Temperature and economic activity: Evidence from India

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Abstract

This paper investigates the impact of temperature on economic activity in India, using state-level data from 1980–2015. We estimate that a 1 °C increase in contemporaneous temperature (relative to our sample mean) reduces the economic growth rate that year by 2.5 percentage points. The adverse impact of higher temperatures is more severe in poorer states and in the primary sector. Our analysis of lagged temperatures suggests that our effects are driven by the contemporaneous effect of temperature on output; we do not find evidence of a permanent impact of contemporaneous temperatures on future growth rates.

Keywords: climate change, economic growth, India, panel data, temperature

JEL codes: O44, Q54

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1 Introduction

Mean global temperatures are projected to increase by as much as 2 °C-4.8 °C by the year 2100, relative to pre-industrial levels (IPCC, 2014). Researchers have estimated that these higher temperatures may have a significant impact on a variety of economic and social outcomes, including agricultural output (Schlenker & Roberts, 2009), labour supply (Graff Zivin & Neidell, 2014), mortality (Deschênes & Greenstone, 2011), energy usage (Auffhammer, Baylis, & Hausman, 2017), conflict (Burke, Hsiang, & Miguel, 2015a; Hsiang, Burke, & Miguel, 2013), health (Deschênes, 2014), poverty (Herrera, Ruben, & Dijkstra, 2018), labour productivity (Somanathan, Somanathan, Sudarshan, & Tewari, 2015), and industrial total factor productivity (Zhang, Deschênes, Meng, & Zhang, 2018). The damages from higher temperatures are expected to be especially severe in low- and middle-income countries (Diffenbaugh & Burke, 2019), due in part to these countries' higher reliance on agriculture and lower capacity to adapt to these temperatures. Furthermore, many low- and middle-income countries are located in low latitudes that are expected to experience heat extremes soonest (Harrington et al., 2016).

Against this backdrop, India is a particularly important country upon which to focus. Indeed, India has been estimated to have the highest country-level social cost of carbon of any nation (Ricke, Drouet, Caldeira, & Tavoni, 2018). Sector-specific research on India provides evidence that higher temperatures reduce agricultural yields (Taraz, 2018) and manufacturing productivity (Somanathan et al., 2015). Yet to date, there has been limited analysis for India that focuses on the impact of higher temperatures on aggregate economic output. This study aims to fill that gap in the growing collection of cross-country and within-country studies exploring the economic consequences of rising temperatures (Colacito, Hoffman, & Phan, 2019; Dell, Jones, & Olken, 2012).

Using state-level data on economic activity spanning the fiscal years 1980-81 to 2014-15 and annual state-level temperature data constructed from the ERA-Interim Archive, we employ a fixed effects model to investigate the relationship between temperature and gross state domestic product (GSDP). Our fixed effects strategy relies on the quasi-random nature of year-to-year fluctuations in weather to capture causal impacts of temperature, an approach pioneered by Deschênes and Greenstone (2007) and subsequently used widely in the environmental economics literature (Dell, Jones, & Olken, 2014). The complex nature of the relationship between temperature and growth apparent from the existing literature motivates our use of subnational rather than national data (Colacito et al., 2019; Zhao, Gerety, & Kuminoff, 2018). Our inclusion of a quadratic function of temperature is informed by earlier research that has found evidence of nonlinear impacts of temperature on economic activity (Burke, Hsiang, & Miguel, 2015b) and we also explore whether the impact of temperature on growth is transitory or permanent by adding lagged temperature to our specification. Moreover, in light of the heterogeneous nature of the relationship found in other studies (Burke et al., 2015b; Dell et al., 2012), we test for heterogeneity in the temperature-growth relationship arising from a state's income level, from its dependence on agriculture, or based on the time period examined. To gain further insight into the outcome of our aggregate GSDP analysis, we examine separately the relationship between temperature and growth for the primary, secondary, and tertiary sectors in each state.

The first of our four key results points to large impacts of contemporaneous temperature on economic output, depressing economic growth in that year. Specifically we find that a 1 °C increase in temperature leads to a 2.5 percentage points reduction in contemporaneous growth rates. This result is robust to several variations in specification. Second, when we control for lagged temperatures in order to test whether the impact on growth is permanent or transitory, we do not find convincing evidence of a permanent impact: While our point estimate suggests a potentially sizeable impact of higher temperatures on permanent growth rates, our estimates are imprecisely measured. Third, we find heterogeneity in the responses of state-level economic output to contemporaneous temperature, based on income levels. Impacts in poorer states are statistically significantly larger than in the richer states. And, fourth, while we find the impact of higher temperatures is largest in the primary sector (that includes agriculture, forestry and logging, fishing, and mining), we also find evidence that manufacturing output and services are influenced by temperature. This is consistent with the existence of other channels of influence beyond the more obvious primary-sector links; for example, the existence of adverse impacts of high temperatures on labour productivity (Somanathan et al., 2015), underpinning the value of adding a macro-level study to the existing sectoral work on India.

These results complement and add to a growing body of evidence that explores the impact of temperature on economic growth rates across a range of settings. This literature is rooted in the seminal paper by Dell et al. (2012), who explore a country-level data set spanning 125 countries and 50 years. The authors find that higher temperatures reduce growth rates, but only in poor countries. Colacito et al. (2019) build on the Dell et al. (2012) methodology and study economic growth in the United States. A significant contribution of these authors is their use of sub-national data; they find that a 1 °F increase in average summer temperature was associated with a reduction in the annual growth rate of US state-level output of 0.15 to 0.25 percentage points. Another notable contribution is Burke et al. (2015b) who focus on economic output, rather than growth rates, as their dependent variable, and introduce the use of a quadratic specification to allow for nonlinear effects of temperature on economic output. As with Dell et al. (2012), Burke et al. (2015b) use country-level data. They find that 13 °C is the optimal temperature for economic output, and that output declines dramatically above this level, both in poor and rich countries. Finally, Zhao (2018) also provides useful context for our study. The author examines the temperature–growth relationship in India and China, using a different form of subnational data (geophysically scaled) than we do, and 5-year growth rates. The results point to a nonlinear relationship between temperature and growth rates, with optimal temperatures peaking at around 12 °C.

Our study combines the nonlinear specification of Burke et al. (2015b) with the use of subnational data in the context of India, a large, developing country, to study the temperature–growth relationship. Thus, we focus on a country that is likely to be hardest hit by the impact of climate change on global temperatures using data that is less likely to aggregate away the relationship of interest. We complement existing sector-specific studies on India with a macro-level analysis at the state level that allows us to uncover potential sources of heterogeneity in the temperature–growth relationship across states with different characteristics. These findings could be potentially useful in framing policy responses to rising temperatures.

The rest of the paper is organised as follows. In Section 2, we describe our data sources and present summary statistics. In Section 3, we outline our empirical strategy, while the presentation of our main results follows in Section 4. In Section 5, we test for transitory versus permanent growth effects. In Section 6, we conclude.

2 Data

2.1 State domestic product data

We use data on real gross state domestic product (GSDP) at factor cost from the Government of India.[1] The data span the fiscal years 1980-81 to 2014-15. Of the 30 states and 3 union territories for which GSDP data are available, we drop the state of Mizoram, because it is missing data for over half of the years in our sample, and the state of Telangana, because it was created in 2014. In addition, we drop the union territory of Andaman and Nicobar Islands due to the absence of weather data. Therefore, our final sample consists of 28 states and 2 union territories, as listed in Appendix Table A1.

In addition to the aggregate GSDP data, we draw upon the sub-categories available in the dataset to create annual series by state for three economic sectors - the primary sector comprising agriculture, forestry and logging, fishing, and mining, the secondary sector covering manufacturing, construction, and electricity, gas and water, and the tertiary sector

[1] The GSDP data are available at `https://niti.gov.in/state-statistics`. These data are also used by other researchers, including Kumar and Managi (2012) and Bhattacharya (2019).

that includes transport, storage and communication, trade, hotels and restaurants, banking, real estate, public administration, and other services.

2.2 Weather data

Our weather data are constructed from gridded temperature and precipitation data from the ERA-Interim Archive.[2] This data set provides daily temperature and precipitation for a 1° latitude by 1° longitude grid. To construct state-level weather outcomes, we use an approach analogous to that in Colacito et al. (2019). First, for each district in India, we construct district-level weather by inverse weighting all the weather data grid points within a 100km radius of the district's geographic centroid. Next, we construct state-level data by averaging together all of the districts within a state, using the district areas as weights. Finally, we aggregate daily weather outcomes to annual weather outcomes—average annual temperature and total annual precipitation—based on India's fiscal year, which runs from April 1st to March 31st.

2.3 Other data

For our heterogeneity analysis of income, we use Census data (Government of India, 1981) to distinguish rich versus poor states, based on GSDP per capita in 1981, the beginning of our sample period. States are characterised as poor (rich) if their GSDP per capita in 1981 is below (above) the median at that time. To analyse heterogeneity relative to reliance on agriculture, we use our sectoral data to classify states as high (low) agriculture if their share of agriculture in GSDP in 1981 is above (below) the median at that time.[3]

[2] The ERA-Interim Archive is available at `https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim`.

[3] We prefer conceptually to base our heterogeneity analysis on values from the beginning of the sample period, as they are more exogenous relative to shocks experienced during the sample period.

2.4 Summary statistics

Table 1 displays summary statistics for our key variables. Column 1 presents means and standard deviations of the variables, weighting all states and union territories equally. In Column 2, summary statistics are presented with each state-year observation weighted by the proportion, averaged over the whole sample, of that state's GSDP, relative to national GDP. For context, Appendix Figure A1 displays the evolution of national GDP, and GDP by sector, over our sample period. Appendix Table A1 provides the list of states and union territories in our sample, and also notes their classification by our heterogeneity measures (rich/poor, high agriculture/low agriculture).

3 Empirical strategy

We use panel data to estimate the impact of temperature on GSDP growth rates, in a fixed effects framework. Our regression specification builds on the approach used by Colacito et al. (2019) to study growth rates in a panel of US states, but we extend that framework to allow for nonlinear effects of temperature on economic activity, as in Burke et al. (2015b). Our main analysis consists of two regression specifications. The first is our baseline regression, which takes the form:

$$\Delta y_{s,t} = \beta_1 T_{s,t} + \beta_2 T_{s,t}^2 + f(P_{s,t}) + \rho \Delta y_{s,t-1} + \alpha_s + \alpha_t + \epsilon_{s,t}, \tag{1}$$

where Δy_{st} is the GSDP growth rate from fiscal year $t-1$ to t for state or union territory s. The term T_{st} is the average annual temperature in fiscal year t and we include a quadratic term in temperature, T_{st}^2, to allow for nonlinear effects of temperature on growth rates, following Burke et al. (2015b). We demean temperature relative to the average temperature over our sample period to improve the precision of our estimates. We control for a quadratic function of precipitation, $f(P_{st})$, since temperature and precipitation may be correlated with each other, in which case omitting precipitation would lead to omitted variable bias (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). We include a control for the one-year-lagged growth rate, $\Delta y_{s,t-1}$, to control for potential autocorrelation in the dependent variable. The term α_s represents state fixed effects, which controls for unobserved state characteristics that may be correlated with temperature or growth rates. The term α_t represents year fixed effects, which controls for nation-wide shocks to temperature or to growth rates. The term ϵ_{st} is an idiosyncratic error term. Following Colacito et al. (2019), we weight each state by the proportion, averaged over the entire sample, of its GSDP relative to GSDP of the full sample. We use heteroskedasticity robust standard errors.

The coefficients of interest in this regression are β_1 and β_2, which capture the impact of temperature on GSDP growth rates. Since temperature is demeaned in this regression, the sum of β_1 and β_2 will capture the impact of a 1 °C increase in contemporaneous temperature, relative to the mean temperature over our sample period.

Our second regression specification extends our baseline model to allow for heterogeneous effects. We estimate:

$$\begin{aligned}\Delta y_{s,t} =& [\beta_l T_{s,t} + \beta_2 T^2_{s,t}]\mathbf{1}\{Poor_s = 1\} + [\beta_3 T_{s,t} + \beta_4 T^2_{s,t}]\mathbf{1}\{Poor_s = 0\} + \\ &+ f(P_{s,t}, Poor_s) + \rho\Delta y_{s,t-1} + \alpha_s + \alpha_t + \epsilon_{s,t},\end{aligned} \tag{2}$$

Here, $Poor_s$ is a dummy that we use to test for heterogeneity by income level. $Poor_s$ equals 1 if a state had below median GSDP per capita in 1981, and is zero otherwise. In this regression, β_1 and β_2 capture the nonlinear effect of temperature on economic growth in the poorer states, while β_3 and β_4 capture that effect in the richer states. To ensure that precipitation is not confounding our effects, we include the quadratic function $f(P_{s,t}, Poor_s)$, which allows precipitation to have a nonlinear effect that can vary across the poorer versus the richer states. We also test for heterogeneity according to each state's reliance on agriculture. To do so, we re-estimate equation 2, but replace $Poor_s$ with $HighAgriculture_s$, where this variable equals 1 if a state's proportion of agricultural GSDP out of total GSDP was above the median in 1981, and is zero otherwise.[4] Lastly, to test for heterogeneous effects over time, we replace $Poor_s$ with $Early_t$, a dummy that equals 1 if the year is 1998 or earlier, and zero otherwise.

Finally, we also explore how effects vary by sector of the economy. We re-estimate Equation 1, but replace the dependent variable to be the growth rate of the primary, secondary, or tertiary sector, in order to explore the differential effects of temperature by sector of the economy.

4 Main results

Table 2 displays the regression results from Equations 1 and 2 and includes columns with both linear and quadratic temperature specifications, for comparison. Throughout the table, temperature is demeaned, relative to the mean temperature for the sample period (23.7 °C). Columns 1 and 2 present the baseline results. We find that higher temperatures have a large and statistically significant effect on economic activity. Looking at the quadratic specification in column 2, we find that a 1 °C increase in temperature (relative to the sample mean) leads to a 2.5 percentage point reduction in the growth rate that year. Compared to the earlier literature, our estimate is larger than the 1.3 percentage point reduction in GDP per capita found by Dell et al. (2012) for poor countries, using country-level data and a linear model. Our larger estimate may be due in part to our use of subnational data, which allows us to detect some effects that country-level averaging may obscure. Our estimate is also larger than the subnational estimates found by Colacito et al. (2019) for a panel of US states, who find that a 1 °C increase in summer temperatures reduces growth rates by 0.27 to 0.45 percentage points. However, following the results from Dell et al. (2012), it is to be expected that temperature impacts would be substantially larger in a lower-middle-income country, such as India, as opposed to a high-income country, such as the United States.

[4] Appendix Table A2 presents a two-way frequency table for the "poor" and "high agricultural" variables. As can be seen from the table, the categorisation varies substantively across the two measures.

Figure 1 displays our baseline results graphically. Our estimates indicate that the optimal annual average temperature for economic output in India is 17.6 °C (64°F). This estimate of optimal temperature is significantly higher than the 13 °C optimum reported by Burke et al. (2015b) for a global panel of country-level data, suggesting India's economy may be comparatively well-adapted to moderately high temperatures. However, this optimum still falls far below India's average annual temperature (23.7 °C). Furthermore, temperatures above 17.6 °C reduce contemporaneous economic growth rates and these reductions are statistically significant at the 95% confidence level for temperatures of 22.5 °C and above.

Columns 3–8 of Table 2 present the results of our heterogeneous regressions. Columns 3 and 4 test for heterogeneity by income level. We find that higher temperatures adversely impact contemporaneous economic growth rates to a greater extent in poorer states than in richer states. Based on the estimates from Column 4, a 1 °C increase in contemporaneous temperatures (relative to our sample mean) reduces current growth rates by 4 percentage points in poorer states, but only by 1.7 percentage points in richer states. The difference between these impacts is statistically significant at the 95% confidence level. Columns 5 and 6 test for heterogeneity according to each state's level of reliance on agriculture. In the linear specification in Column 5, we find the unexpected result that losses due to high temperatures are greater in low agricultural states than high agricultural states. However, this difference is not statistically significant, due to a lack of precision in the estimate of the coefficient on high agriculture. In the quadratic specification (our preferred specification), we find that the losses from a 1 °C increase are similar in magnitude for high and low agricultural states and are not statistically different from each other. The last two columns look at heterogeneity by time period, comparing impacts pre- and post-1998. Here we fail to find evidence of heterogeneity, suggesting that the temperature–growth relationship has not changed substantively over this time period.

Figure 2 displays the heterogeneity results graphically. The left panel displays heterogeneity by income level. Here we see that although the optimum temperature for growth is roughly the same for both the poorer and the richer states, the decline in growth rates for temperatures above the optimum is sharper for the poorer states, suggesting that they are less able to cope with higher temperatures. The centre panel compares states by their level of reliance on agriculture. Here we see that, at high temperatures, the estimated magnitude of losses for high agricultural states exceeds that of low agricultural states, although the difference is not statistically significant.

The final panel of Figure 2 compares the earlier years of our sample (pre-1998) to the later years. Here, we see graphically the lack of a statistically significant difference in the response curves, pre- and post-1998. This suggests that, despite India's economic development over this period, economic growth has not become less sensitive to temperature.[5] This lack of difference is surprising since we might expect adaptation to occur over time (Barreca, Clay, Deschênes, Greenstone, & Shapiro, 2016; Taraz, 2017). On the other hand, the lack of adaptation over time mirrors results found in Burke and Emerick (2016), who use a long-difference method applied to US agriculture and fail to find evidence of substantial long-run adaptation to temperature. Our result also mirrors Carleton (2017) who fails to find evidence that farmer suicides in India are becoming less sensitive to temperature over time. Along similar lines, Burgess, Deschênes, Donaldson, and Greenstone (2017) find only weak evidence of adaptation over 1956-2000 when looking at the temperature–mortality relationship in India. The relatively short window of time that we are studying may also be a factor in why we fail to find a difference over time.

An important caveat to our heterogeneity analysis is that, although adaptation to temperature doesn't seem apparent, the overall economy of India is dynamic and has changed dramatically during our sample period. As a result, the classification of states as poor/rich or high/low agriculture would vary, depending on which year of data we relied on for classification. To demonstrate this, Appendix Tables A3 and A4 display the GSDP per capita and agricultural share for each state, for several different years from our sample, relative to

[5] We also fail to find evidence of a change over time of the relationship, if we restrict the analysis to only the richer states, or only the high agriculture states. Results available from the authors upon request.

the median for that year.[6] We prefer to use the classification based on 1981, the first year of our sample, as early values are more likely to be exogenous relative to shocks experienced during the sample period. However, as Appendix Tables A3 and A4 demonstrate, there are a lot of relative movements of these variables over time across states. Therefore to test the robustness of our heterogeneity results, Appendix Table A5 presents the heterogeneous results, but based on categorising states as poor/rich or high/low agriculture based on 2014 values, the last year of our sample. The magnitudes of our coefficient estimates for "poor" versus "rich" states are very similar to those in Table 2, although they are estimated with less precision in the case of the quadratic specification. Over all, we take these results as suggesting that our "poor" state heterogeneity results are fairly robust to alternate specifications. For agriculture, if we classify states based on their 2014 values, we find that losses are greater in high agriculture states, and that the difference is significant at the 90% level for the quadratic specification, a stronger result than we find in Table 2. Taken as a whole, this exercise reveals the difficulty of doing a heterogeneity analysis in the context of a country that is changing dramatically over the sample period.

In Table 3, we explore the robustness of our baseline results to several changes in specification. Column 1 presents our baseline quadratic specification, for reference. Our baseline specification includes a control for the one-year lagged growth rate, to address potential autocorrelation of growth rates. However, controlling for the lagged dependent variable in a short panel can potentially induce Nickell (1981) bias. To explore whether this is an issue for us, in Column 2, we drop the lagged growth rate from our regression. The estimated impact of a 1 °C increase (relative to the mean) falls from 2.5 to 1.9 percentage points, and the estimate loses statistical significance.[7] Given our relatively small sample size of about 900 observations, this is perhaps not surprising. However, it is worthwhile to note that the magnitude of the point estimate is still large and economically significant. Furthermore,

[6] In Appendix Table A3, values are coloured blue (black) if GSDP per capita in a given year and state was below (above) that year's median GSDP per capita, and similarly in Appendix Table A4 for agricultural shares.

[7] The R-squared of the regression also falls dramatically, from 0.401 to 0.265.

along the lines of Figure 1, if we recompute that figure using the new estimates from Column 1, we find that the optimal temperature for economic growth is 17.4 °C, which is essentially unchanged from our baseline specification. Temperatures over 22 °C have statistically significant losses, relative to this optimum, at the 90% confidence level, and temperatures over 29 °C have statistically significant losses at the 95% confidence level.

Our baseline specification uses heteroskedasticity robust standard errors that allow for the possibility that the residuals in our regression may be heteroskedastic; for example, the residuals from different states or years may have different variances. In Column 3 of Table 3, we test the robustness of our results to an alternate standard error specification. Namely, we use wild cluster bootstrap standard errors, where the unit of clustering is the state or union territory. Clustered standard errors allow for the possibility that the residuals associated with a state may be arbitrarily correlated with each other. We choose wild cluster bootstrap standard errors because our relatively small number of clusters (n=30) implies that regular cluster-robust standard errors would be downwards biased and hence inappropriate in this context (Cameron, Gelbach, & Miller, 2008). As can be seen in Column 3, with the use of the wild cluster bootstrap standard errors, the coefficient on quadratic temperature loses statistical significance. However, the linear term remains statistically significant at the 5% significance level, as does the impact of a 1 °C temperature increase (relative to the sample mean). The robustness of our results to an alternate standard error specification is reassuring.

In Column 4 of Table 3, we trim the top and bottom 1% of our observations, by GSDP growth rates, to verify that our results are not being driven by any outliers. Our results are robust to this variation in specification. Lastly, in Column 5, we exclude the hilly states of India, which are substantially colder than the rest of the country, to verify that these states are not driving our results.[8] As can be seen from the table, the coefficients on linear temperature and quadratic temperature do shift once the hilly states are excluded. Nevertheless, the magnitude of a 1 °C temperature increase (relative to the sample mean) on

[8] The hilly states that we exclude are Arunachal Pradesh, Himachal Pradesh, Jammu and Kashmir, Sikkim, and Uttarakhand. These states are small and together represent less than 3% of India's GDP.

current growth rates is virtually unchanged, both in size and significance level, demonstrating that these states are not overly driving our results.

In Table 4, we explore the impacts of temperature on sectoral output. We note that over our sample period, the primary, secondary, and tertiary sectors contributed an average of 28%, 26%, and 46%, respectively, to total economic output in India. Columns 1 and 2 look at the primary sector (agriculture, forestry and logging, fishing, and mining). Here we see large impacts of current temperature on contemporaneous growth rates, as would be expected. The quadratic specification in Column 2 suggests that a 1 °C temperature increase (relative to the sample mean) would decrease primary sector growth rates that year by 5.7 percentage points. This point estimate is substantially larger than our estimate for the impact of temperature on aggregate economic growth rates. But, it is also measured less precisely, and is only significant at the 90% confidence level.

Columns 3 and 4 of Table 4 look at the secondary sector (manufacturing, construction, and electricity, gas and water). Here, the point estimates of our coefficients are negative, but they are dramatically smaller in magnitude than those for the primary sector, and they are not statistically significant. However, we note that research with micro-data has found significant impacts of higher temperature on manufacturing in India (Somanathan et al., 2015). In addition, if we look at the manufacturing sector individually, we do indeed find a negative and significant effect of higher temperatures on contemporaneous growth rates (results available upon request). Columns 5 and 6 look at the tertiary sector (transport, storage and communication, trade, hotels and restaurants, banking, real estate, public administration, and other services). Here the coefficient magnitudes are similar to what we see for the secondary sector, but they are more precisely estimated. We find that the impact of a 1 °C increase in temperature (relative to the sample mean) is associated with a 1.2 percentage point reduction in growth rates that year, and that this estimate is significant at the 90% confidence level. Our results for the tertiary sector align with the results from Colacito et al. (2019), who find negative impacts of higher summer temperatures on the service sector and the financial sector. Another potential driver behind the tertiary sector results could be sectoral linkages in the Indian economy (Sastry, Singh, Bhattacharya, & Unnikrishnan, 2003).

5 Level versus growth effects

Having explored the impact of contemporaneous temperatures on growth rates in the same year, we now explore the impact of lagged temperatures. By simultaneously considering contemporaneous and lagged temperatures, we can test whether the effect of higher temperatures on economic activity is transitory or whether there is a more permanent impact on the underlying growth rate itself. To explore this idea, we draw from the discussions in Dell et al. (2012) and Colacito et al. (2019). We first present a simple model to clarify the difference between a level effect on output and a growth effect. We then describe our empirical strategy to test for these effects. Finally, we present our empirical results.

To fix ideas, let us assume that economic output is given by the following equation:

$$y_t = \alpha + y_{t-1} + \beta_1 T_t + \beta_2 T_t^2 + \beta_l^{lag} T_{t-1} + \beta_2^{lag} T_{t-1}^2 + \epsilon_t. \tag{3}$$

In this equation, β_1 and β_2 capture the nonlinear effect of current temperature on economic output, while β_l^{lag} and β_2^{lag} capture the nonlinear effect of lagged temperature on economic output. To simplify, let us assume that $\epsilon_t = 0\,\forall t$. Following Colacito et al. (2019), let us consider the impact of a shock in year $t = 1$ that permanently raises temperatures by 1 °C, from $T_0 = 0$ to $T_t = 1, \forall t \geq 1$. This is a simplified way of capturing climate change, which we just use to fix ideas. Given this hypothetical path of temperatures, we can use equation 3 recursively to calculate both the level of economic output and the growth rate of economic output in each subsequent year to the temperature increase. We get that:

$$y_t = (y_0 + \beta_1 + \beta_2) + (t-1)[\alpha + (\beta_1 + \beta_2 + \beta_l^{lag} + \beta_2^{lag})], \text{ and} \tag{4}$$

$$\Delta y_1 = \alpha + \beta_1 + \beta_2, \text{ and } \Delta y_t = \alpha + (\beta_1 + \beta_2 + \beta_l^{lag} + \beta_2^{lag}), \forall t \geq 2. \quad (5)$$

Following Colacito et al. (2019), there are three cases of interest. First, if neither contemporaneous nor lagged temperature has an effect on economic output, then $\beta_1 = \beta_2 = \beta_l^{lag} = \beta_2^{lag} = 0$. Second, if $\beta_1 + \beta_2 + \beta_l^{lag} + \beta_2^{lag} = 0$, then the 1 °C increase in temperature has a permanent effect on output (as captured by the terms $\beta_1 + \beta_2$ in equation 5), but it only affects the growth rate in the first period. This scenario has been referred to as the "level effects" case. Third, if $\beta_1 + \beta_2 + \beta_l^{lag} + \beta_2^{lag} \neq 0$ then the permanent 1 °C increase in temperature will affect both the level of output and the growth rate of output, on an ongoing basis. We refer to this as the "growth effects" case. Any effects detected under a "growth effects" scenario will compound over time, leading to greater potential economic losses than those sustained under the "level effects" scenario.

To test whether the temperature–output relationship in India is best characterised by a level effects or a growth effects scenario, we follow Dell et al. (2012) and Colacito et al. (2019) and integrate lagged temperature into our regression specification. Specifically, we estimate a regression of the format:

$$\Delta y_{s,t} = \beta_l T_{s,t} + \beta_2 T_{s,t}^2 + \beta_l^{lag} T_{s,t-1} + \beta_2^{lag} T_{s,t-1}^2 + f(P_{s,t}, P_{s,t-1}) + \rho \Delta y_{s,t-1} + \alpha_s + \alpha_t + \epsilon_{s,t}, \quad (6)$$

where $T_{s,t-1}$ represents temperature from the previous fiscal year, and $f(P_{s,t}, P_{s,t-1})$ is a quadratic function of contemporaneous and lagged precipitation. Since temperature is demeaned in this regression, the sum of β_1, β_2, β_1^{lag} and β_2^{lag} will capture the impact on growth rates of a permanent 1 °C increase in temperatures, relative to the sample mean temperature in India.

Table 5 presents our analysis of level effects versus growth effects. Columns 1 and 2 present our baseline linear and quadratic specifications, for reference, and Columns 3 and 4 integrate controls for lagged temperature. In Columns 3 and 4, the coefficients on contemporaneous temperature (and its square) remain negative and in fact increase in magnitude. In contrast, the coefficients on lagged temperature are positive. This makes sense: if temperatures were high last year, and growth last year was lower than usual as a result, then growth this year may be relatively higher, as economic output returns to its expected trajectory. When we sum the temperature coefficients to determine the impact of a permanent 1 °C increase on growth rates, the point estimate of the effect we find is substantial—a 1 percentage point permanent decrease in growth rates—but it is imprecisely estimated and not statistically significant. This result holds for both our linear and quadratic specifications, and is in contrast to Colacito et al. (2019), who find that temperature has significant impacts on US economic output, both in terms of levels and growth rates.

In considering our growth versus level effects analysis, there are two possibilities. One possibility is that for the Indian economy, higher temperatures affect economic activity contemporaneously, depressing the current growth rate, but do not have persistent effects on the growth rate. A possible mechanism for this result could be the fact that the Indian economy is more reliant on agriculture than the US economy: it is possible that shocks to agricultural growth are less persistent than shocks to the other sectors of the economy. We note that, when studying a panel of African countries, Abidoye and Odusola (2015), failed to find evidence of long-run impacts of temperature on growth rates, when looking at five-year averages, a result that is potentially consistent with what we are finding here. On the other hand, looking at a global panel of countries, Dell et al. (2012) find that higher temperatures have a permanent impact on growth rates in poor countries. Therefore, a second, and perhaps more likely, possibility is that we are insufficiently powered to detect persistent growth rate effects. To compare to another study that uses subnational data, for example, we note that Colacito et al. (2019) have a sample size that is over three times as large as ours (2856 observations versus 926 observations).

6 Conclusion

As climate change accelerates, the economies of low- and middle-income countries may be especially vulnerable to climate-induced economic damages. In this paper, we explored the impact of temperatures on economic output in India, using subnational data. We found that contemporaneous temperature has a large and statistically significant effect on the economic growth rate in the current year. This effect is robust to multiple variations in specification. We found evidence of larger impacts in poorer states. Looking at sectoral output, we found the largest effects come from the primary sector (agriculture, forestry, fishing, and mining). In contrast to these contemporaneous effects of temperature on current economic output, we did not find evidence that a permanent 1 °C increase in temperature would permanently reduce the growth rate. This may be because we are relatively underpowered to detect such an effect, or it may be due to structural differences between the Indian economy as compared to the US economy (the focus of earlier similar analysis).

Our analysis augments existing sector-specific research on India by providing evidence of a significant link between temperature and contemporaneous overall economic activity at the state level. It underscores the potential for uncovering a richer understanding of the temperature-growth relationship by exploiting information in state-level data that may be lost through aggregation when only country-level data is used. Our use of subnational data also facilitates heterogeneity analysis that, by shedding light on specific states in India that may be most vulnerable to climate change, could potentially inform policy approaches to mitigation and adaptation.

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Figures

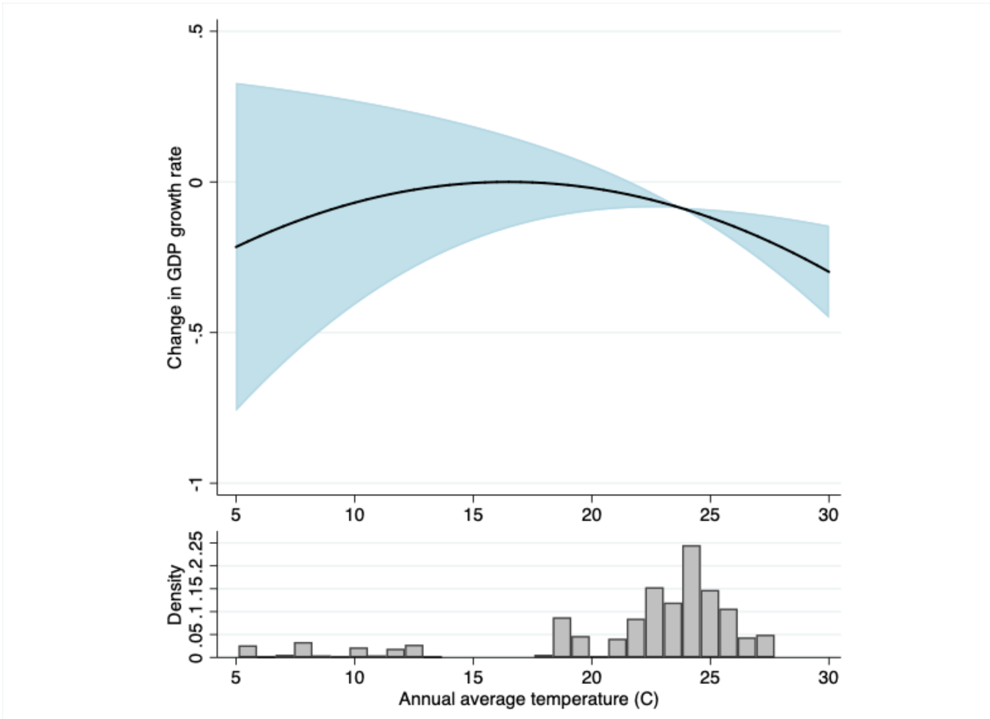

Figure 1: Effects of annual average temperature on GDP growth rates

The figure displays the nonlinear relationship between annual average temperature and GDP growth rates for the fiscal years 1982-83 to 2014-15. The black line represents the impact of temperature on growth, relative to the optimum. The shaded blue area denotes the 95% confidence interval. The regression model controls for one-year lagged growth rates, state fixed effects, year fixed effects, and precipitation. The histogram shows the distribution of annual temperature.

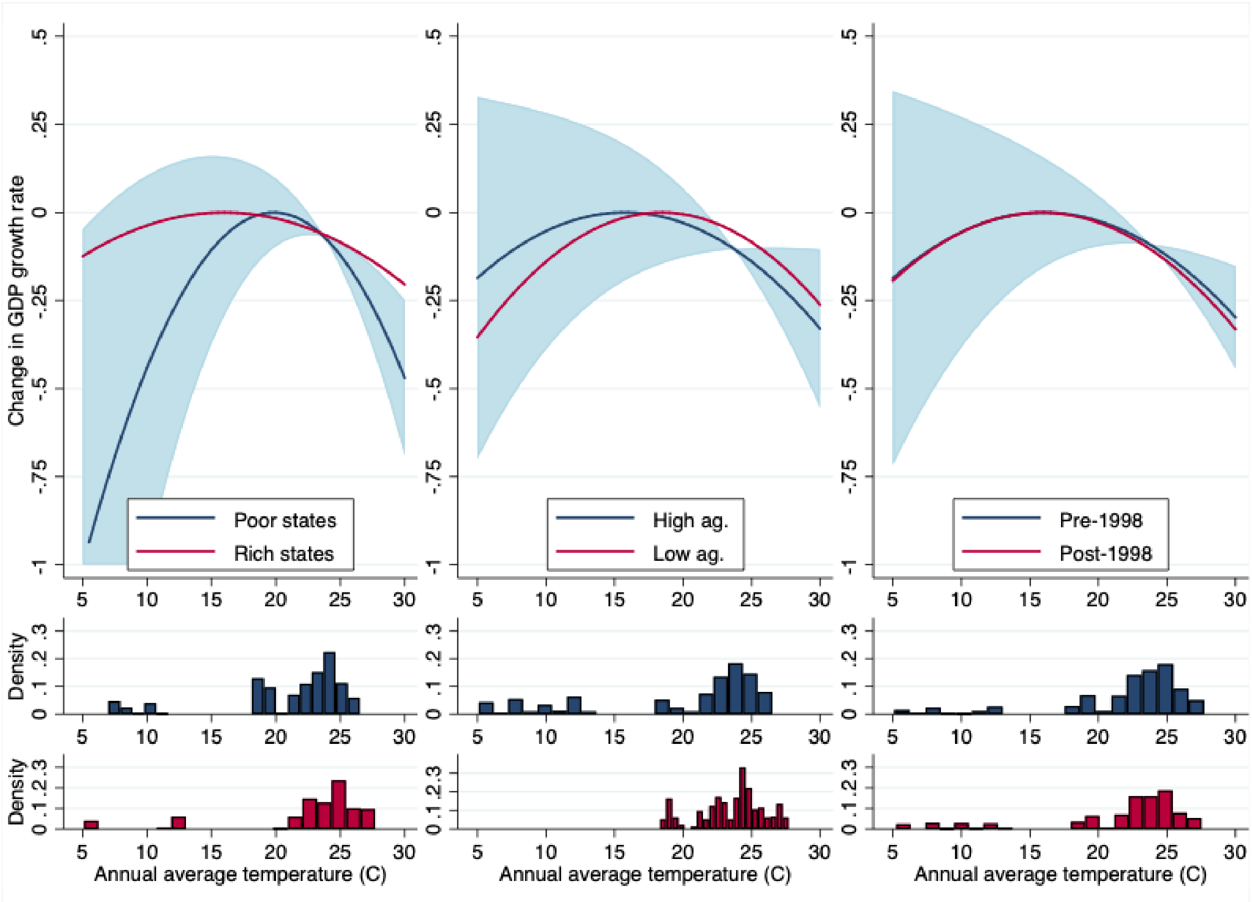

Figure 2: Heterogeneous effects of annual average temperature on GDP growth rates

The figure displays heterogeneous nonlinear relationships between annual average temperature and GDP growth rates for the fiscal years 1982-83 to 2014-15, for six subgroups (poor states, rich states, high agriculture states, low agriculture states, pre-1998 observations, and post-1998 observations). The blue and red lines represents the impact of temperature on growth, relative to the optimum, for each subgroup. The shaded blue area denotes the 95% confidence interval for the subgroup denoted with the blue line. The regression model controls for one-year lagged growth rates, state fixed effects, year fixed effects, and precipitation. The histograms show the distribution of annual temperature, by subgroup.

Tables

Table 1: Summary statistics

	(1) Unweighted	(2) Weighted
Temperature	20.73	23.74
	(6.758)	(3.422)
Precipitation	1.479	1.063
	(0.800)	(0.500)
Growth rate, total	0.0649	0.0630
	(0.0591)	(0.0524)
Growth rate, primary sector	0.0343	0.0363
	(0.114)	(0.127)
Growth rate, secondary sector	0.0771	0.0692
	(0.123)	(0.0770)
Growth rate, tertiary sector	0.0777	0.0766
	(0.0489)	(0.0380)
Share of GSDP in primary sector	0.284	0.281
	(0.124)	(0.116)
Share of GSDP in secondary sector	0.256	0.263
	(0.0937)	(0.0676)
Share of GSDP in tertiary sector	0.459	0.456
	(0.116)	(0.104)
Observations	926	926

Note: The table displays mean coefficients, with standard deviations in parentheses. The time period is the fiscal years 1982-83 to 2014-15. In the first column, all state-year observations are evenly weighted. In the second column, each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GSDP, relative to the national GDP.

Table 2: Impact of temperature on growth rates: Baseline results and tests for heterogeneity

	(1) Growth	(2) Growth	(3) Growth	(4) Growth	(5) Growth	(6) Growth	(7) Growth	(8) Growth
Temperature	-0.0300**	-0.0237**						
	(0.0112)	(0.0107)						
Temperature * Temperature		-0.00164**						
		(0.000696)						
Poor * Temperature			-0.0415**	-0.0355**				
			(0.0173)	(0.0135)				
Poor * Temperature * Temperature				-0.00455***				
				(0.00140)				
Rich * Temperature			-0.0232***	-0.0161**				
			(0.00773)	(0.00671)				
Rich * Temperature * Temperature				-0.00104**				
				(0.000474)				
High agriculture * Temperature					-0.0274	-0.0259*		
					(0.0165)	(0.0149)		
High agriculture * Temperature * Temperature						-0.00162*		
						(0.000825)		
Low agriculture * Temperature					-0.0329***	-0.0207*		
					(0.00916)	(0.0116)		
Low agriculture * Temperature * Temperature						-0.00196		
						(0.00146)		
Early * Temperature							-0.0306***	-0.0235**
							(0.0111)	(0.0101)
Early * Temperature * Temperature								-0.00153**
								(0.000693)
Late * Temperature							-0.0319***	-0.0261**
							(0.0113)	(0.0104)
Late * Temperature * Temperature								-0.00165**
								(0.000713)
Observations	926	926	926	926	926	926	926	926
R^2	0.3877	0.4008	0.3910	0.4106	0.3880	0.4013	0.3898	0.4036

Note: The regression covers 30 Indian states and union territories, for the fiscal years 1982-3 to 2014-15. Temperature is demeaned relative to the mean for this sample period. All columns control for one-year lagged growth rates, state fixed effects, and year fixed effects. Each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GDP, relative to the national GDP. Heteroskedasticity robust standard errors are reported. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Impact of temperature on growth rates: Robustness

	(1) Growth	(2) Growth	(3) Growth	(4) Growth	(5) Growth
Temperature	-0.0237**	-0.0169	-0.0237**	-0.0223**	-0.0191*
	(0.0107)	(0.0107)	(0.0106)	(0.00919)	(0.0107)
Temperature * Temperature	-0.00164**	-0.00167**	-0.00164	-0.00143**	-0.00529***
	(0.000696)	(0.000812)	(0.00114)	(0.000591)	(0.00149)
R^2	0.401	0.265	0.418	0.372	0.417
Impact of a 1C increase	-0.0253	-0.0186	-0.0253	-0.0237	-0.0244
Wald's test p-value	0.0274	0.101	0.0180	0.0169	0.0359
Observations	926	926	926	908	777

Note: The regression covers 30 Indian states and union territories, for the fiscal years 1982-3 to 2014-15. Temperature is demeaned relative to the mean for this sample period. All columns control for state fixed effects and year fixed effects. Each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GDP, relative to the national GDP. Column 1 is the baseline specification. Column 2 drops lagged growth rates as a control. Column 3 uses wild cluster bootstrap standard errors. Column 4 trims the top and bottom 1% of observations by GDP growth rates. Column 5 excludes the hilly states. Heteroskedasticity robust standard errors are reported in all columns except Column 3. The impact of a contemporaneous 1 °C (relative to the sample mean), is reported for each column, along with its corresponding p-value. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Impact of temperature on growth rates. Effects by sector

	(1) Primary	(2) Primary	(3) Secondary	(4) Secondary	(5) Tertiary	(6) Tertiary
Temperature	-0.0814***	-0.0532*	-0.00670	-0.0109	-0.0109	-0.0119
	(0.0293)	(0.0300)	(0.0111)	(0.0134)	(0.00661)	(0.00704)
Temperature * Temperature		-0.00381**		-0.00103*		-0.000771**
		(0.00175)		(0.000604)		(0.000333)
R^2	0.339	0.362	0.216	0.218	0.254	0.257
Impact of a 1C increase		-0.0570		-0.0119		-0.0127
Wald's test p-value		0.0684		0.382		0.0864
Observations	926	926	926	926	926	926

Note: The regression covers 30 Indian states and union territories, for the fiscal years 1982-83 to 2014-15. Temperature is demeaned relative to the mean for this sample period. All columns control for one-year lagged growth rates, state fixed effects, and year fixed effects. Each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GDP, relative to the national GDP. Heteroskedasticity robust standard errors are reported. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Impact of temperature on growth rates. Testing for level versus growth effects

	(1) Growth	(2) Growth	(3) Growth	(4) Growth
Temperature	-0.0300**	-0.0237**	-0.0423***	-0.0359***
	(0.0112)	(0.0107)	(0.0128)	(0.0108)
Temperature * Temperature		-0.00164**		-0.00197**
		(0.000696)		(0.000824)
Lagged temperature			0.0322***	0.0264***
			(0.00958)	(0.00847)
Lagged temperature * Lagged temperature				0.00111
				(0.000680)
R^2	0.388	0.401	0.406	0.424
Impact of a permanent 1C increase			-0.0102	-0.0103
Wald's test p-value			0.288	0.393
Observations	926	926	926	926

Note: The regression covers 30 Indian states and union territories, for the fiscal years 1982-83 to 2014-15. Temperature is demeaned relative to the mean for this sample period. All columns control for one-year lagged growth rates, state fixed effects, and year fixed effects. Each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GDP, relative to the national GDP. Heteroskedasticity robust standard errors are reported. * p<0.10, ** p<0.05, *** p<0.01

A Appendix Figures and Tables

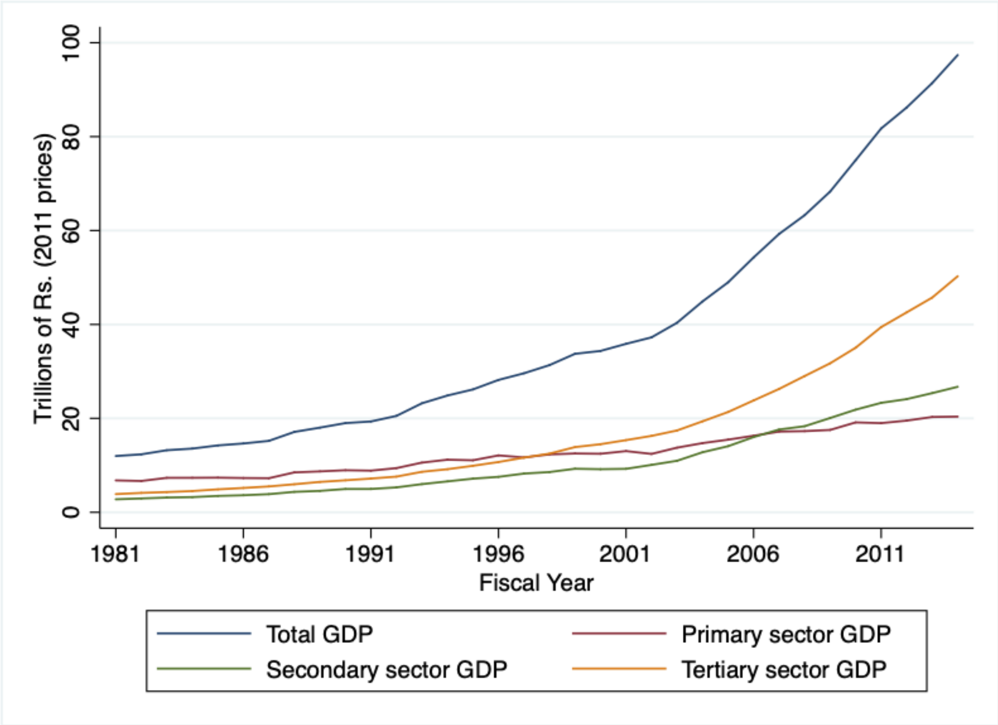

Figure A1: Gross domestic product (GDP) of India, 2011 prices (in trillion Rs.)

The figure displays total GDP and GDP by sector for the fiscal years 1981-82 to 2014-15.

Table A1: Classification of States and Union Territories

State or union territory	Income classification	Agricultural classification
Andhra Pradesh	Poor	High
Arunachal Pradesh	Rich	High
Assam	Poor	Low
Bihar	Poor	Low
Chandigarh	Rich	Low
Chhattisgarh	Rich	High
Delhi	Rich	Low
Goa	Rich	Low
Gujarat	Rich	Low
Haryana	Rich	High
Himachal Pradesh	Rich	High
Jammu and Kashmir	Rich	High
Jharkhand	Poor	Low
Karnataka	Poor	Low
Kerala	Poor	Low
Madhya Pradesh	Rich	High
Maharashtra	Rich	Low
Manipur	Poor	High
Meghalaya	Poor	Low
Nagaland	Poor	Low
Odisha	Poor	High
Puducherry	Rich	Low
Punjab	Rich	High
Rajasthan	Poor	High
Sikkim	Poor	Low
Tamil Nadu	Rich	High
Tripura	Poor	High
Uttar Pradesh	Poor	High
Uttarakhand	Poor	High
West Bengal	Rich	Low

Note: States are characterised as poor (rich) if their GSDP per capita is below (above) the median in 1981, the first year of our sample. States are characterised as high (low) agriculture if their share of agriculture in GSDP is above (below) the median in 1981. See Section 2 for more details.

Table A2: Two-Way Frequency Table of Poor States versus High-Agriculture States

	High Agriculture	Low Agriculture	Total
Poor	8	7	15
Rich	7	8	15
Total	15	15	30

Note: States are characterised as poor (rich) if their GSDP per capita in 1981 is below (above) the median. States are characterised as high (low) agriculture if their share of agriculture in 1981 is above (below) the median. See Section 2 for more details.

Table A3: GSDP Per Capita, by Year, 2011 Prices (Thousands of Rs.)

State	1981	1991	2001	2011	2014
Andhra Pradesh	16.983	19.844	37.991	73.317	102.017
Arunachal Pradesh	18.846	31.970	36.023	63.492	68.604
Assam	14.785	17.099	27.257	45.418	50.401
Bihar	14.384	17.017	13.262	24.000	27.581
Chandigarh	45.135	65.283	111.017	177.650	215.222
Chhattisgarh	20.495	24.166	27.820	60.704	71.349
Delhi	45.135	65.283	85.595	180.992	209.904
Goa	36.062	56.343	93.534	275.698	212.304
Gujarat	23.178	27.448	44.364	92.951	111.551
Haryana	26.478	38.137	56.304	108.270	124.004
Himachal Pradesh	19.110	24.252	51.471	106.675	125.799
Jammu and Kashmir	17.446	17.513	32.529	60.904	62.167
Jharkhand	14.384	17.017	24.299	43.430	49.661
Karnataka	17.323	24.845	39.666	91.750	108.677
Kerala	16.346	20.884	46.871	103.143	119.226
Madhya Pradesh	20.495	24.166	26.217	43.039	49.093
Maharashtra	26.423	36.931	51.702	102.793	116.204
Manipur	15.855	20.378	28.162	49.019	54.343
Meghalaya	15.211	20.561	34.650	65.869	64.937
Nagaland	17.594	21.528	36.247	65.261	74.834
Orissa	13.704	16.756	24.255	53.792	61.784
Puducherry	29.971	32.330	79.991	120.848	138.118
Punjab	31.692	42.159	58.044	94.396	103.643
Rajasthan	14.197	19.650	31.534	62.847	69.479
Sikkim	17.082	37.501	38.041	179.947	199.073
Tamil Nadu	17.937	25.014	44.615	97.148	110.043
Tripura	13.428	18.016	36.494	55.519	70.486
Uttar Pradesh	14.830	18.934	21.824	34.931	38.718
Uttarakhand	14.830	18.934	34.833	110.028	126.567
West Bengal	18.049	24.350	37.267	56.404	67.029
Median	17.520	24.166	36.881	69.593	88.425

Note: Values are coloured blue (black) if GSDP per capita in a given year and state was below (above) that year's median GSDP per capita. GSDP per capita is unavailable for Chandigarh prior to 2001, so it is imputed with the values of Delhi, the most comparable unit.

Table A4: Agricultural Share of GSDP, by Year

State	1981	1991	2001	2011	2014
Andhra Pradesh	0.450	0.362	0.285	0.286	0.300
Arunachal Pradesh	0.478	0.442	0.282	0.307	0.292
Assam	0.416	0.377	0.328	0.243	0.235
Bihar	0.412	0.343	0.329	0.281	0.225
Chandigarh	0.039	0.028	0.010	0.007	0.005
Chhattisgarh	0.493	0.388	0.251	0.212	0.190
Delhi	0.039	0.028	0.013	0.008	0.004
Goa	0.187	0.123	0.100	0.067	0.089
Gujarat	0.400	0.227	0.181	0.190	0.160
Haryana	0.508	0.436	0.281	0.233	0.186
Himachal Pradesh	0.478	0.355	0.255	0.211	0.192
Jammu and Kashmir	0.474	0.375	0.313	0.188	0.155
Jharkhand	0.412	0.343	0.221	0.175	0.154
Karnataka	0.448	0.344	0.244	0.139	0.116
Kerala	0.352	0.328	0.212	0.155	0.123
Madhya Pradesh	0.493	0.388	0.272	0.316	0.331
Maharashtra	0.273	0.175	0.155	0.128	0.099
Manipur	0.448	0.351	0.290	0.242	0.233
Meghalaya	0.357	0.238	0.222	0.172	0.188
Nagaland	0.313	0.295	0.319	0.388	0.375
Orissa	0.513	0.369	0.315	0.209	0.203
Puducherry	0.180	0.144	0.060	0.058	0.056
Punjab	0.499	0.484	0.362	0.322	0.276
Rajasthan	0.505	0.414	0.324	0.306	0.280
Sikkim	0.505	0.399	0.215	0.085	0.079
Tamil Nadu	0.275	0.233	0.166	0.127	0.119
Tripura	0.500	0.377	0.272	0.349	0.372
Uttar Pradesh	0.500	0.418	0.337	0.274	0.235
Uttarakhand	0.500	0.418	0.247	0.139	0.116
West Bengal	0.276	0.304	0.294	0.176	0.158
Median	0.448	0.353	0.264	0.199	0.187

Note: Values are coloured blue (black) if agricultural share of GSDP in a given year and state was above (below) that year's median agricultural share of GSDP. Agricultural share of GSDP is not available for Chandigarh prior to 2001, so we impute it with the values of Delhi, the most comparable unit.

Table A5: Impact of temperature on growth rates: Heterogeneous effects using 2014 values

	(1) Growth	(2) Growth	(3) Growth	(4) Growth
Poor * Temperature	-0.0388**	-0.0304*		
	(0.0163)	(0.0152)		
Poor * Temperature * Temperature		-0.00133		
		(0.000829)		
Rich * Temperature	-0.0249***	-0.0147		
	(0.00868)	(0.00904)		
Rich * Temperature * Temperature		-0.00202**		
		(0.000951)		
High Agriculture * Temperature			-0.0364**	-0.0334**
			(0.0160)	(0.0138)
High Agriculture * Temperature * Temperature				-0.00250*
				(0.00141)
Low Agriculture * Temperature			-0.0242**	-0.0130
			(0.00925)	(0.00857)
Low Agriculture * Temperature * Temperature				-0.00105*
				(0.000562)
Observations	926	926	926	926
R^2	0.3902	0.4122	0.3891	0.4123

Note: The regression covers 30 Indian states and union territories, for the fiscal years 1982-3 to 2014-15. Temperature is demeaned relative to the mean for this sample period. All columns control for one-year lagged growth rates, state fixed effects, and year fixed effects. Each state-year observation is weighted by the proportion, averaged over the whole sample, of that state's GDP, relative to the national GDP. Heteroskedasticity robust standard errors are reported. * p<0.10, ** p<0.05, *** p<0.01