	0.514	-0.452	-0.127	
Panel B: Impact of Rainfall and Tariffs on Crime (Reduced Form)				
	Total crimes	Violent crimes	Property crimes	Economic crimes
Impact of rainfall	-0.067	-0.078	-0.041	-0.071
Impact of tariff	-0.392	-0.446	-0.513	-1.018
Panel C: Impact of Consumption/Poverty on Crime (Implied Instrumental Variable Estimates)				
	Total crimes	Violent crimes	Property crimes	Economic crimes
Log mean consumption (rainfall instrument)	-2.91	-3.39	-1.78	-3.09
Log mean consumption (tariff instrument)	-0.76	-0.87	-1.00	-1.98
Head count ratio (rainfall instrument)	0.80	0.93	0.49	0.85
Head count ratio (tariff instrument)	0.87	0.99	1.13	2.25
Poverty gap (rainfall instrument)	2.31	2.69	1.41	2.45
Poverty gap (tariff instrument)	3.09	3.51	4.04	8.02

Table 8
The Role of NREGA and Dams in the Rainfall-Crime Relationship

	Total crimes	Violent crimes	Property crimes	Crimes against public order	Economic crimes	Crimes against women
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: The Role of NREGA, 1991-2010					
Log Rain	-0.015	-0.109 ***	-0.030 *	-0.043	0.024	-0.010
	[0.014]	[0.034]	[0.018]	[0.033]	[0.029]	[0.025]
Log Rain * NREGA	-0.089 *	-0.017	-0.064	-0.054	-0.187	-0.073
	[0.052]	[0.105]	[0.068]	[0.141]	[0.119]	[0.060]
R-squared	0.92	0.81	0.89	0.86	0.84	0.89
N	5371	5372	5372	5348	5358	5369
	Panel B: The Role of Dams, 1970-2000					
Log Rain	-0.021	0.013	-0.014	-0.025	0.005	-0.032
	[0.013]	[0.019]	[0.014]	[0.026]	[0.020]	[0.026]
Log Rain * 1 if Dam Upstream	-0.027	-0.041	0.001	-0.006	-0.096	-0.067
	[0.031]	[0.060]	[0.033]	[0.084]	[0.076]	[0.068]
R-squared	0.82	0.83	0.86	0.81	0.71	0.89
N	8871	8871	8874	8804	8864	8692

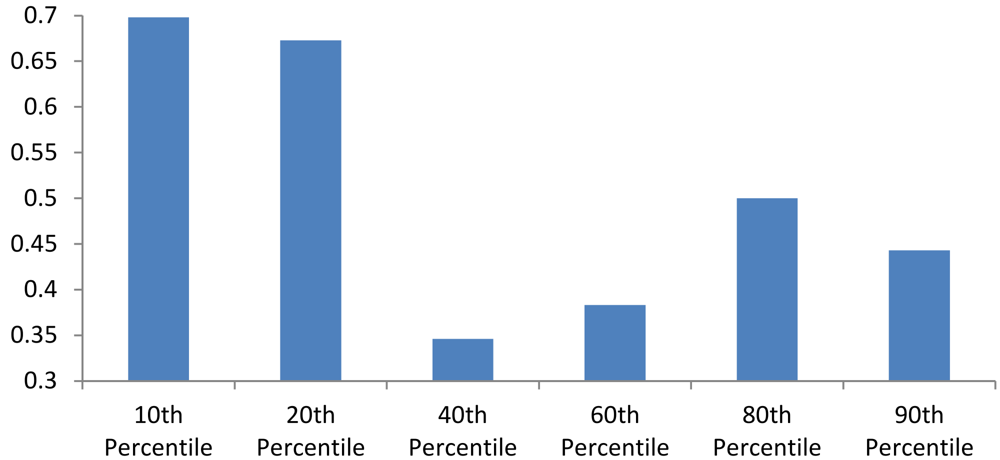
Notes: All specifications use district-level data from India's 16 major states and include district and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as log of number of crimes per capita. Rain is the precipitation in a district in units of 100 mm per year. Data on upstream dams is from Duflo and Pande (2007). All regressions control for state-specific time trends, percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers. Regressions in Panel A are at the 1991 district level, regressions in Panel B are at 1971 district level.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

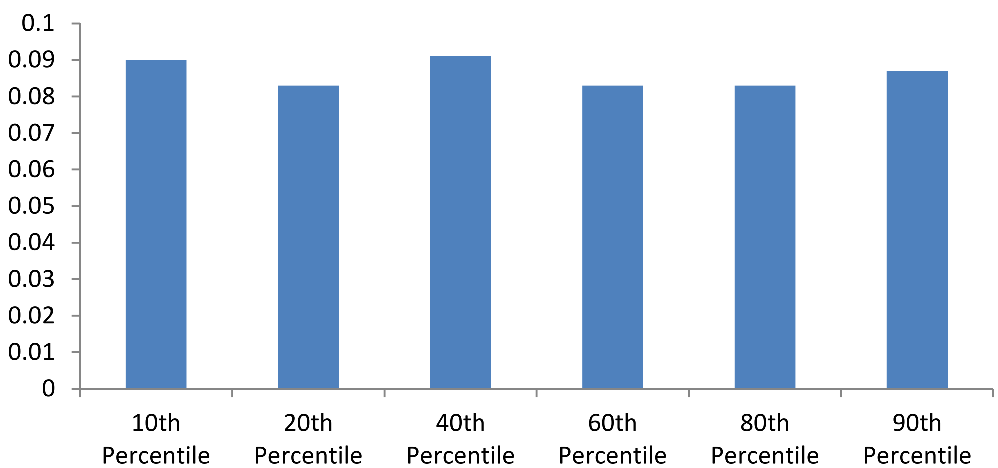
Figure 1

The Impact of Trade and Rainfall on Per Capita Consumption Across the Consumption Distribution

Panel A. Trade and Consumption



Panel B. Log Rain and Consumption



Note: The figure represents the estimated effects of trade shocks and rainfall shocks on per capital consumption for various deciles of the income distribution. Data for Panel A is from Topalova (2010), Table 6, Panel A. The coefficients in Panel B are estimated using district-level data from India's 16 major states. All specifications include district and year fixed effects and include data from 1987/88 and 1999/00. Robust standard errors are in parentheses, adjusted for clustering at the district level. Rain is the precipitation in a district in units of 100 mm per year. All regressions control for percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

Table A.1
The Impact of Weather Shocks on Income and Poverty: Alternative Specifications

	Log Mean Consumption		Head Count Ratio		Poverty Gap	
	(1)		(2)		(3)	
Panel A: Positive and Negative Rainfall Shocks						
Negative rainfall shock	-0.009	***	0.025	**	0.006	
	[0.003]		[0.012]		[0.004]	
Positive rainfall shock	0.010	***	-0.036	***	-0.015	***
	[0.002]		[0.009]		[0.003]	
Average Temperature	0.001		0.008		0.006	
	[0.003]		[0.011]		[0.004]	
R-squared	0.98		0.73		0.87	
N	1487		1487		1487	
Panel B: Monthly Temperature Variations						
Log Rain	0.022	***	-0.085	***	-0.032	***
	[0.003]		[0.015]		[0.005]	
Monthly Temperature Variation	0.001		-0.004		-0.002	
	[0.001]		[0.004]		[0.001]	
R-squared	0.98		0.74		0.87	
N	1477		1477		1477	

Notes: All specifications use district-level data from India's 16 major states and include district and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. Data are from the years 1973, 1983, 1987, 1993 and 1999. Rain is the precipitation in a district in units of 100 mm per year. Temperature variation is the "cumulative number of degrees-times-months that exceed 32 C in a district and year". Negative rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation below the averge district rainfall. Positive rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation above the average district rainfall. Temperature is the average air temperature in degrees Celsius. Regressions control for percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table A.2

The Impact of Rainfall & Temperature Shocks on Crime: Broad Crime Categories

	Total crimes		Violent crimes		Property crimes		Crimes against public order		Economic crimes		Crimes against women	
	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A: Log Rainfall, 1988-1997												
Log Rain	-0.066	***	-0.084	*	-0.038	*	-0.047		-0.072	*	-0.010	
	[0.016]		[0.048]		[0.020]		[0.040]		[0.039]		[0.048]	
R-squared	0.92		0.84		0.90		0.90		0.81		0.88	
N	2994		2995		2995		2961		2987		2991	
Panel B: Log Rainfall, 1970-2010												
Log Rain	-0.034	***	-0.035	**	-0.030	**	-0.042	*	-0.022		-0.045	**
	[0.011]		[0.015]		[0.012]		[0.024]		[0.017]		[0.021]	
R-squared	0.82		0.85		0.86		0.78		0.70		0.92	
N	11869		11869		11872		11796		11858		11690	
Panel C: Positive and negative rainfall shocks, 1970-2010												
Negative rainfall shock	0.027	***	0.029	**	0.038	***	0.036	**	0.007		0.025	*
	[0.007]		[0.011]		[0.009]		[0.014]		[0.012]		[0.014]	
Positive rainfall shock	0.005		0.011		0.027	***	0.019		-0.008		0.017	
	[0.006]		[0.011]		[0.007]		[0.013]		[0.012]		[0.013]	
Average Temperature	0.000		0.023		0.007		0.051	**	0.012		0.064	***
	[0.012]		[0.019]		[0.014]		[0.024]		[0.018]		[0.022]	
R-squared	0.82		0.85		0.86		0.78		0.70		0.92	
N	11869		11869		11872		11796		11858		11690	

Notes: All specifications use district-level data from India's 16 major states and include district and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. Data are from the years 1973, 1983, 1987, 1993 and 1999. Rain is the precipitation in a district in units of 100 mm per year. Negative rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation below the averge district rainfall. Positive rainfall shock is an indicator equal to 1 if rainfall is more than one standard deviation above the average district rainfall. Temperature is the average air temperature in degrees Celsius. Regressions control for percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table A.3
The Impact of Trade Shocks on Crime: OLS Estimates

	Total crimes		Violent crimes		Property crimes		Crimes against public order	Economic crimes		Crimes against women
	(1)		(2)		(3)		(4)	(5)		(6)
					Panel A: 1988-1997					
Tariffs	-0.347	**	-0.622	***	-0.453	**	0.156	-0.983	***	-0.307
	[0.156]		[0.240]		[0.200]		[0.306]	[0.363]		[0.327]
R-squared	0.19		0.76		0.36		0.14	0.10		0.77
N	3403		3405		3405		3363	3392		3401
					Panel B: 1988-2010					
Tariffs	-0.256	*	-1.153	***	-0.553	**	-0.111	-0.112		-0.217
	[0.142]		[0.358]		[0.253]		[0.259]	[0.354]		[0.238]
R-squared	0.33		0.71		0.59		0.53	0.24		0.82
N	7834		7836		7836		7788	7816		7832

Notes: All specifications use district-level data from India's 16 major states and include district, and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as the log of number of crimes per capita. Tariff is the employment weighted district tariff. All regressions control for state-specific time trends, and the initial literacy rate, percent of Scheduled Caste and Scheduled Tribe population and initial district industrial structure interacted with a post reform indicator.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table A.4
The Role of NREGA and dams on the weather-crime relationship

	Total crimes	Violent crimes	Property crimes	Crimes against public order	Economic crimes	Crimes against women
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: The Role of NREGA, 1991-2010			
Log Rain	-0.009	-0.074 **	-0.027	-0.035	0.022	0.009
	[0.015]	[0.034]	[0.019]	[0.034]	[0.030]	[0.026]
Log Rain * NREGA	-0.084	-0.028	-0.061	-0.061	-0.169	-0.075
	[0.052]	[0.105]	[0.068]	[0.142]	[0.119]	[0.060]
Average Temperature	0.018	0.102 ***	0.011	0.023	-0.001	0.058 ***
	[0.012]	[0.028]	[0.016]	[0.024]	[0.022]	[0.021]
Average Temperature	0.011 **	0.000	0.006	-0.006	0.030 ***	0.007
* NREGA	[0.005]	[0.011]	[0.005]	[0.010]	[0.010]	[0.009]
r2	0.92	0.81	0.89	0.86	0.84	0.89
N	5371	5372	5372	5348	5358	5369
			Panel B: The Role of Dams, 1970-2010			
Log Rain	-0.027 *	0.013	-0.018	-0.025	0.002	-0.014
	[0.014]	[0.019]	[0.014]	[0.028]	[0.021]	[0.027]
Log Rain * 1 if Dam Upstream	-0.028	-0.037	-0.000	-0.009	-0.095	-0.063
	[0.030]	[0.058]	[0.033]	[0.083]	[0.077]	[0.071]
Average Temperature	-0.021	-0.001	-0.010	-0.000	-0.010	0.055 **
	[0.013]	[0.021]	[0.015]	[0.026]	[0.021]	[0.025]
Average Temperature	-0.014	0.056	-0.015	-0.038	0.019	0.041
* 1 if Dam Upstream	[0.020]	[0.034]	[0.020]	[0.049]	[0.057]	[0.035]
R-squared	0.82	0.83	0.86	0.81	0.71	0.89
N	8871	8871	8874	8804	8864	8692

Notes: All specifications use district-level data from India's 16 major states and include district and year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. All crime variables are measured as log of number of crimes per capita. Rain is the precipitation in a district in units of 100 mm per year. Temperature is the average air temperature in degrees Celsius. Data on upstream dams is from Duflo and Pande (2007). All regressions control for state-specific time trends, percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers. Regressions in Panel A are at the 1991 district level, regressions in Panel B are at 1971 district level. *** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.

Table A.5
The Role of Dams in the Rainfall-Poverty Relationship

	Log Mean Consumption	Head Count Ratio	Poverty Gap
	(1)	(2)	(3)
Log Rain	0.018 ***	-0.069 ***	-0.020 ***
	[0.005]	[0.020]	[0.007]
Log Rain * 1 if Dam Upstream	-0.015	0.051	0.019
	[0.010]	[0.036]	[0.013]
1 if Dam Upstream	0.101	-0.371	-0.136
	[0.065]	[0.249]	[0.089]
R-squared	0.98	0.80	0.92
N	1487	1487	1487

Notes: All specifications use district-level data from India's 16 major states and include district and state-year fixed effects. Robust standard errors are in parentheses, adjusted for clustering at the district level. Data are from the year 1973, 1983, 1987, 1993 and 1999. Rain is the precipitation in a district in units of 100 mm per year. Data on upstream dams is from Duflo and Pande (2007). Regressions control for percent of population that is rural, literacy rate, sex ratio, percent of Scheduled Caste and Scheduled Tribe population and percent farmers.

*** Significant at 1 percent level; ** significant at 5 percent level; * significant at 10 percent level.