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The Dynamic Causal Impact of Climate Change on Economic Activity - A Disaggregated Panel Analysis of India

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The Dynamic Causal Impact of Climate Change on Economic Activity - A Disaggregated Panel Analysis of India

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Abstract

This paper investigates the long-term impact of climate change on Indian economic growth, both at aggregate and dis-aggregated levels across regions and sectors. A simple Ramsey model is built to show that the resource abundance, climatic exposure, and state capacity affecting the rate of resource mobilisation for productivity and efficiency improvement determine regional growth. A cross-sectional augmented auto-regressive distributed lag model (CS-ARDL), addressing endogeneity, heterogeneity, and cross-sectional dependence with stochastic trends, employed in 29 major states from 1980 to 2019, confirms a significant and negative impact of temperature rise on total factor productivity and the resultant economic growth. On average, one Celcius degree of temperature rise has depressed economic growth by approximately 3.89%, with substantial variations across states, sectors, and income groups. The variation in labour relations, industrialisation level, forest cover, and debts across the states affecting the ecological damage and efficiency changes in labour and capital differentially has been found responsible for the variation in TFP and the resultant growth. Our estimated coefficients combined with the projected temperature reveal that poorer and less developed states are expected to be more vulnerable than others because of their dependence on agriculture and ecological resources. The GSDP growth is projected to decrease by a range of 5.25% to 24.51% during 2020 to 2100 from the Stringent Mitigation scenario (SSP1-2.6) to the Business-as-Usual scenario (SSP5-8.5).
JEL Code: O44, Q54,Q51, Q54.
Keywords: climate change, economic growth, India, panel data, adaptation

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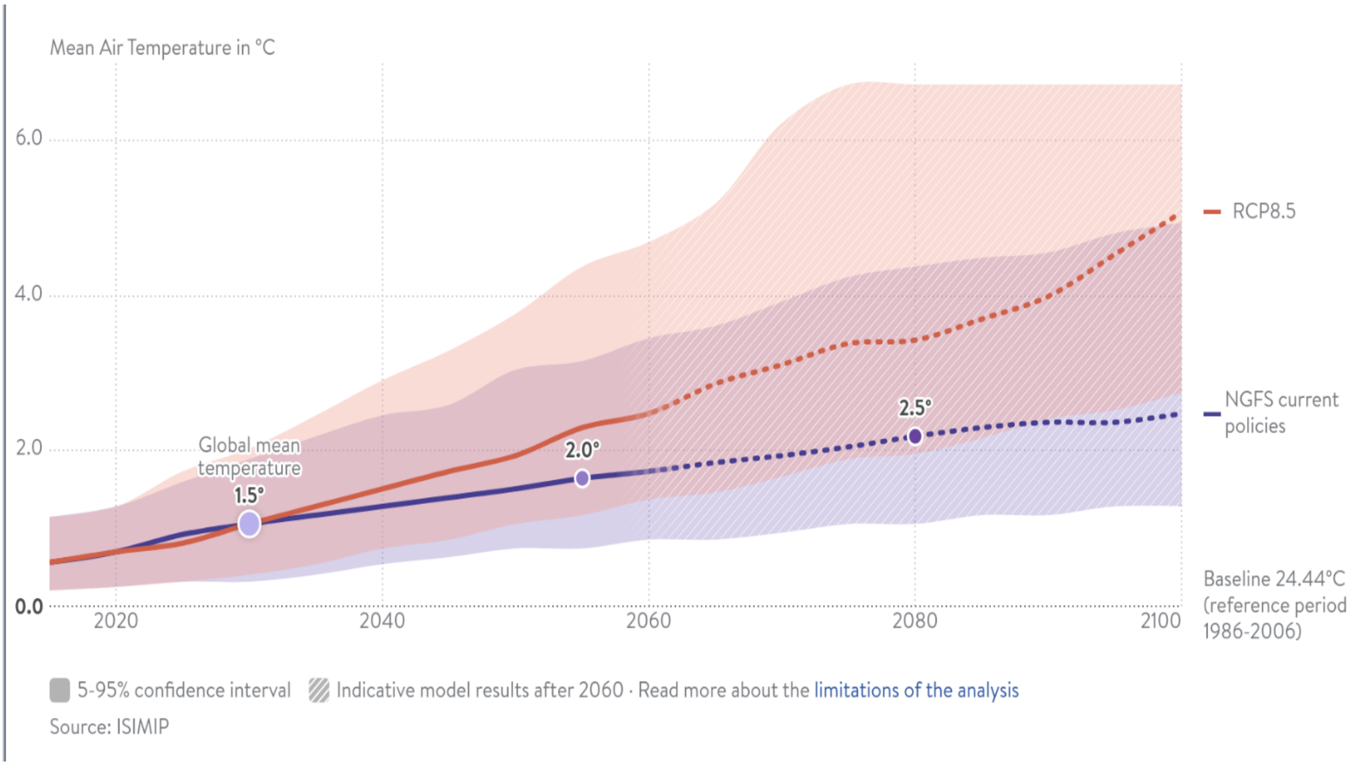
1 Introduction

The growing consumption of fossil fuels raises the stock of Greenhouse gases, degrades the environmental quality and thereby increases surface temperature. The temperature rise tends to reduce the total factor productivity of emerging economies by damaging ecological services and efficiency losses of labour and capital (Kumar and Maiti, 2024). If so, the drop in productivity must dampen economic growth, and a typical developing economy needs to take care and effectively implement mitigation strategies for environmental challenges to sustain economic growth. Since a small economy receives the global temperature exogenously, it can only deploy mitigation strategies to minimise the local impact by reducing the fossil fuel consumption and investing for renewable resources. In a country under a federal setting, the loss of growth may vary and be even higher in regions with resource abundance, greater climatic exposures, and the state's capacity constraint to deal with mitigation strategies. Therefore, this paper investigates the impact of temperature rise on the economic growth of a typically large developing economy like India and its variation across federal states.

Figure (1) Future Temperature Rise in India



Notes: Absolute change in mean temperature in NGFS and RCP Scenarios
Source- Climate Analytics-Climate impact explorer

Climate change has dual economic implications, affecting both supply and demand. On the demand side, the escalating frequency and severity of extreme weather events introduce heightened uncertainty into markets. These events disrupt value chains, leading to increased insurance costs and decreased consumer purchasing power. Simultaneously, shifting consumer preferences towards sustainable products and services and heightened environmental awareness reshape demand patterns. This dynamic creates a dual challenge for businesses: adapting to market uncertainties while aligning with evolving consumer expectations for eco-friendly practices. Conversely, the supply side experiences direct ramifications from climate change. The altering climate conditions, such as rising temperatures and erratic precipitation patterns, directly influence production processes and resource availability. For instance, agriculture, a critical component of many supply chains, faces challenges due to changing weather patterns, impacting the supply of raw materials. Moreover, regulatory shifts to mitigate climate change may increase production costs, requiring businesses to reevaluate supply chain strategies and invest in sustainable practices to align with evolving norms (Andersson et al., 2020; RBI, 2023).

In recent research, several studies have shown the adverse impact of climate-related variables on global economic growth across societies and economies (Chang et al., 2023; Kolstad and Moore, 2020). Since India is located in the tropical region where the consequence of climate change-induced weather disturbances has been thriving fast, it has experienced its hottest February in 2023, indicating a significant departure from the historical climate trend. Moreover, extreme weather events, including hailstorms, unseasonal rain, and rising temperatures, have wreaked havoc on the country, causing loss of life, crop damage, and extensive property damage (IMD, 2022). The diverse geographical features of India intensify its susceptibility to climate events, ranging from the Himalayas to the far desert, making it susceptible to a wide range of temperature and precipitation patterns. Additionally, India's economic structure, with the growing contribution of service sector and changing emission profiles from different industries, is closely tied to environmental factors. Specific sectors, like metal industries and transport, heavily dependent on fossil fuels, are particularly emission-intensive. The annual mean temperature has steadily increased, with recent years experiencing unprecedented warmth (RBI, 2023). Moreover, India emitted 2299 million tonnes of carbon dioxide in 2018. According to the scientific literature, such irregularities in temperature are the outcomes of global warming and can have profound economic implications (Krishnan et al., 2020). Several studies showed that climate change has significantly and negatively impacted productivity growth, influencing the developing world more than that of developed economies (Moore and Diaz, 2015a; Dietz and Stern, 2015; Moore and Diaz, 2015b). The declined productivity is expected to slow down the economic growth. During the last two or three decades, the Indian economy has experienced significant economic growth and revealed much resilience to sustain it during the global crises due to financial turmoil in

2008 and the COVID pandemic in 2020-21. The sustainability of such growth momentum has been questioned without a sound mitigation strategy (Maiti et al., 2023). There is a consistent upward trend in temperatures across most Indian states. India is estimated to have the highest social cost of carbon at the country level (Ricke et al., 2018). There has been limited research on how seasonal temperature variations impact India's overall economic output.

A few works exist in India showing the impact of climate change on growth by state. A study by Jain et al. (2020) found that a one-degree Celsius temperature increase in India was associated with a 2.5% reduction in the growth rate. This impact was more severe in poorer states and the agricultural regions. On the other hand, Sandhani et al. (2023) revealed that rising temperatures harm economic growth, especially in poorer districts with poor socio-economic environments. However, they failed to show the channels affecting their growth rates and their variations across the states in the same federal setting. Moreover, their estimates from such a large panel database may have suffered from endogenous and cross-sectional dependence bias (Kumar and Maiti, 2024; Kahn et al., 2021). The choice of temperature variables in climate econometrics research has played a pivotal role in estimating the impact of temperature on economic growth (Chang et al., 2023).

Seasonal temperature dynamics emerge as a pivotal factor in unravelling the intricate economic repercussions of climate change. Beyond traditional metrics, such as annual averages, delving into seasonal variations unveils nuanced impacts across diverse sectors (Colacito et al., 2019). While rising summer temperatures may detrimentally affect agricultural value addition, they paradoxically bolster economic production in other sectors. By scrutinising seasonal temperature dynamics, we aim to comprehensively understand the multifaceted nexus between climate change and economic growth. To the best of our knowledge, this study is the first to study the ramifications of seasonal climate change (temperature) on GDP within the unique context of India. This study reveals that temperature plays a significant role in driving seasonal economic cycles, alongside preferences and technology shifts in India.

Our study examines how rising temperatures due to climate change impacted India's long-term economic growth and its variation from 1980 to 2019 across 29 major states. It builds on a conceptual framework using a simple Ramsey framework, assuming that climate change can significantly impact productivity growth in three channels by damaging ecological services and reducing the labour and capital efficiencies arising from rising temperatures. The model captures how climate change (specifically temperature), arising from global warming at the national and provincial levels, negatively affects labour and capital efficiencies and ecosystem services and, consequently, dampens the growth of the Gross State Domestic Product (GSDP) growth rate. The econometric model used here to analyse them empirically considers the dynamic and feedback effects between climate change and economic variables. We use annual temperature as a proxy for climate change to avoid common statistical issues related to trended variables like temperature.

The existing studies, which quantified the impact of temperature on macroeconomic indicators, have mainly used reduced-form econometrics methods and hence suffered from potential biases in panel data analysis (Kahn et al., 2021; Chang et al., 2023). Climate change variables have primarily been regarded as exogenous indicators, neglecting the possibility of reverse causality. In assessing the impact of climate change on economic growth, it is essential to acknowledge that temperature might not be strictly exogenous but rather semi-endogenous. In other words, economic growth in the past could have feedback effects on future temperature (Kahn et al., 2021; Kumar and Maiti, 2024). Moreover, Schultz and Mankin (2019) emphasised that national governments run weather stations for collecting meteorological data. The extent of impacts depends on the level of its coverage and the continuity of such coverage depending on their political capabilities. Severe instability can damage such infrastructure, diverting resources from weather data collection and causing gaps in records, affecting the outcome of interest. This raises an endogeneity issue. Moreover, prior research has neglected the possibility of unit roots in panel data despite indicating stochastic trends reflected in the persistent temperature increases observed across nearly all states in our dataset. The CS-ARDL model addresses cross-sectional dependence, heterogeneous impacts, and endogeneity in the stochastic variables (Chudik and Pesaran, 2015; Herzer, 2019; Kumar and Maiti, 2024). This study relies on the cross-sectional augmented autoregressive distributed lag model (CS-ARDL) (Chudik and Pesaran, 2015; Ditzen, 2021) to avoid the cross-sectional dependence and heterogeneous effect of temperature on GSDP growth rate across states that allows us to test for weak exogeneity and find the consistent parameter in the presence of feedback effects from GSDP growth rate to temperature.

Our study distinguishes itself from previous research on conceptual and empirical grounds, such as (Jain et al., 2020; Sandhani et al., 2023; Dell et al., 2012). A substantial body of climate econometrics literature has employed panel models with various Fixed Effects (FE) to explore the relationship between temperature change and GDP (Dell et al., 2012; Jain et al., 2020). When applying the panel FE estimator, one or more dependent variables may not be strictly exogenous (Kahn et al., 2021). Even their limitation lies in prioritising short-term, weather-related shocks over the variability in long-term climate conditions (Kalkuhl and Wenz, 2020). To address this issue, we utilise the CS-ARDL model in our analysis. Our study focuses on average seasonal temperatures. We tackle prevailing challenges by utilising random fluctuations in seasonal temperatures across years and states, resulting in more accurate and robust estimates. Furthermore, we demonstrate that temperature can influence economic activities distinctively through its effects on the efficiency changes in labour, capital and ecosystem services. Using the estimated parameters, our paper attempted to project future growth losses by incorporating the projected temperature of the Indian economy under various scenarios for Representative Concentration Pathways (RCPs) and Network for Greening the Financial System (NGFS) [1] during the period from 2021 to 2100. This comprehensive approach advances our understanding of the complex interplay between temperature rise and economic growth in the face of climate change.

Hence, this paper adds to the literature on the relationship between climate and economic growth in multiple facets. We empirically identify three potential pathways—the total factor productivity damage due to the efficiency changes of labour, capital and ecosystem services influenced by the temperature rise and fluctuations reduce the long-term growth of Gross State Domestic Product (GSDP). It distinctively decomposes the losses of growth due to the damage of labour, capital and ecological performances theoretically and empirically. Understanding temperature impact on growth rates guides targeted policies for adaptation and mitigation, addressing specific sectors or broader strategies to minimise productivity decline (Kumar and Maiti, 2024). This study categorically argues how growth may differ across regions in the same federal setting due to the variations in factor endowments, climatic exposure, and socioeconomic capabilities to mitigate them at the state level, affecting the efficiency changes of labour, capital, and ecological resources.

Additionally, this paper uses an improved econometric model (CS-ARDL) to establish long-term relationships, utilising diverse datasets across time and space that may contain unobserved omitted variables. This model enables various specifications to differentiate short- and long-term climate impacts, facilitating the identification of potential adaptation effects through suitable specifications. More specifically, this paper explicitly focuses on the long-term impact of a persistent increase in temperature using a panel cointegration technique. Kumar and Maiti (2024) applied cointegration methods for estimating climate responses and evaluating their feedback (also see (Kaufmann et al., 2010; Pretis et al., 2018)). It also enables the evaluation of uncertainty in integrated economic climate change models using estimated parameters. Using CS-ARDL tests, the study addresses long-term relationships, tackling heterogeneous shocks and providing estimates for countries with similar climate exposure, state capacity and

[1] The Network for Greening the Financial System (NGFS) consists of 116 central banks and supervisors, along with 19 observers. It strives to promote best practices, enhance climate and environment-related risk management in the financial sector, and facilitate the transition to a sustainable economy.

development levels. The methods effectively handle potential cross-sectional dependence from simultaneous shocks or spillovers among economies. While the result with state-specific fixed effects offers a modest 2.17% reduction in economic growth associated with temperature increases, the CS-ARDL model estimates -3.89%, which is significantly higher. This is the first study using seasonal temperature in the Indian context. Contrary to the existing literature concerned with short-term growth effects, this study explicitly modelled to find the long-run growth effects for the persistent increases in temperature.

Thirdly, in contrast to existing studies, this paper empirically examines the presence of reverse causality between temperature and economic growth. Kahn et al. (2021) argued for potential feedback effects of economic growth on temperature. Even Schultz and Mankin (2019) argued that economic and political factors arising from declined production could alter meteorological measurement. Our study employs the Xiao-juodis method of Granger causality to rigorously examine the causal relationship between annual mean temperature and GDP growth rate. Based on recent work of (Xiao et al., 2022; Juodis et al., 2021), our results reveal bidirectional causality between temperature and GDP growth rate in the short run, providing strong evidence of reverse causality.

Fourth, the study found a differential impact of climate change across regions because of their socio-economic and geographical differences. The Southern and Eastern states are particularly vulnerable compared to the rest. We have also noted that extremely hot regions experience greater GDP growth losses. These findings highlight the need for tailored climate adaptation strategies and region-specific policies to mitigate temperature-related economic disruptions. We also find a decline in industrial output growth. Our paper challenges the conventional belief that only specific sectors are affected by rising temperatures. Our analysis reveals that rising temperatures have a widespread detrimental impact across various sectors in India, including construction, services, and manufacturing. Notably, our study represents the first systematic documentation within the literature of the pervasive effect of temperatures on the cross-section of industries in India [2].

Lastly, our projection analysis reveals that India would experience a substantial decline in Gross State Domestic Product (GSDP) growth rates to the existing estimates under a high-emission scenario (RCP 8.5) and under adopting a net-zero emissions target by 2050 (NGFS Net Zero 2050 Scenario). The projected GSDP growth loss from 2020 to 2100 under various Shared Socioeconomic Pathways (SSPs) reveals distinct economic trajectories. Notably, SSP1-2.6, prioritising sustainability, experiences a marginal decrease, resulting in an overall -5.25% by 2100. SSP2-4.5, a 'middle-of-the-

[2](Somanathan et al., 2021) has studied the impact of heat on labour supply on industries, but they are specific to certain cities. Our result is representative of All India

road' approach, shows consistent growth loss, totalling -13.07%. SSP 3-7.0, emphasising competitiveness, faces continuous decline, reaching -16.42% by the end of the century. SSP5-8.5, driven by fossil fuel exploitation, exhibits the highest cumulative growth loss at -24.51% over the 2020-2100 period. These results suggest that India can mitigate future GDP losses and contribute to global efforts to combat climate change, subject to the release of greater resources and efforts than planned so far.

The paper unfolds as follows: Section 2 reviews the temperature-growth nexus in India. Section 3 delineates the conceptual framework and mechanisms underlying temperature's potential impact on the growth rate of Gross Domestic Product (GSDP). Section 4 outlines the econometric methodology and database used in the study. Section 5 presents the estimated results, and Section 6 concludes the paper

2 Related Literature

There has been growing interest in investigating the adverse impact of Climate Change on economic outcomes (Nordhaus, 2019; Chang et al., 2020; Tol, 2022; Chang et al., 2023). Moreover, an extensive body of research has consistently revealed that developing nations experience a disproportionately severe negative impact of temperature variations on macroeconomic activities compared to their advanced economies (Burke et al., 2015; Dell et al., 2012; Kumar and Khanna, 2019). The anticipated severity of temperature rise is greater in developing nations, primarily attributable to their heightened dependence on agriculture and constrained adaptive capacity.

Dell et al. (2009) documented a decline in per capita national income for one-degree Celsius temperature increase in panels of both developed and developing countries. However, this approach does not take into account the time factor that plays a critical role in the Climate Change literature and may be influenced by other factors like institutional quality (Acemoglu et al., 2001). In a related study covering 125 countries from 1950 to 2003, Dell et al. (2012) revealed that annual temperature fluctuations are detrimental to economic growth in poorer nations in the short term, with a one-degree Celsius temperature rise leading to a 1.3% decrease in economic growth for these countries. Numerous studies have employed various temperature measurements to assess how temperature affects GDP under different time frames. For example, studies have used different time resolutions, including annual (Burke et al., 2015; Dell et al., 2012), monthly (Pretis et al., 2018), and seasonal temperature (Colacito et al., 2019). However, relying solely on annual temperature data may not capture the full complexity of climate change's economic impacts. This is because it overlooks events like summer heatwaves, prolonged cold spells, and changing precipitation patterns, which can have significant short-term effects on socioeconomic systems. Seasonal data provides valuable insights into when and where interventions are most needed to mitigate the detrimental impact of climate change on economic growth.

Another issue is how climate econometrics should be specified. Advanced climate econometric models use various data types. They distinguish short- and long-term climate effects and identify potential adaptations (Chang et al., 2023). Recent research in climate econometrics employs panel models with various fixed effects to examine the relationship between temperature changes and GDP (e.g., (Dell et al., 2012; Letta and Tol, 2019)). These panel models incorporate economic variables (e.g., GDP or its determinants like TFP), weather data, fixed effects, and control variables that vary across time and space. The models employ linear or non-linear functions comprising these components. Nordhaus (1991) posits a feedback loop: higher economic growth leads to more GHGs, causing global temperatures to rise and slowing down economic growth. The existing works on the Indian economy do not offer sound explanations for regional variations of the impacts in the same federal setting. Moreover, the impact estimate in the existing studies suffers from endogenous and cross-sectional dependence bias. In this paper, we use the CS-ARDL model to avoid this problem. Persistent temperature increases and volatile weather events can exert lasting macroeconomic impacts by decreasing labour and capital efficiencies and disrupting ecosystem services. These long-term effects are often overlooked in the literature, primarily focusing on short-term growth effects. Additionally, in contrast to many existing studies concentrated on short-term effects, we explicitly model and test the long-term growth consequences of continual temperature increases using the panel cointegration technique.

The choice of functional form specification is a critical issue in the temperature-GDP literature, as there are no prescribed, measurable structural connections between temperature and GDP in the current framework (Dell et al., 2012; Burke et al., 2015). In this paper, we provide a conceptual framework to link the impact of temperature on GDP at the sub-national level. However, when temperature is trended, as is the case in most states in India, including temperature in the regression introduces an unwanted quadratic trend in equilibrium log per capita output (or, equivalently, a linear trend in terms of per capita output growth) (Kahn et al., 2021). This undesirable effect can lead to biased estimates in the climate change-growth equation. An ad hoc approach is typically employed, where real income growth is regressed on arbitrarily selected variables or a theoretical model is developed but not subjected to rigorous empirical testing (Kahn et al., 2021).

In a recent study by Jain et al. (2020), a one-degree Celsius temperature increase in India was associated with a 2.5% point reduction in the growth rate. The study found this impact was more severe in poorer states and the agricultural sector Sandhani et al. (2023). It reveals that rising temperatures harm economic growth, especially in poorer districts with poor socio-economic environments, where temperature increases lead to a decline in per-capita income growth. The choice of temperature variables in climate econometrics research plays a pivotal role in understanding the impact of temperature on economic growth. These studies have not seen the impact of seasonal temperature and mainly relied on traditional fixed effect estimation. Previous research on India has not shown the future impact of rising temperatures on GSDP growth. Without a conceptual framework, these studies fail to provide the mechanism for the temperature growth relationship and its heterogeneous implications in different regions. Prior research on the impact of temperature on the Indian economy has often overlooked the crucial aspect of adaptation pathways.

3 Conceptual framework: Temperature and Growth

It is assumed that the economies are small, so the rise in temperature is exogenously given to an economy due to global warming. Nevertheless, the impact of this rise in temperature can differ across various regions within the economy due to the difference in climatic conditions, economic standards, and financial capabilities contingent upon the strategies employed to mobilise resources for mitigating ecological damage at the regional level. The economy of each region is too small to influence the global climate and environment but can deploy strategies to reduce fossil fuel consumption and invest in renewable resources to minimise the impact.

Let us assume that there are N regions in an economy. Each of them receives temperature T as given and holds two types of agents - households who consume goods and firms supplying the goods. Household members offer (L) amount of labour to earn wage income (w). The government collects tax revenue allocated between infrastructure and renewable resource generation. For future consumption, the residue after the current consumption is saved for investments that accumulate capital. The household income that goes for saving earns rental income at the rate of (r) for capital (K) accumulated from the investment. The income of households consumes (C) in the current period. On the other hand, each region owns one firm. The firm employs workers (L) and takes the capital from households against its rental payments.

Households

If $c(t)$ is denoted as per capita consumption at the t-th period, a household aims to maximise lifetime utility, given by

$$U = \int_0^\infty u[c_t]e^{-\rho t}dt \quad \text{where} \quad u'(c) > 0,\, u''(c) < 0$$

with ρ as the discount factor. If the household has Constant Relative Risk Aversion (CRRA), the instantaneous utility function has been considered, for simplicity, as follows:

$$u(c_t) = \frac{c_t^{1-\theta} - 1}{1-\theta} \tag{1}$$

where $\theta > 0$, making the elasticity of marginal utility equal to $-\theta$. Households use unconsumed income to accumulate assets, with capital depreciating at a rate of δ. Capital owners and workers receive payments based on their marginal productivities, denoted as r (rent) and w (wage). Assuming K as assets and C as consumption, the capital motion can be expressed as:

$$\dot{K} = (r - \delta)K + wL - C$$

With labor L fixed, dividing both sides by L yields the per capita expression:

$$\dot{k} = (r - \delta)k + w - c \tag{2}$$

Here, $k = K/L$ and $c = C/L$. This above expression serves as the household's budget constraint in maximising lifetime utility.

Firms and Government

If the global temperature is assumed to be given as T at the regional level, each region will experience it. Similar to Kumar and Maiti (2024), the production function exhibits a Cobb-Douglas with the productivity or efficiency components attached to the factors and ecological contents. If A_K and A_L denote the efficiencies of capital and labour, respectively, and $A(T_i)$ captures the level of ecosystem services, giving the quality of the environment in a region. Labour L_{it} and capital K_{it} are taken to produce output (Y_{it}) at $t-$th period in the i-th region. G_t is assumed to be the current level of renewable environmental resources with public goods characteristics. A regional government can augment its level by investing in it. The production function of the region can be specified as follows:

$$Y_t = A\left(T\right)\left[A_K\left(T\right)K_t\right]^{\alpha}\left[A_L\left(T\right)L_t\right]^{\beta}G_t^{1-\alpha-\beta} \tag{3}$$

Note that if the $A(T)$ is reduced due to the rise in temperature, a higher value of G_t can minimise the damage. It can be financed from the tax revenues. A state imposes a τ rate of tax on the income. Suppose a regional government spends s share in resources to run administrative services out of the tax rate, τ. The rest is invested in renewable resources and abatement of the environmental damages. However, the effective investment in the public sector for infrastructure and governance depends on the state's capacity in a federal setting. So, if ϕ is assumed as the leakages and additional transaction costs of the state depending the presence of its institution, labour rigidity and natural resources, the investment in public resources for the environment can be presented as follows:

$$E_t = (1-\phi)(\tau(T)-s)Y_t; \tau' > 0 \tag{4}$$

where, τ is the tax rate and ϕ is the leakage. τ is assumed to depend on temperature, T, positively, $\tau' > 0$, meaning that the tax needs to rise for more renewable resource mobilisation to neutralise the greater damage, give same s. Therefore, $E_t/Y_t = (1-\phi)(\tau(T)-s)$ captures the share public spending as a percentage GDP used for the renewable resources. Assume the state has a G level of renewable environmental resources, which may neutralise the efficiency losses of capital, labour and ecology damages. If G represents the steady-state level of renewable resources, E_t improves the effective investment in the renewable resources as follows:

$$G_t = GE_t^{\theta} \tag{5}$$

After substituting (6) in (7), we get

$$\begin{aligned} G_t &= G\left[(1-\phi)(\tau(T)-s)Y_t\right]^{\theta} \\ G_t &= G[(1-\phi)(\tau(T)-s)]^{\theta}Y_t^{\theta} \end{aligned} \tag{6}$$

Where θ represents the elasticity of investment in renewable resources. If μ_A is positive and captures the rate of ecological damages in response to the temperature rise, the damage function of ecological services due to global warming is represented as $A(T) = A(1-\mu_A T)$. This could also be expressed as $A(T) = Ae^{-\mu_A T}$ in the exponential terms. Similarly, if the efficiency losses of labour and capital damages at the rate of μ_L and μ_K, respectively, the loss functions for these two efficiency terms can be represented as follows: $A_L(T) = A_L e^{-\mu_L T}; A_K(T) = A_K e^{-\mu_K T}$. Substituting (8) into (5) and replacing the efficiency terms using the expression mentioned above, we get.

$$Y_t = (BD)^{\frac{1}{(1-\theta)(1-\alpha-\beta)}} \quad K_t^{\frac{\alpha}{1-\theta(1-\alpha-\beta)}} L_t^{\frac{\beta}{1-\theta(1-\alpha-\beta)}} \tag{7}$$

where, $B = A.A_k^{\alpha}A_L^{\beta}G^{1-\alpha-\beta}$ and $D = e^{-(\mu_1+\alpha\mu_k+\beta\mu_L)T} \cdot [(1-\phi)(\tau(T)-s)]^{\theta(1-\alpha-\beta)}$ Note that B represents the part of total factor productivity not influenced by the damages of temperature rise. Whereas, D contains another part of productivity impacted by the damages. It is inversely related to ϕ and s but positively influenced by τ. The higher the damage rates (μ's), the greater the value of D.

Steady State and Growth

If the labour is fixed at $L_t = L$, the growth rate of the economy can be found as follows.

$$\frac{\dot{c}}{c} = \frac{1}{\sigma}\left[\frac{\alpha}{1-\theta(1-\alpha-\beta)} \cdot (BD)^{\frac{1}{1-\theta(1-\alpha-\beta)}} k_t^{-\frac{[(1-\theta)(1-\alpha)+\theta\beta]}{1-\theta(1-\alpha-\beta)}} L^{\frac{(1-\theta)(1-\alpha-\beta)+2\beta}{1-\theta(1-\alpha-\beta)}} - (\delta+\rho)\right]$$

The higher the τ for renewable resources, the higher the growth rate. Because more tax revenues are invested in the regeneration of environmental resources, it improves the environment, and the resultant TFP rises. This raises the growth rate. On the other hand, the higher the ϕ, the lower the leakage and its growth rate would be higher. The region showing higher s cannot afford to spend more τ required for the faster regeneration of the environment.

Since the power of k_t is negative, the growth rate converges to a steady state with the capital accumulation. At steady-state, $k_t = k^*$.

$$k^* = \left(\frac{H}{\rho+\delta}\right)^{\frac{1-\theta(1-\alpha-\beta)}{(1-\theta)(1-\alpha)+\theta\beta}}$$

Where, $H = \frac{\alpha}{1-\theta(1-\alpha-\beta)} \cdot (BD)^{\frac{1}{1-\theta(1-\alpha-\beta)}} L^{\frac{(1-\theta)(1-\alpha-\beta)+2\beta}{1-\theta(1-\alpha-\beta)}}$

It should be noted that a rise of T reduces D and, thereby, H, leading to a drop in TFP and growth rate. To maintain the same level of steady-state growth, a higher amount of k is required to compensate for the damage of climate change. The state with higher investment elasticity for renewable resources, θ, and lower level of leakages, ϕ, restrain the pace of damage.

At a steady state value of capital per worker one can find output per capita fixed. The Output per capita expression would be given by

$$y_t = (BD)^{\frac{1}{(1-\theta)(1-\alpha-\beta)}} k^{*\frac{\alpha}{1-\theta(1-\alpha-\beta)}} L^{\frac{-(1-\theta)(1-\alpha-\beta)}{1-\theta(1-\alpha-\beta)}} \tag{8}$$

This expressions suggests that output per capita is fixed at steady state but is affected by productivity damage part(D).

Now TFP expression would be given by :

$$\frac{Y_t}{K_t^{\alpha} L_t^{\beta}} = (BD)^{\frac{1}{1-\theta)(1-\alpha-\beta)}} \cdot (K_t)^{\frac{\alpha}{1-\theta(1-\alpha-\beta)}-\alpha} \cdot (L)^{\frac{\beta}{1-\theta(1-\alpha-\beta)}-\beta}.$$

Substituting the value of k* in place of k_t and solving the above expression we find the total factor productivity expression as follows:

$$\text{TFP} = \left(\frac{\alpha}{(\rho+\delta)(1-\theta(1-\alpha-\beta))}\right)^{\frac{\alpha\theta(1-\alpha-\beta)(1-\theta(1-\alpha-\beta))}{(1-\theta)(1-\alpha)+\beta\theta)}} (BD)^{\frac{\theta\alpha(1-\alpha-\beta)}{(1-\theta)(1-\alpha)+\beta\theta}} L^{\frac{(1-\theta)(1-\alpha-\beta)+2\beta}{(1-\theta)(1-\alpha)+\beta\theta}} \tag{9}$$

Taking logarithmic transformation and differentiating with respect to time, we find the change in TFP as follows:

$$\text{TFPG} = -\frac{\theta\alpha(1-\alpha-\beta)}{(1-\theta)(1-\alpha)+\beta\theta}\left[(\mu_1+\alpha u_K+\beta\mu_L) - \frac{\theta(1-\alpha-\beta)}{(1-\phi)(\tau(T)-s)}\tau'\right]\frac{dT}{dt}. \tag{10}$$

This expression reveals that the first part of TFPG is negative while the last term is positive. The efficiency damage of labour, capital, and ecology dampens the growth of productivity, but the higher tax resources are diverted for renewable resources to limit the damages. Since T is exogeneously given to the states, it can vary across them and the steady-state level must be different. Moreover, the state capacity to effectively utilise resources, captured by $(1-\phi)$, would minimise the damage. This TFPG determines the growth rate of an economy or region. Note that the parameters affecting the resource mobilisation for renewable resources that determines the TFPG across regions differently and hence the growth rate would vary between them.

4 Data and Empirical Strategy

4.1 Data Sources, Sample Composition, and Descriptive Statistics

This paper takes the relevant data sourced from two databases - the EPWRF India Time Series Database and the Reserve Bank of India for the States of India. We use EPWRF India Time Series data from 1980 to 2019, adjusting Gross State Domestic Product (GSDP) figures to the 2011-12 GDP base year for state-level analysis. Population and industry outputs from the EPWRF India Time Series data were also used. In addition to GSDP data, we incorporate variables from the RBI Handbook of Indian States such as forest cover, productive capital, working capital, and the number of persons engaged (See Table A1). Data frequency for these economic indicators is annual.

In this paper, we sourced state-wise seasonal and annual temperature data from the (WorldBankGroup, 2024) Climate Change Knowledge Portal[3]. The Climate Change Knowledge Portal (CCKP), established by the World Bank, stands as a pivotal resource for climate data services. Utilising cutting-edge datasets such as the ERA5 Reanalysis database and the Climatic Research Unit (CRU) of the University of East Anglia, CCKP furnishes an extensive range of climate data and products, offering unparalleled insights into global climate trends. The ERA5 dataset, a product of the Copernicus Climate Change Service (C3S) at ECMWF, covers the period from January 1950 to 2022 and provides a comprehensive view of atmospheric conditions worldwide. Our primary analysis relies on ERA5 Reanalysis weather data from CKCP (World Bank). Further, we have created three sub-samples in terms of average temperature, defined as cold, moderate and hot regions for the range of 0-15, 15-20, and above 20 degrees Celsius, respectively. Such categorisation of temperature into distinct bins is employed as a method to discern the heterogeneous impacts of temperature on economic indicators, considering the varying effects of different temperature ranges (Zhang et al., 2018; Deschênes and Greenstone, 2011; Barreca, 2012; Behrer and Park, 2017).

We have collected annual temperature data from 29 states spanning from 1980 to 2019. The variables and their sources are detailed in Table A1. Additionally, our analysis incorporated temperature projection data for four RCP Scenarios and three NGFS scenarios obtained from NGFS Climate Analytics. We use state-wise figures illustrating trends in annual temperature variations and GSDP growth rates. Seasonal and annual temperatures show increasing trends (See Online Appendix Figure A1-A5). The summary statistics in Table A3 of the Online Appendix suggest significant variations in economic and environmental variables across states. For instance, the logarithm of Gross State Domestic Product (GSDP) varies from 10.94 to 19.14, highlighting economic disparities. Moreover, climate-related indicators, such as mean temperature (mean: 23.55, standard deviation: 5.224), precipitation (mean: 1495.18, standard deviation: 800.158), and temperature anomalies (mean: 2.93, standard deviation: 0.988), exhibit distinct variations among different geographical regions.

[3]https://climateknowledgeportal.worldbank.org/download-data

Figure (2) India- Temperature trends

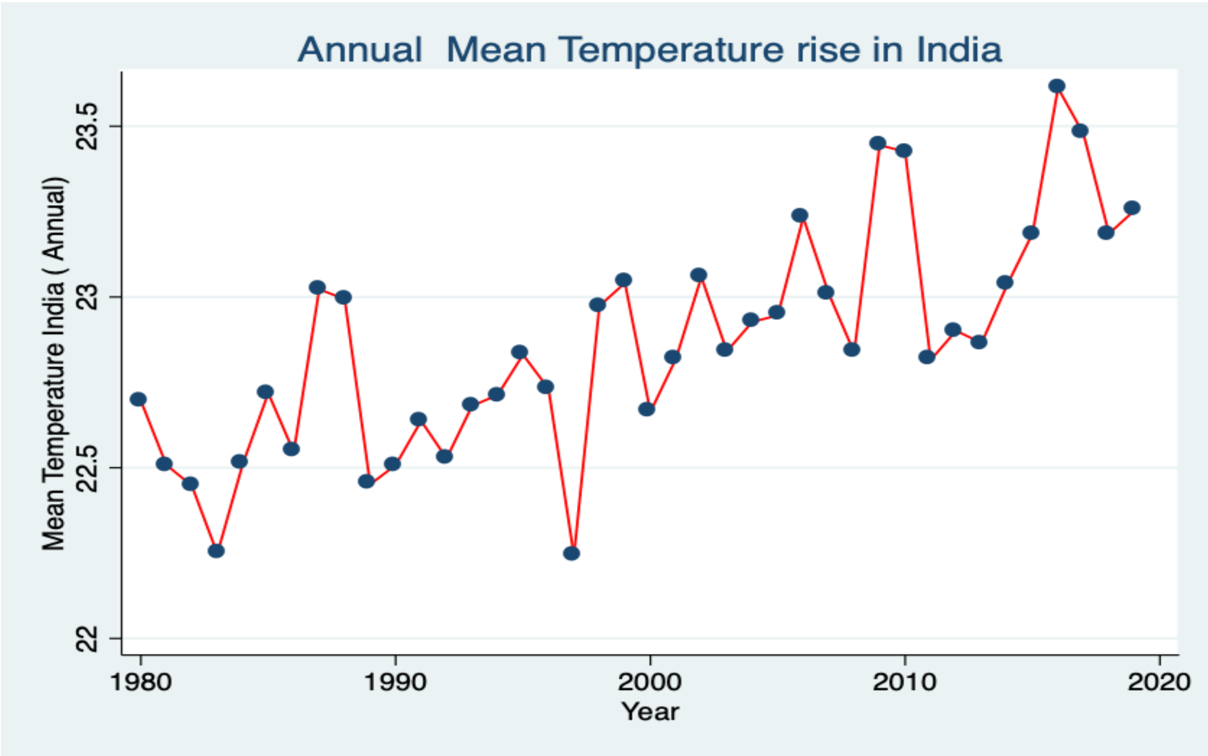


Figure 2 illustrates the increase in annual temperature in all the states, and a rising trend in all of India's mean annual temperature can be seen. We also show how temperature has evolved over the past four decades (1980-2019) across the Indian States. We estimate state-specific regressions where the temperature of state i at year t is our independent variable in the regression. The annum average increase in temperature for states i is given by an estimated coefficient from ERA 5 Reanalysis data obtained from the Climate Change Knowledge Portal (World Bank). Table 1 summarises individual state estimates with their significance level. As shown in every state-specific result, temperature shows an increasing trend—the estimated coefficient ranges from Puducherry (0.0100) to Manipur(0.0302). Kahn et al. (2021) suggested that if temperatures are trended, which is the situation in almost all states, the inclusion of temperature levels that induce a quadratic trend in equilibrium log per capita output is not desirable and can produce a bias in the estimation from growth - Climate Change equation. The existing research in the Indian context has mainly used the Panel data fixed effect approach and temperature levels, which can bias the impact estimates (Jain et al., 2020; Sandhani et al., 2023). Mondal et al. (2015) has also shown an increasing trend in both seasonal and annual temperatures in Indian states. To deal with this, this paper used difference temperature variables[4] and improved methodology, i.e., CS-ARDL.

[4]Empirical studies have demonstrated its effectiveness in transforming non-stationary data into the

Table (1) INDIVIDUAL INDIA ESTIMATE OF THE AVERAGE YERALY RISE IN TEMPERATURE OVER THE PERIOD 1980-2019

STATE	Coefficient	STATE	Coefficient	STATE	Coefficient
		HARYANA	0.0191*	NAGALAND	0.0258***
ANDHRA PRADESH	0.0154***	HIMACHAL PRADESH	0.0285***	ODISHA	0.0129**
ARUNACHALPRADESH	0.0152***	JHARKHAND	0.0222***	PUDUCHERRY	0.0100***
ASSAM	0.0255***	KARNATAKA	0.0177***	PUNJAB	0.0214**
BIHAR	0.0159***	KERALA	0.0228***	RAJASTHAN	0.0185**
MADHYA PRADESH	0.0171***	SIKKIM	0.0286***	CHHATTISGARH	0.0174***
MAHARASHTRA	0.0156***	TAMIL NADU	0.0201***	DELHI	0.0123*
MANIPUR	0.0302***	TRIPURA	0.0258***	GOA	0.0208***
MEGHALAYA	0.0245***	UTTAR PRADESH	0.0155**	GUJARAT	0.0173***
MIZORAM	0.0298***	UTTARAKHAND	0.0246***	WEST BENGAL	0.0188***

Notes: The dependent variable is Annual mean temperature. Independent variable is Time (year). Simple OLS estimation is used with constant. ERA weather data from (WorldBankGroup, 2024) is used. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

4.2 Empirical Strategy

Given the likelihood of stochastic trends in most economic variables, it is reasonable to test for the presence of a unit root. Two primary types of panel unit root tests have been utilised in the literature. The first-generation unit root test is susceptible to size distortion in the presence of simultaneous common shocks among countries. However, the preferred second-generation unit root test, the Pesaran unit root test (Pesaran, 2007a, 2003), incorporates cross-sectional dependence with serially correlated terms.

Contrary to prior studies that neglected cross-sectional dependent errors while estimating long-run effects using panel data, employing techniques like Panel Data Fixed Effect (Letta and Tol, 2019; Dell et al., 2012; Jain et al., 2020; Sandhani et al., 2023), Fully Modified Ordinary Least Squares (FMOLS) (Pedroni, 2001), and Panel Dynamic Ordinary Least Squares (DOLS) (Mark et al., 2005), the CS-ARDL approach appropriately incorporates cross-sectional averages into individual regressions to mitigate the impact of common factors, similar to Common Correlated Effects (CCE) estimators (Pesaran, 2015). A notable strength of CS-ARDL lies in its ability to estimate long-run effects in large dynamic heterogeneous panel data models with cross-sectionally dependent errors. Firstly, they incorporate lagged variables to capture historical patterns, enabling the model to account for underlying trends. Secondly, these models rely on co-integration analysis, assuming stable long-run relationships between variables encompassing trend components. Additionally, CS-ARDL includes an error correction mechanism (ECM) to address short-term deviations from the long-run equilibrium, thereby capturing adjustment processes related to trends. A distinctive strength of the

stationary form, which is essential for accurate statistical modelling. For example, research by Perron (1989) demonstrates how differencing can help stabilise the variance and eliminate trends, making the data suitable for further analysis. Similarly, studies (Kwiatkowski et al., 1992; Enders, 2004) emphasise the importance of first differencing in dealing with non-stationary trends.

CS-ARDL method lies in its careful consideration of three critical panel characteristics: dynamics, heterogeneity, and cross-sectional dependency.

The $\Delta log(GSDP)$ measures the Growth rate of gross state domestic products (GSDP). T denotes the annual temperature. This model can be presented as follows:

$$\Delta log(GSDP)_{i,t} = \alpha_i + \sum_{l=1}^{p_{\Delta log(GSDP)}} \lambda_{l,i}\Delta log(GSDP)_{i,t-l} + \sum_{l=0}^{p_T} \beta_{l,i}(T)_{i,t-l} + \sum_{l=0}^{p_T} \gamma'_{i,l}\overline{\mathbf{z}}_{t-l} + e_{i,t}. \tag{11}$$

with $\overline{\mathbf{z}}_{t-l} = \left(\overline{\Delta log(GSDP}_{i,t-l}, \overline{(T)}_{i,t-l}\right)$. Further, $\overline{\Delta log(GSDP)_t} = N^{-1}\sum_{i=1}^{N} \ln \Delta GSDP_{it}$ and $\overline{T}_t = N^{-1}\sum_{i=1}^{N} T_{it}$ are the averages of the lagged $\Delta log(GSDP)$ and the annual mean temperature.

We focus on the long-run average effect of temperature on $\Delta log(GSDP)$, which can be calculated from the mean values of the individual state coefficients (Pesaran et al., 1995). The subscript i refers to their coefficients and shows that they can vary across cross-section observations. α_i represents individual state specific factors. The parameters p_T and $p_{\Delta log(GSDP)}$ denote the lags of $log(GSDP)$ and annual mean temperature. Using CS-ARDL helps estimate the long-run coefficients and tests for the absence and presence of cointegration[5]. Following previous literature, we also use this confirmatory in the cointegration test. We present cross-sectional dependence robust p-values obtained from Westerlund (2007) panel cointegration tests[6], conducted with one lead and one lag.

In the presence of cointegration, no relevant integrated variables are omitted[7]. The cointegration between nonstationary variables implies no missing relevant variables or need for additional ones for unbiased parameter estimates. Any omitted nonstationary variable in a regression with cointegrated variables would lead to nonstationary residuals, causing failure in detecting cointegration. Cointegration's stability across information set extensions eliminates the classical problem of omitted variables. In panel data estimation,

[5]If $\ln(GSDP)$ and Temperature$_i$ are cointegrated and $\ln(GSDP_i)$ is endogenous, a significant negative error correction term indicates cointegration(Herzer and Nagel, 2019). We utilize the error correction representation of the CS-ARDL model, as suggested by (Eberhardt and Presbitero, 2015), to estimate the long-run impact of climate variables on per capita GSDP growth and assess both the absence of cointegration and the weak exogeneity of $\ln(GSDP)$.

[6]The dependent variable in these tests is GDP Growth Rate. The null hypothesis is that the variables are not cointegrated. p-values indicate that the null hypothesis of no cointegration can be rejected at standard significance levels. We use stata xtwest command for our analysis(Persyn and Westerlund, 2008). Results of Westerlund (2007) panel cointegration are provided in supplementary material Table A4 Online Appendix

[7]In a cointegrated regression, the presence of a stationary error term implies the absence of relevant omitted nonstationary variables. If any such variables are part of the cointegrating relationship, their omission will result in nonstationary residuals, leading to a failure in detecting cointegration (Everaert, 2011).

overlooking shared common factors between annual temperature[8] and $log(GSDP)$ (equation 11) can produce bias coefficients. CS-ARDL's Common Correlated Effects (CCE) approach accommodates heterogeneous effects using a cross-sectional average for common factors. Chudik et al. (2011) proves the CCE estimator's consistency and asymptotic normality, especially with a finite number of observed common factors. We explicitly test for cross-sectional dependence using Pesaran (2021)'s procedure.

Cointegration provides robust and superconsistent[9] estimates of long-run parameters, mitigating concerns about endogeneity (Pesaran et al., 1995; Engle and Granger, 1987). The CS-ARDL estimator remains robust to heteroscedasticity, relying on the difference between individual and mean group estimates (Ditzen, 2021). After establishing the long-run relationship, we assess the causal relationship between GSDP and annual temperature using the Granger non-causality test (Xiao et al., 2022). Existing studies ((Dell et al., 2012)) indicate heterogeneous climate change impacts across countries. Conventional dynamic panel estimators like OLS, IV, and GMM may produce misleading estimates due to the imposed slope homogeneity ((Pesaran et al., 1995)). We employ a heterogeneous CS-ARDL mean estimator and consider sub-sample estimates based on development level and climate exposure. Additionally, we examine potential non-linearity by introducing the squared term of temperature, a common practice in climate-growth nexus literature (Letta and Tol, 2019; Acevedo et al., 2020; Hsiang et al., 2013).

5 Empirical results

5.1 Panel unit root test and cointegration

This paper applies Pesaran (2007a) unit root statistics using lag orders of 0, 1, and 2, respectively. The panel unit root analyses, based on Pesaran (2007b) test for both the level and first difference of economic and climatic indicators, reveal that the null hypothesis of a unit root in economic indicators at the level cannot be rejected. However, it can be rejected for the first difference. This implies that economic indicators are stationary at the first difference. On the other hand, all climate indicators exhibit stationarity at the level (see details in Table A3 Online Appendix). The unit root cannot

[8]The inter-connectedness of climate across different states within our extensive sample of states implies the existence of hidden common factors influencing temperature changes. Similar to Byrne and Vitenu-Sackey (2024) findings .

[9]In a regression model featuring cointegrated variables, the coefficient estimates exhibit super-consistency, converging to the true parameter values at a rate of T rather than $\sqrt{T}$ as observed in standard regressions with stationary variables Stock (1987). Notably, cointegration coefficient estimates maintain super-consistency even in the presence of correlation between the stationary error term ϵ_{it} and the regressor(s) Stock (1987), thereby ensuring unbiased estimates regardless of any omitted stationary variables Bonham and Cohen (2001).

be rejected for economic indicators in different forms. This study using Westerlund (2007) panel co-integration test finds the presence of cointegration as p values for all co-integration statistics suggest that the null hypothesis of no co-integration between temperature and growth rate can be rejected at 1 % significance level (See Table A4 Online Appendix).

5.2 Main result

Table 2 reports the outcomes derived from the baseline specification equation (equation 11), presenting the estimated coefficient for economic growth and annual temperature variations. The findings indicate a statistically significant negative impact of annual temperature fluctuations on economic growth in Indian states. To be precise, a one-degree Celsius increase in temperature resulted in a 3.89 percentage point reduction in economic growth rate. Sandhani et al. (2023) and Jain et al. (2020) found that an increase in one degree Celsius temperature decreases per capita income growth by 1.7% and 2%, respectively.

Underestimation of the economic impact of temperature fluctuations is a pressing concern in climate macroeconomic research. Using state-specific panel fixed effects, this study found that temperature increases lead to a -2.17% decline in the economic growth rate, but the CS-ARDL model indicates greater growth loss by -3.89% (See Column 5, Table 8). This discrepancy highlights a crucial underestimation issue when relying solely on conventional panel fixed effect approaches, particularly in regions with evidence of rising temperature trends across all states. Failing to assess the economic consequences of temperature variations accurately can result in inadequate resource allocation and the formulation of sub-optimal mitigation and ineffective adaptation policies.

Table (2) MAIN RESULTS: EFFECTS OF ANNUAL AND SEASONAL TEMPERATURES ON GDP GROWTH

	(1)	(2)	(3)	(4)	(5)
	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL
Variables	GSDP Growth	GSDP Growth	GSDP Growth	GSDP Growth	GSDP Growth
d.Annual Temperature	-0.0389**				
	(0.0147)				
d.Summer Temperature		-0.0079*			
		(0.0041)			
d.Monsoon Temperature			-0.0190		
			(0.0135)		
d.Autumn Temperature			-	-0.0086**	
				(0.0044)	
d.Winter Temperature					-0.0232**
					(0.0086)
CADF Statistics	-11.523***	-12.320***	-12.509***	-11.754***	-10.786***
Cointegration	Yes	Yes	Yes	Yes	Yes
CD Statistics	-2.63*	-2.20*	-2.39*	-1.88*	-1.53
R Squared	0.75	0.80	0.80	0.79	0.78
Number of observation	1076	1076	1076	1076	1076
Number of States	29	29	29	29	29

Notes: The dependent variable is GSDP Growth rate. The Independent variable is the annual variation in mean temperature. CD: Cross-sectional dependence test of Pesaran (2021) - The CD statistics have a null hypothesis of no cross-sectional independence in the residual of the estimated model. The four columns on the right report the estimated coefficients for each of the four seasonal temperature averages (regressions (2) and (5)). In the panel regressions, all 29 states and Union territories of India are included. Temperatures are in degrees Celcius. The sample is 1980–2019 for annual regression and seasonal. Summer (Average of March, April, and May), Monsoon (Average of June, July, August and September), Autumn (October and November) and Winter(Average of December, January and February). Extended summer is the average of Summer, Monsoon and Autumn. ERA5 Reanalysis weather data (WorldBankGroup, 2024) is used. Standard errors are in parentheses. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

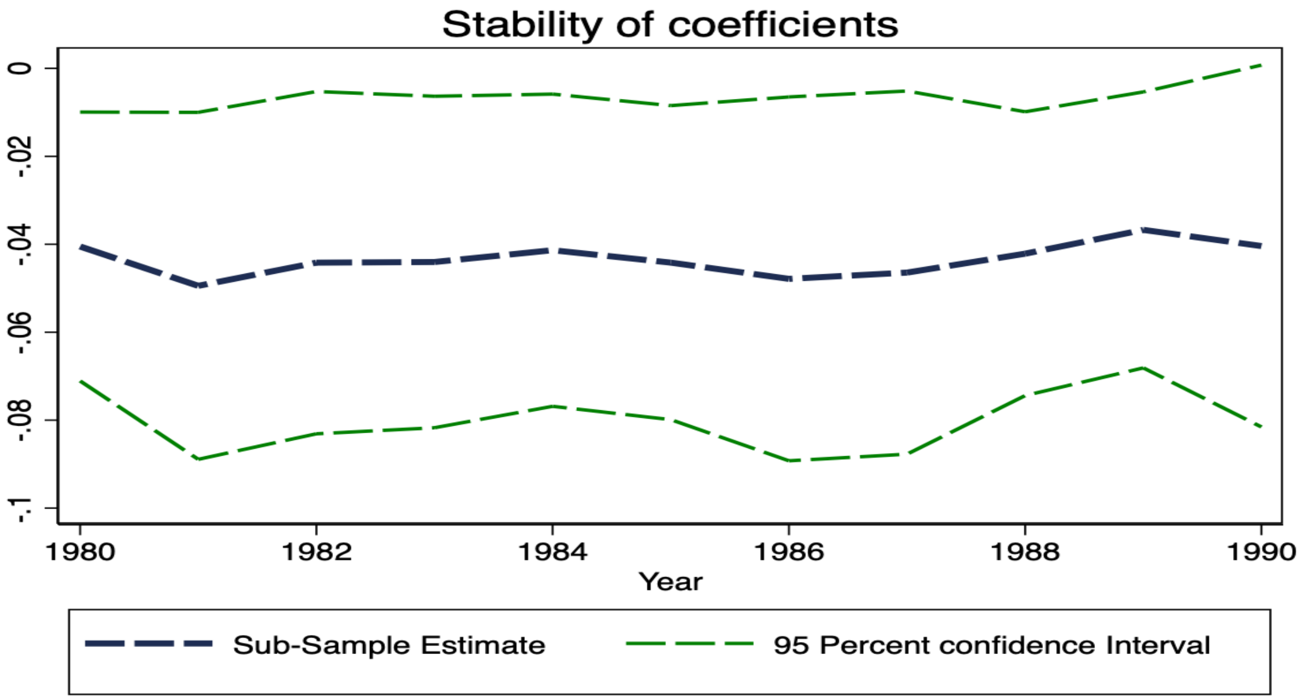
However, upon analyzing the impact of temperatures by season, all four seasons demonstrate a negative economic impact on economic growth. The selection of temperature variables in climate econometrics research is crucial for a nuanced understanding of temperature's effects on economic growth(Chang et al., 2023; Colacito et al., 2019). Numerous studies have employed various temperature variables to assess how temperature affects GDP under different time frames. For example, studies have used different time resolutions, including annual (Burke et al., 2015; Dell et al., 2012), monthly (Pretis et al., 2018), and seasonal temperature variables (Colacito et al., 2019). However, relying solely on annual temperature data may not capture the full complexity of climate change's economic impacts. This is because it overlooks events like summer heatwaves, prolonged cold spells, and changing precipitation patterns, which can have significant short-term effects on socioeconomic systems. For example, Colacito et al. (2019) found that summer temperatures negatively affected GDP growth in US states, highlighting the need for seasonally resolved data to capture these effects accurately. Colacito et al. (2019) linked temperature fluctuations to increased GDP volatility.

Economic sectors and regions exhibit varying sensitivities to temperature changes across seasons. Seasonal data can provide valuable insights into when and where interventions are most needed to mitigate the adverse effects of Climate Change on economic growth. The rightmost four columns of Table 2 provide results regarding seasonal temperature estimates, seasonal coefficients, associated standard errors, and additional diagnostic statistics. Notably, a decrease of one degree Celsius in autumn, summer, and winter temperature is found to have a statistically significant negative effect on economic growth, reducing it by 0.8 %, 0.7 % and 2.32 % points respectively. In India, cooler seasons like autumn and winter can have a more pronounced impact on economic growth due to their critical reliance on agriculture, energy consumption patterns, tourism, and labour productivity. While warmer seasons have their significance, the economic dynamics in India are often more sensitive to cooler seasonal variations. As is also shown significant warming of cooler seasons compared to hotter seasons, i.e. past results, in general, indicate warming during the post-monsoon (October–December) and winter (January–February) and no change in the temperatures during the monsoon season (June–September) (Dash et al., 2007).

The CD test rejects the presence of cross-sectional dependence Pesaran (2021) as reported in Table 2, Column 1. We compute Pesaran (2007a) CADF panel unit root test for the residual as a test for cointegration (Holly et al., 2010; Baltagi and Griffin, 1997). The presence of cointegration implies a long-term relationship between economic growth and annual temperature shocks.

We explore how the estimated coefficients in Table 2 evolve similarly to Kahn et al.

Figure (3) Stability of coefficients for Annual temperature



Note: Figures show the long-run effect (and their 95% standard error bands) of climate change on GSDP Growth rate on the sub-sample of different windows, using the CS-ARDL specification. We start the estimation with the full sample and then drop one year at a time

(2021); Colacito et al. (2019) in the Indian context. Using the CS-ARDL methodology on both the full sample and a sub-sample created by omitting one year subsequently, Figure 3 illustrates that the estimated coefficients remain consistent and steady, without showing a diminishing trend over time. The results consistently indicate negative and statistically significant coefficients for summer temperature, even as the sample size decreased. However, this raises a key question: If the Indian economy effectively adapts to temperature shocks, should we not expect a declining impact of temperature and seasonal variations over time? Nevertheless, we cannot definitively conclude that the Indian economy has not adapted to address the climate changes significantly. Several plausible reasons could explain this pattern. The limited adaptation in the Indian economy to Climate Change can be attributed to several factors, including constrained funding for climate adaptation, a predominant focus on growth-oriented measures, insufficient policy support, the concentration of adaptation efforts within specific sectors or regions, a pace of adaptation that may not align with the rapidity of climate change, structural economic shifts toward climate-vulnerable sectors, and under-estimation of the severity of future weather events. These multifaceted challenges collectively hinder India's ability to effectively respond to the evolving impacts of climate change, necessitating a more comprehensive and coordinated approach to climate adaptation.

5.3 Economic Mechanisms

The decline in the growth rate can be due to the drop in total factor productivity triggered by the rise in temperature. The TFP can be affected by the change in the efficiencies of labour and capital and ecological services, as discussed in Kumar and Maiti (2024) and the conceptual model shown in section 3. The annual variation in temperature may impact economic growth by affecting input productivity and reducing ecosystem services. To measure labour productivity, we employ the output-to-labor ratio, and for capital productivity, we use the output-to-capital ratio. The forest cover area serves as a proxy for ecological services. The regression results for the annual mean temperature on these three variables are presented in Table 3. We break down gross state domestic product into industry categories and reveal that the rising annual temperature variation has a detrimental impact on output growth across several sectors. Notably, climate change has economically significant negative impacts on the Mining, Construction, Electricity, Hotel & Trade, Agriculture, and Manufacturing industries.

5.3.1 Input productivity

India faces a significant concern due to rising temperatures and heat stress, especially given its reliance on agriculture and a large labour force in heat-exposed sectors (Woetzel et al., 2020). The reduced productivity due to rising temperatures threatens India's economic growth, affecting labour-intensive sectors such as agriculture and construction. Lower labour productivity can lead to reduced agricultural output, slower construction, and manufacturing inefficiency. Additionally, the diminished capital productivity affects industries' competitiveness and overall economic growth. Projections indicate that by 2030, agricultural and construction labourers are set to bear the brunt of global heat stress, with anticipated work hour losses of 60% and 19%, respectively. This is particularly significant for India, where agriculture engages nearly 46% of the workforce (approximately 512 million individuals in 2019-20), contributing around 20% to the country's gross value added (GVA) and employing roughly 75% of the labour force (around 380 million people) (ILO, 2019). The production would be adversely affected by the uncertainty arising from extreme weather events caused by climate change (IPCC, 2014). Extreme weather events can trigger resource reallocation, impacting the GSDP Growth rate (GSDP) by disrupting resource allocation efficiency.

Annual mean temperature significantly impairs resource allocation efficiency, negatively affecting labour and capital productivity growth rates (see Table 3, Models

2 and 4). Developing countries, reliant on agriculture, encounter challenges in capital accumulation during high temperatures due to reduced agricultural productivity and potential damage to physical capital. The elevated temperature-induced extreme weather events can damage physical capital, and hence, a higher temperature can have a negative effect on capital productivity. The temperature rise can limit the effectiveness of lubricants in reducing surface friction between mechanical components (Mortier et al., 2010), increase failure rates by increasing the volume of input materials required (Collins, 1963), and slow down hardware processing speed. Climate change-induced disasters heighten physical risks to capital, as temperature negatively impacts capital efficiency and productivity, exacerbating the growth rate reduction through disrupted resource allocation and production efficiency in heat-intensive sectors.

The existing literature on micro-level studies indicates that temperature can harm various aspects of economic productivity, including labour productivity (Adhvaryu et al., 2018) and cognitive abilities (Hancock et al., 2007). Micro-level studies consistently demonstrate the negative impact of extreme temperatures on labour productivity in labour-intensive manufacturing industries (Stevens, 2019; Cai et al., 2018). Chen and Yang (2019) found that rising temperatures decrease labour productivity, reduce investment, and increase inventory levels. Somanathan et al. (2021) conducted a comprehensive study in India, highlighting the link between high temperatures, decreased outputs, and the impact on firm-level production. Our aggregate state-level sub-national estimates support them (refer Table 3).

Table (3) EFFECTS OF ANNUAL TEMPERATURES ON INPUT PRODUCTIVITY AND FOREST COVER

Variables	(1) CS-ARDL FOREST COVER	(2) CS-ARDL LP GROWTH	(3) CS-ARDL CP GROWTH	(4) CS-ARDL POWER
d.Mean temperature	-4300.581*	-0.1510*	-.7435**	-536.45
	(2312.427)	(0.0789)	(0.2625)	(467.9991)
CADF Statistics	-0.170	-2.048**	-0.810	-2.215**
Cointegration	Yes	Yes	Yes	YES
CD Statistics	-0.26	3.05**	1.63	0.00
Number of observation	496	466	466	494
Number of States	31	31	31	31

Notes: We use the output-labour ratio as a proxy of labour productivity (LP) and the output-capital ratio as a proxy of capital productivity (CP). Forest cover area has been taken as a proxy for ecological services. CD: Cross-sectional dependence test of Pesaran (2021). All 29 states and Union territories of India are included in the panel regressions, with Andaman and Nicobar Island and Chandigarh included in the analysis, and temperatures are in degrees Celcius. The sample is for 2004–2019. ERA Reanalysis (WorldBankGroup, 2024) weather data is used. Standard errors are in parentheses. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.3.2 Ecosystem services

Extreme events can impact the growth rate through a third mechanism by diminishing ecosystem services, represented by forest cover. Using forest cover as a proxy for these services, our findings reveal that temperature fluctuations have both economically and statistically significant negative impacts on ecosystem services (See Column 1 Table 3). The reduced forest cover leads to fewer natural resources, soil erosion, and disrupted ecosystem services, negatively impacting economic growth. The diminishing ecological balance may elevate the risk of zoonotic disease transmission, as decreased ecology leads to heightened human-wildlife interactions. This can result in compromised human health, increased healthcare expenses, and productivity losses, ultimately impeding the growth rate. Reduced forest cover in developing nations like India hinders economic growth by impacting essential ecosystem services such as water purification, carbon sequestration, and biodiversity conservation, underpinning various economic activities (Shukla et al., 2019). The decreased forest cover can contribute to urban heat island effects, resulting in greater energy consumption for cooling and associated expenses (see column 4 Table 3). Moreover, biodiversity loss often accompanies declining forest cover, disrupting sectors such as tourism that rely on India's rich biodiversity.

5.3.3 Industry Analysis

Examining the impact of climate change on specific sectors in India is vital due to the diverse challenges each sector faces. Different sectors possess distinct decarbonization pathways, necessitating customized approaches. By prioritizing sectors with significant emissions and potential for mitigation, policymakers can minimize trade-off costs and effectively mitigate climate risks while enhancing economic resilience(RBI, 2023).

There is a common belief that the consequences of global warming mainly affect sectors related to agriculture, which make up a relatively small share of India's GDP. This section reassesses this notion and examines the specific impacts outlined in Table 2's panel regressions. Guided by existing micro-level evidence on temperature's influence on economic activities, our analysis focuses on assessing Climate Change impacts across six sectors of the Indian economy. Because of limitations in worker-per-sector at the state level, we exclusively present the findings related to output growth at the state level. The disaggregated sector analysis is crucial due to varied climate conditions across regions. Weather impacts on growth differ by sector, depending on factors like heat exposure and input productivity. Understanding these sector-specific effects, especially with changing GDP contributions, is vital for targeted policy formulation.

Climate Change exhibits significant and widespread negative impacts across all sectors, as reported in Table 4. Recognizing these impacts is vital for shaping effective mitigation strategies, including resilient infrastructure, improved crop management, and sustainable manufacturing. Stationary residuals further affirm the presence of cointegration. The rising heat stress in India is anticipated to lead to a 5.8% reduction in working hours by 2030, equivalent to the loss of 34 million full-time jobs, and an estimated 6% decrease in GDP (Woetzel et al., 2020; ILO, 2019). While agriculture, a significant contributor to employment, is set to be severely impacted due to its sensitivity to climate conditions, manufacturing sectors, particularly those lacking climate control systems, will also see substantial declines in worker productivity. This study finds that a one-degree temperature increase decreases agricultural output growth by 2.19 %. When temperatures rise, crops experience heat stress, resulting in reduced yields. This decline in cereal yield may affect food prices and supplies, potentially jeopardizing food security. It is well established that climate change impacts agricultural productivity and output (Gupta et al., 2014; Kumar and Khanna, 2023; Pattanayak and Kumar, 2014). We find the adverse negative impact of temperature variations on manufacturing output growth at the state level. Working conditions play a vital role; predominantly outdoor and manual agriculture exposes workers directly to extreme heat, leading to efficiency losses. In contrast, certain segments of the manufacturing sector provide controlled indoor environments, mitigating heat stress effects to some extent. (Jain et al., 2020) do not find evidence of the impact of temperature on manufacturing, whereas (Somanathan et al., 2021), using microdata of manufacturing firms, find a significant impact on labour supply.

We also find the negative and economically significant impact in the Mining, Construction, Electricity, and Hotel & trade sectors. Extreme heat poses significant risks to construction workers' health (in terms of loss in working days) and productivity, potentially resulting in fatigue, heat-related illnesses, and reduced efficiency. Work delays are common as construction materials, like concrete, may cure too quickly in high temperatures, affecting the quality of work. Similarly, temperature increases can have a range of adverse consequences on the mining sector in India. Higher temperatures can pose significant risks to the safety and health of miners working in both open-pit mines and underground tunnels. Some mineral resources, like water-dependent minerals, may become scarcer or more challenging to extract due to changing climate conditions, affecting the availability and profitability of mining ventures. Rising temperatures in India pose significant challenges to two vital sectors: electricity and tourism. In the electricity sector, extreme heat can lower power generation efficiency, potentially resulting in electricity shortages that can disrupt industries and households. India's diverse tourism offerings, including historical sites, wildlife reserves, and scenic landscapes, are vulnerable to climate-related changes, such as frequent heatwaves and changing monsoon patterns. Reduced tourist activity can negatively impact hotels, restaurants, and related businesses, contributing significantly to India's GDP. Moreover, heat-related discomfort can discourage outdoor shopping and exploration, potentially affecting the retail and trade sectors. The literature extensively investigates how temperature affects energy consumption, particularly in residential settings (Auffhammer and Mansur, 2014). This relationship is crucial for electricity system design, gaining renewed attention amid potential climate change. Residential energy demand varies with temperature and is influenced by heating and cooling preferences. The impact of an 'unusually warm day' on energy demand is contingent upon season, location, and the existing stock of heating and cooling equipment. Analyzing data from 28 Indian states over 2005-2009, Gupta (2016) predicted a 6.7% and 8.5% increase in electricity demand by 2030. Significantly, the impact of a warmer climate is magnified at higher income levels. Over 50% of the rise in demand stems from extensive adjustments due to the current low penetration of cooling equipment. Our results suggest that an increase of one degree Celsius temperature leads to a decline of 12 percentage points in electricity sectoral growth.

Implementing energy-efficient technologies in power generation and distribution and diversifying energy sources can enhance the resilience of the electricity sector. Similarly, promoting climate-resilient tourism practices and infrastructure and developing tourism offerings that can withstand extreme temperatures can help mitigate the adverse impacts on the hotel, trade, and tourism sectors. Our results are similar to findings (Colacito et al., 2019) in the USA.

Table (4) EFFECTS OF ANNUAL TEMPERATURES ON INDUSTRIES OUTPUT GROWTH

Variables	(1) CS-ARDL Mining	(2) CS-ARDL Agriculture	(3) CS-ARDL Manufacturing	(4) CS-ARDL Construction	(5) CS-ARDL Electricity	(6) CS-ARDL Hotel
D.MeanTemp	-0.0352	-0.0491**	-0.0219	-0.0202	-0.1651**	-0.0112
	(0.0791)	(0.0224)	(0.0668)	(0.0396)	(0.0761)	(0.0267)
CADF Statistics	-12.536 ***	-11.330***	-12.446***	-11.971***	-11.946***	-10.936***
Cointegration	Yes	Yes	Yes	Yes	Yes	Yes
CD Statistics	-2.37*	-1.63	-0.14	-3.35**	-2.15**	-2.97**
R Squared	0.90	0.69	0.76	0.82	0.82	0.80
Number of observation	959	1076	1076	1076	1059	1076
Number of States	29	29	29	29	29	29

Notes: The dependent variable is Industries output Growth. The Independent variable is the annual variation in mean temperature. CD: Cross-sectional dependence test of Pesaran (2021). The first column reports the estimated coefficients on average annual temperature from a regression of the industry's output growth rate. ERA 5 Renalysis weather (WorldBankGroup, 2024) data is used. Standard errors are in parentheses. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.4 Panel Granger Causality

Historically, Climate Change Indicators have often been viewed as exogenous indicators, overlooking the potential for reverse causation. When gauging the impact of Climate Change on economic growth, it is important to recognize that temperature may not be purely exogenous but rather weakly endogenous, even when assuming a scenario of a small economy (Kahn et al., 2021; Kumar and Maiti, 2024). In other words, economic growth in the past could have feedback effects on future temperature (Kahn et al., 2021). Moreover, Schultz and Mankin (2019) emphasised national governments run the weather stations from which meteorological data is collected, and this impacts the level of coverage and the continuity of such coverage depending on their political capabilities. State capacity affects meteorological station maintenance and instability may divert resources, causing gaps in weather records. The results in table 5 reveal bi-directional causality between annual mean temperature and GDP growth rate. To test for causality, we use the Xiao-Juodis method of Granger causality (Xiao et al., 2022; Juodis et al., 2021).

Granger causality tells us if one indicator causes changes in another, and it helps determine the direction of this cause-and-effect relationship. Panel Granger causality is a statistical method used in panel data analysis to investigate whether the past values of a variable in one entity can predict the future values of a variable in another entity. It extends the traditional Granger causality test to assess temporal causal relationships in datasets with both cross-sectional and time-series dimensions. Analyzing predictive causality and feedback in time series and panel data is crucial. Notably, the methods by Dumitrescu and Hurlin (2012) are widely used for Granger causality testing. Recently, Juodis et al. (2021) proposed a novel method applicable to homogeneous or heterogeneous coefficient models, addressing issues like the "Nickell bias" using the Half Panel Jackknife (HPJ) approach. Their method excels in scenarios with moderate time dimensions, heterogeneous parameters, and high persistence. Compared to existing approaches, especially Holtz-Eakin et al. (1988) GMM method with challenges in large T and Dumitrescu and Hurlin (2012) limitations with $N/T^2 \to 0$, Juodis et al. (2021)'s method offers improved validity and accuracy in various empirical conditions. The results obtained from Juodis et al. (2021); Xiao et al. (2022) for Granger non-causality indicate bidirectional causality between temperature and GDP Growth rate in the short-run, indicating the presence of reverse causality

5.5 Heterogeneity

The impact of temperature shocks on macroeconomic outcomes is heterogeneous among countries, with differential effects observed between developed and developing nations

Table (5) Causality tests between Growth and Temperature

Juodis, Karavias and Sarafidis (2021) Granger non-causality test		
	HPJ Wald Statistic	Number of Lags(BIC Criterion)
H0- Δ average temperature do not granger cause ΔLog (GDP)	20.6755***	1
H0- ΔLog (GDP) do not granger cause Δaverage temperature	8.9007**	3
H0- Δ maximum temperature do not granger cause ΔLog (GDP)	10.1303**	1
H0- ΔLog (GDP) do not granger cause Δ maximum temperature	16.7405**	2
Number of observations	1076	
Number of States	29	

Notes: We use Xiao et al. (2022) panel granger causality test. We first report a joint test of Granger causality of mean temperature and maximum temperature to GDP Growth. The other two test reports ΔLog (GDP) do not granger cause average temperature, and ΔLog (GDP) do not granger cause maximum temperature.
(*)(**) (*) indicate the level of signifance at the (1%) (5%) level (10%) level**

(Dell et al., 2012; Hsiang et al., 2013; Acevedo et al., 2020; Letta and Tol, 2019). The effects of temperature shocks in India are likely to vary across states due to differences in geography, climate, and economic conditions. In such cases, employing fixed-effect models with homogeneous slope parameters is inappropriate and will result in biased outcomes. Acknowledging this heterogeneity is crucial for obtaining accurate and reliable results when assessing the impacts of temperature variations in Indian States(Herzer, 2019, 2020; Chudik et al., 2011). In contrast, the CS-ARDL utilizes a heterogeneous mean estimator addressing the issue of slope heterogeneity. We also tackle parameter heterogeneity by stratifying our dataset based on climate exposure, development level, and the share of agriculture in GDP. This results in three main sub-sample categories: cold, moderate, and hot regions for temperature, poor and rich states for development, and low and high agricultural share.

5.5.1 Regional Analysis

To determine whether certain broad geographical characteristics are responsible for the effect of annual temperature on GSDP growth rate, We divide India into four broad regions, i.e. North, South, East, and West. Furthermore, the kind, size, and even way of Climate Change have been different all over India. For example, as we explain in the paper, the average temperature has increased in Western and Southern states since 1980, but it has slightly decreased in the Eastern and Northern regions. Utilising the CS-ARDL estimation method, we evaluated the impact of annual temperature on GSDP growth rates. The results, detailed in Table 6, unveiled a substantial regional and spatial disparity in temperature sensitivity. Notably, Southern and Western states are adversely impacted by temperature fluctuations compared to their Eastern and Northern counterparts, with the estimated coefficient for the Southern region notably exceeding the national-level coefficient, accentuating the region's vulnerability to temperature-induced economic disruptions (See Column 4 Table 6). Southern states, on average, experience higher temperatures, making them more prone to frequent and severe heat stress events.

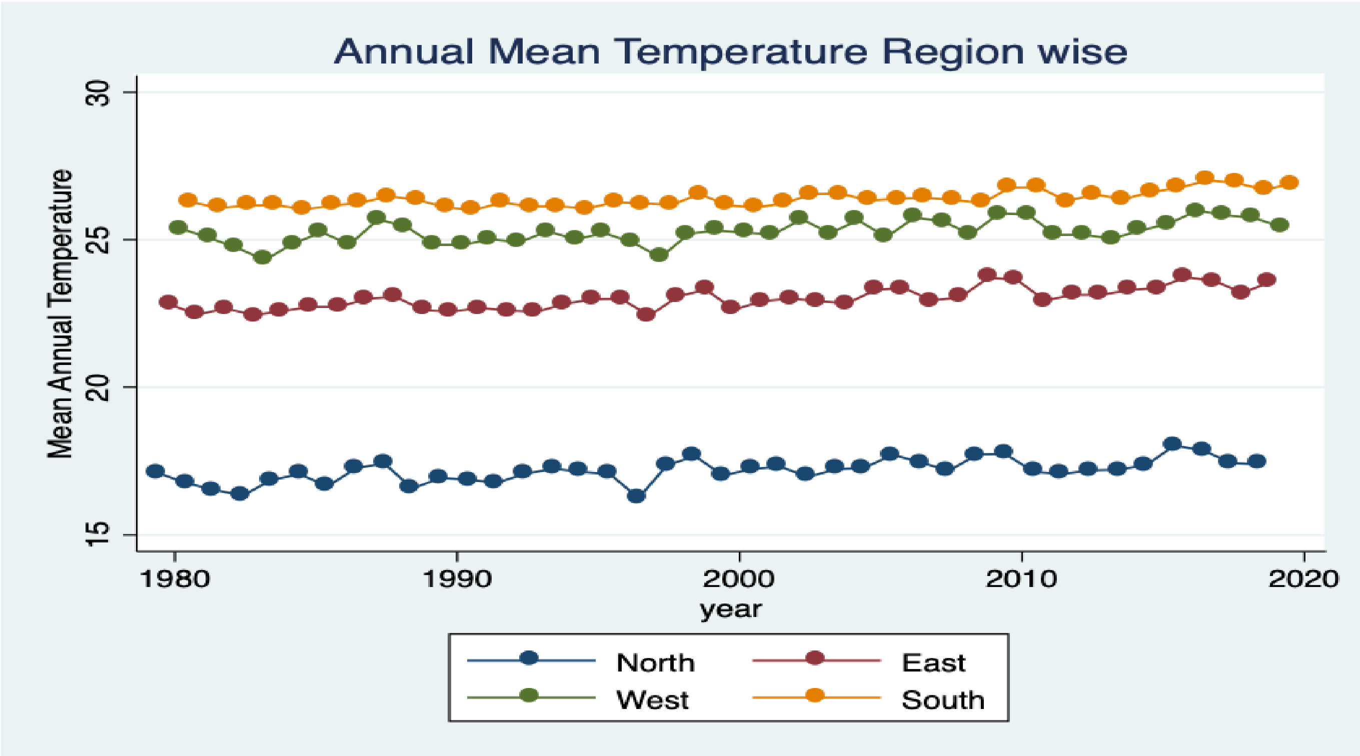


Figure (4) Region-wise temperature trends

Since agriculture plays a substantial role in their economies, these temperature fluctuations can significantly disrupt crop yields leading to a drop in agricultural output. Importantly, the Southern region collectively contributes significantly to India's Gross Domestic Product (GDP), and any adverse effects on its economic activities have a proportionately larger impact on the national GDP. Lastly, varying levels of climate-resilient infrastructure within the Southern states can exacerbate the economic consequences of high temperatures.

Table (6) REGIONAL ANALYSIS: EFFECTS OF ANNUAL TEMPERATURES ON GDP GROWTH IN DIFFERENT REGION

VARIABLES	(1) CS-ARDL GSDP Growth North	(2) CS-ARDL GSDP Growth East	(3) CS-ARDL GSDP Growth West	(4) CS-ARDL GSDP Growth South
D.MeanTemp	-0.0078	-0.0549	-0.0224	-0.1231**
	(0.0206)	(0.0650)	(0.0123)	(0.0438)
CADF Statistics	-4.859***	-6.267***	-6.039***	-3.323***
R-Squared	0.73	0.87	0.91	0.79
Number of observation	294	275	240	267
Number of States	8	8	6	7

Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature. CD: Cross-sectional dependence test of Pesaran (2021).
North - Himachal Pradesh, Uttarakhand, Uttar Pradesh, Haryana, Bihar, Assam, Sikkim, Arunachal
East - Jharkhand, Odisha, West Bengal, Nagaland, Meghalaya, Mizoram, Tripura
West - Rajasthan, Gujarat, Goa, Maharashtra, Punjab, Delhi
South - Madhya Pradesh, Chhattisgarh, Andhra Pradesh, Karnataka, Kerala, Tamil Nadu, Puducherry
(*)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.5.2 Role of Development

A state's development level directly affects its ability to handle weather shocks and minimize associated damages. This study unveils a pronounced negative effect of temperature on GSDP growth rate, particularly accentuated in economically disadvantaged states compared to affluent ones. Specifically, a one-degree Celsius rise in average temperature results in a long-term reduction of 5.23% in GSDP in poorer states contrasted with a 1.80% decrease in GSDP growth rate in wealthier states (refer to columns 1-2, Table 7). It is vital to note that India's economy is dynamic and has significantly evolved during our study period. The classification of states as poor or rich varies based on the year of data considered. We opt for the 1981 classification, our initial year, as early data points are more likely to be exogenously determined, providing a stable baseline amid the fluctuations observed in subsequent years (Jain et al., 2020). We also find similar results with this strategy. The disproportionate impact of rising temperatures in India, with poorer states experiencing more severe effects than wealthier ones, can be attributed to several intertwined socio-economic factors. Limited financial resources hinder these states' ability to invest in climate-resilient infrastructure and adaptive measures. Agriculture, a primary livelihood source in most regions, is highly vulnerable to the changing climate patterns, leading to reduced crop yields and economic instability. Inadequate housing, limited access to essential services like healthcare and clean water, and crowded living conditions intensify the risks of heat-related illnesses. Moreover, these states often lack comprehensive education and awareness programs, leaving residents ill-equipped to cope with the challenges posed by rising temperatures. Economic dependence on climate-sensitive sectors and limited access to social safety nets further amplify vulnerability.

This study finds an adverse impact in the states with a greater reliance on agriculture (See Column 3-4, Table 6). The impact of temperature on GSDP growth rates in agriculturally reliant states in India is pronounced due to several key factors. These states exhibit a heavy economic dependency on agriculture, which is inherently sensitive to climate conditions (Gupta et al., 2014). Temperature fluctuations can lead to heat stress and drought, causing reduced crop yields and agricultural output (Pattanayak and Kumar, 2014). Given that agriculture serves as a primary income and employment source for many in these regions, any decline in productivity directly affects income levels and economic activity (Pattanayak and Kumar, 2014). Additionally, agriculture plays a crucial role in ensuring food security, meaning that temperature-related reductions in output can lead to food shortages and increased food prices, and thus tend to influence overall consumption patterns. Limited access to modern farming practices and climate-resilient technologies further exacerbates vulnerability. The interconnectivity of the agricultural sector with other segments of the economy also magnifies the economic repercussions of reduced agricultural output. Our results are aligned with the findings of (Jain et al., 2020).

Table (7) SUBSAMPLE ESTIMATE: EFFECTS OF ANNUAL TEMPERATURES ON GDP GROWTH BASED ON DEVELOPMENT, AGRICULTURE AND CLIMATE EXPOSURE

VARIABLES	(1) CS-ARDL GSDP Growth Poor	(2) CS-ARDL GSDP Growth Rich	(3) CS-ARDL GSDP Growth Low Agri	(4) CS-ARDL GSDP Growth High Agri	(5) CS-ARDL GSDP Growth Low	(6) CS-ARDL GSDP Growth Moderate	(7) CS-ARDL GSDP Growth Hot
D.MeanTemp	-0.0523**	-0.0180	-0.0192	-0.0550**	0.0891	-0.1125	-0.0484**
	(0.0217)	(0.0228)	(0.0665)	(0.0283)	(0.0618)	(0.0870)	(0.0209)
CADF Statistics	-6.599***	-8.259***	-8.692***	-8.230***	-1.927 ***	-5.493***	-11.172***
R-Squared	0.64	0.83	0.68	0.76	0.80	0.84	0.75
Number of observation	569	507	614	462	94	248	734
Number of States	16	13	16	13	3	7	18

Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature. CD: Cross-sectional dependence test of Pesaran (2021). We categorise our data into three sub-sample groups according to average temperature ranges: the 'cold region' (0-15 degrees Celsius), the 'moderate region' (15-25 degrees Celsius), and the 'hot region' (above 25 degrees Celsius). In the second sub-sample analysis, we employ the level of development as a criterion, dividing our data into 'poor' states (those with GSDP below the median GSDP of states in 1981) and 'rich' states (those with GSDP at or above the median GSDP of states in 1981). Additionally, we introduce the reference year 1981 for GDP analysis for robustness. Our third sub-sample examination classifies states as 'low agri' if their 2014 agricultural share is below the median GSDP of states and 'high agri' otherwise.". Similar to other papers (Jain et al., 2020; Colacito et al., 2019)

(*)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.5.3 Climate exposure

This study establishes a causal relationship between annual mean temperature and GSDP growth rate in regions with distinct geo-climatic profiles. It suggests that as temperatures rise, growth initially increases by 8.91% in cold regions, but subsequently declines to -11.25% in moderately hot regions and further decreases to -4.84% in very hot regions (refer to columns 5-7, Table 7). Greater GDP growth losses are observed in regions with extremely high temperatures compared to those with moderately high temperatures. Economic activities thrive within optimal temperature ranges, benefiting sectors like agriculture in colder regions, but suffer productivity losses beyond these ranges, particularly in labour-intensive and temperature-sensitive processes. Our findings suggest the absence of a non-linear temperature in contrast to (Jain et al., 2020; Sandhani et al., 2023). We have also examined the non-linear relation between temperature and GSDP growth with the inclusion of quadratic temperature terms and found the absence of non-linearity.[10]

5.6 Robustness

We check the robustness of the estimated results in several ways. Using alternative estimation methods, we confirm a robust causal relationship between temperature and economic growth. Exploring alternative proxies for temperature, we observe negative impacts on Gross State Domestic Product (GSDP) growth. Additionally, alternative indicators such as per capita income validate temperature's impact on economic growth. Finally, analyzing the impact of different labour regulations reveals diverse economic effects of temperature variations.

5.6.1 Alternative estimation method

We examine the relationship between GSDP growth rate and annual mean temperature using two alternative techniques: de-factored instrumental variable estimation (Norkutė et al., 2021) and conventional Panel data fixed effect approach. The de-factored instrument variable estimation introduced a two-stage instrumental-variables (2SIV) approach for estimating panel regressions with unobserved common factors in large cross-sectional (N) and time-series (T) datasets. We also used the State fixed effect model to estimate the relationship between GSDP growth rate and annual variation in mean temperature. Estimates from the State FE model and de-factored instrumental variable estimation (Norkutė et al., 2021) produce quantitatively similar results (see Columns 4 and 5 in Table8).

[10]See Table A10 Online Appendix

5.6.2 Alternative proxies for climate change

Our investigation delves into the relationships between annual maximum temperature and the growth rate of Gross State Domestic Product (GSDP). As temperatures rise, conducive to living, potentially impacting both labour and capital efficiencies. In a related study, Giovanis and Ozdamar (2022) utilized maximum temperature as an indicator of climate change's effect on fiscal balance. Our findings reveal a negative relationship between higher annual maximum temperatures and GSDP growth, as evidenced in Table 8, column 1.

In addition to examining temperature levels, we conduct additional robustness checks by considering temperature anomalies and volatility as alternative factors. Temperature anomalies, temperature from a specific temperature observation and then dividing the difference by the temperature's standard deviation., account for climate variations across states, ensuring a fair comparison of temperature changes (Barrios et al., 2010; Portmann et al., 2009). Meanwhile, temperature volatility, measured as the difference between maximum and minimum temperatures, provides insight into changes in temperature distribution (Diebold and Rudebusch, 2022). Extreme temperatures, such as heatwaves, can significantly impact society and the economy, with high-temperature volatility potentially reducing labour productivity due to increased stress among workers.

Our investigation suggests the detrimental impact of temperature anomalies and volatility on GSDP growth, as illustrated in Table 8, columns 2 and 3. This established causal relationship persists across all models, providing robust evidence of the direct influence of temperature fluctuations on economic growth. The statistical significance of their coefficients emphasizes the substantial economic consequences of even minor temperature variations.

Table (8) ROBUSTNESS RESULTS: EFFECTS OF ANNUAL TEMPERATURE ON GDP GROWTH WITH ALTERNATIVE ESTIMATION TECHNIQUE

Variables	(1) CS-ARDL GSDP Growth	(2) CS-ARDL GSDP Growth	(3) CS-ARDL GSDP Growth	(4) NSYC-IV GSDP Growth	(5) FE MODEL GSDP Growth
Mean temperature				-0.0037	-0.0217***
				(0.0070)	(0.0056)
Maximum temperature	-0.0343**				
	(0.0152)				
Temperature volatility			-0.0623**		
			(0.0300)		
Temperature anomalies		-0.0085			
		(0.0070)			
Cointegration	Yes	Yes	Yes	NA	NA
CD Statistics	-2.05	-2.43*	-1.26	NA	NA
R Squared	0.80	0.79	0.79	NA	0.26
Number of observation	1076	1076	1076	1076	1076
Number of States	29	29	29	29	29

Notes: The dependent variable is GSDP Growth.CS-ARDL: Cross-sectional auto-regressive distributed lag of (Chudik and Pesaran, 2015; Ditzen, 2021). NSYC-IV: Defactored instrument variable estimation Norkutė et al. (2021). CD: Cross-sectional dependence test of Pesaran (2021) - The CD statistics have a null hypothesis of no cross-sectional independence in the residual of the estimated model. In the panel regressions, all 31 states and Union territories of India are included Temperatures are in degrees Celcius. The sample is 1980–2019 for annual regression. ERA weather data (WorldBankGroup, 2024) is used. Standard errors are in parentheses. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.6.3 Alternative indicators for Growth rate

We replaced the dependent variable in our regression with per-capita GDP and Total Gross State Value Added to validate our initial findings on the impact of temperature on economic growth. The results show that our earlier conclusions remain robust, unaffected by factors like population growth or inflation. (See Table A7 Online Appendix)

5.6.4 Impact via different labour regulation

The variation of state capacity and natural resources in the presence of different institutions and labour rigidity can affect the effective resource mobilisation for renewable resources and investment, the impact may vary across the federal states. Building upon the work of (Colmer, 2021; Besley and Burgess, 2004), we categorized three regions according to their labour regulation stance: Pro Worker, Pro Employer, and Pro Neutral. Subsequent analysis of temperature variations unveiled diverse impacts on economic growth within these regions. Notably, Pro Employer areas were found to undergo more pronounced negative effects in comparison to Pro Worker and Neutral states. This study also delves into the impact of temperature on Gross State Domestic Product (GSDP) growth, considering the level of industrialization as a pivotal factor. Notably, our analysis reveals a heterogeneous influence of temperature on GSDP growth across regions characterized by varying degrees of industrialization. Intriguingly, irrespective of the industrialization level – be it high or low – our quantitative results demonstrate a striking similarity in the observed effects of temperature on GSDP growth.

We then classified states into two categories, distinguished by their levels of forest cover – high or low. Our findings indicate states characterized by low forest cover exhibit an adverse impact of temperature on economic growth. We also created four distinct categories by considering both forest cover and the level of fiscal sustainability. Our analysis revealed that regions characterized by high forest cover and low fiscal sustainability experience more adverse impacts compared to their counterparts in terms of economic outcomes (See Figure A6 Online Appendix)

5.6.5 Using District level data

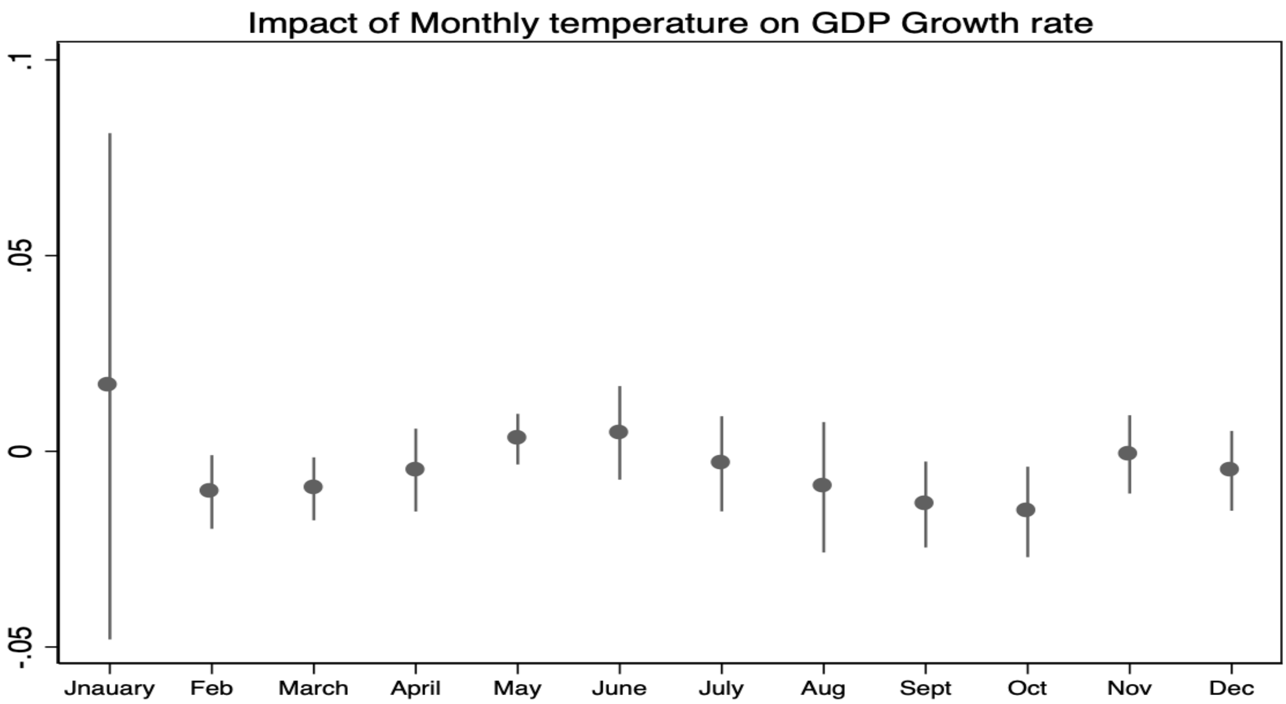
Sandhani et al. (2023) rely on a database compiled from diverse publicly available sources. However, the absence of systematically available, consistent, and validated GDP data at the district level in India, spanning extended time periods and covering all districts, constrains both the spatial and temporal is problematic when analysis is done for climate change. As we have a smaller panel. We use ICRISAT–TCI (2024) GDP data for our analysis spanning from 2007-2015 having 3745 observations. Our District-level analysis produced similar results to state-level results. These results suggest evidence of climate change's negative impact on economic growth. All the seasons have an economically significant impact on economic growth. The issue of the availability of credible district-level GDP data in India poses a significant challenge. Our study encounters difficulties due to the lack of systematically compiled, consistent, and validated GDP data at the district level. The absence of such granular data inhibits a nuanced understanding of economic dynamics at the local level, hindering policymakers and researchers in formulating targeted strategies for regional development. (See Figure A7 Online Appendix)

5.6.6 Using Monthly Temperature data

Instead of relying on arbitrary seasonal definitions, We also tested the sensitivity of our results with monthly temperature fluctuations on the GSDP growth rate for a thorough analysis. However, it is noteworthy that the Colacito et al. (2019) does not provide a report of these monthly coefficients. As suggested by Barker (2022), in opting for a more detailed approach, exploring the specific variations and patterns each month would contribute to a more nuanced understanding of the data. The omission of monthly coefficients in the paper might limit the comprehensiveness of the analysis, as it overlooks potential fluctuations and trends that could be critical in discerning the underlying dynamics.

Figure 5 displays the monthly coefficient estimates, revealing notable month-to-month fluctuations. Importantly, all months, except January, May, and June, exhibit a negative impact on growth. Adverse weather conditions during certain months might impede productivity, affecting industries sensitive to weather changes. Conversely, favourable climate conditions(Rainfall) in January, May, and June could positively impact outdoor industries or agriculture, contributing to growth. Consumer behaviour, responsive to weather patterns, may also play a role in influencing spending and demand.

Figure (5) Impact of Monthly temperature on GSDP growth rate



Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in monthly mean temperature. The graph only shows the estimated coefficients

5.7 Projected impact of temperature on Growth 2021-2100

India faces high economic growth reduction risk with a 2-degree Celsius increase in global temperature versus 1.5 degrees Celsius (IPCC, 2018). To contribute to climate policy discussions, we conduct projections of estimated coefficients under different SSP, RCP and NGFS scenarios. This section focuses on quantifying the effects of annual temperatures, as estimated in panel CS-ARDL model baseline specification 10, over an extended timeframe. We projected the future impact of Climate Change on the GSDP growth rate in Indian states by combining the estimated coefficients (see model 1, Table

2) with the projection of climate change under different SSP scenarios for the period 2021-2100. We assumed future Climate Change effects on growth would respond similarly to our observed sample.

To quantify the long-term growth projection, we use temperature projection data from two sources NGFS Climate Analytics and CCKP (World Bank). The projected temperature level data for the sub-national unit was obtained from the World Bank Climate Change Knowledge Portal. Similarly, we also use three The Network for Greening the Financial System (NGFS) scenarios for temperature and combine that with estimated coefficients. We use NGFS current policies[11], NGFS Delayed transition[12] and NGFS net zero 2050[13] for future growth projection. We find that the increase in temperature is highest under the RCP 8.5 scenario and modest under the RCP 2.6 Scenario. Similarly for the NGFS Scenario temperature increase is highest under NGFS Current policies and moderate under delayed transition under NGFS Net-Zero 2050 and NGFS Delayed transition (NGFS, 2023).

Model-based simulations and cross-country studies suggest the adverse impact of temperature rise in India than its counterpart in Europe or the USA. Kahn et al. (2021) suggest that under business as usual scenario, per capita GDP losses in India may go up to 9.9% to 13.4% by 2100, which is twice that of the EU, namely, 4.7% to 6.7%. Under different NGFS (2023) scenarios, GDP growth rate decline in the future varies. In the NGFS Current Policies Scenario, which assumes limited climate action, India faces the grim prospect of substantial GDP losses in the future. This scenario underscores the critical necessity for India to adopt more ambitious and immediate climate policies. Moving forward, the NGFS Delayed Transition Scenario offers a more optimistic outlook. The economic impact can be less severe even if the transition to a greener economy is somewhat delayed. To leverage this scenario's potential benefits, India should prioritise policies that expedite the transition to a low-carbon economy. This could involve aggressively promoting renewable energy sources, stringent emissions regulations, and sustainable land use practices. However, the most promising scenario is the NGFS Net Zero 2050 Scenario. In this scenario, countries commit to achieving net-zero greenhouse gas emissions by 2050. India can significantly reduce its vulnerability to Climate Change by setting clear net-zero targets, aggressively decarbonising key sectors like energy and transportation, and fostering innovation in clean technologies. By embracing the NGFS Net Zero 2050 Scenario and implementing robust climate policies, India can not only

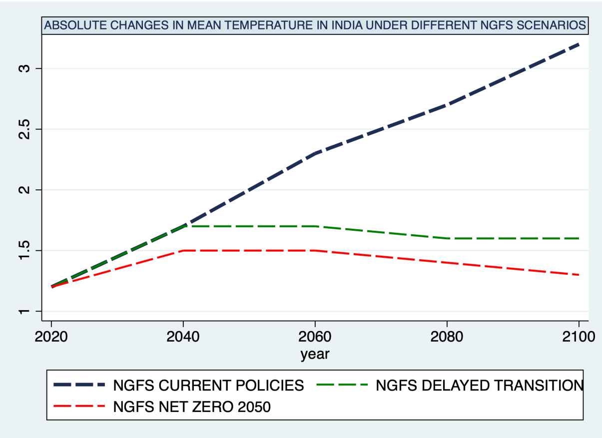
[11] Current Policies assumes that only currently implemented policies are preserved, leading to high physical risks(NGFS, 2023)

[12] Delayed transition assumes annual emissions do not decrease until 2030. Strong policies are needed to limit warming to below 2°C. Negative emissions are limited(NGFS, 2023)

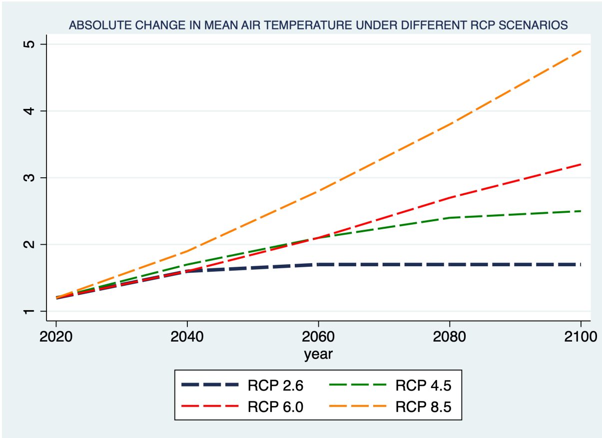
[13] Net Zero 2050 limits global warming to 1.5°C through stringent climate policies and innovation, reaching global net zero CO2 emissions around 2050 (NGFS, 2023).

mitigate future GDP losses but also position itself as a global leader in sustainable economic growth. These policies will safeguard India's economic future and contribute to global efforts to combat climate change.

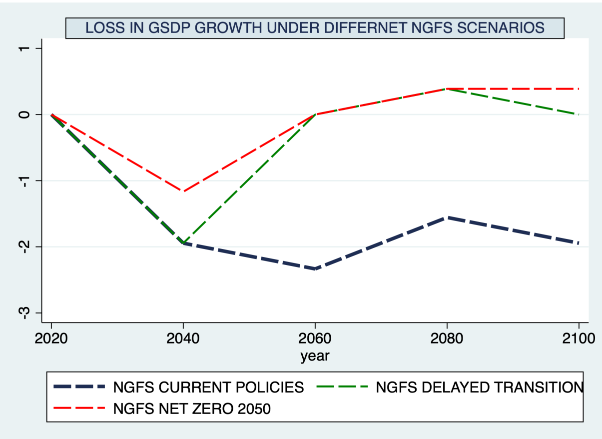
Figure (6) Future Growth Loss and Temperature Rise Projections under different RCP and NGFS Scenario 2020-2100



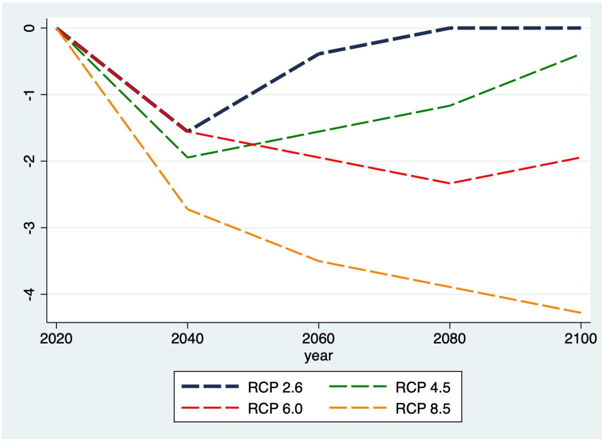
(a) NGFS Scenario temperature rise 2021-2100



(b) RCP Scenario temperature rise 2021-2100



(c) NGFS Scenario gsdp growth loss during 2021-2100

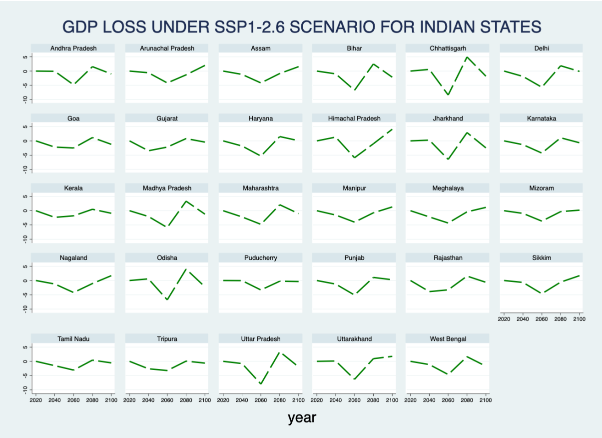


(d) RCP Scenario gsdp growth loss during 2021-2100

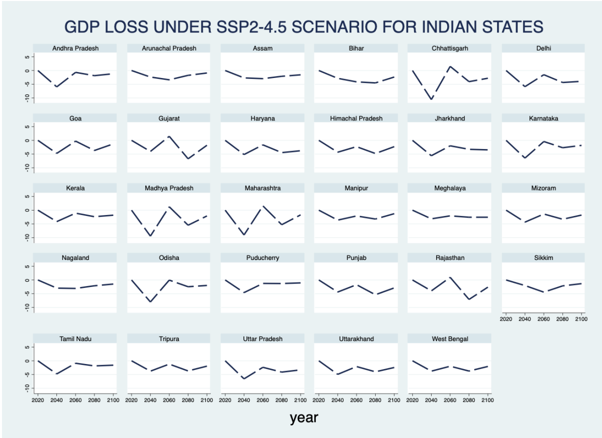
Considerable variation exists in the future impact of temperature on GSDP growth rates among states. To examine if this heterogeneity extends to future Climate Change impacts on growth, we utilize sub-national temperature projections from CCKP (World Bank) under different CMIP6 Scenarios, which replace the previous RCPs with SSPs. These scenarios reflect updated climate models and incorporate recent emissions trends. The scenarios SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 are then integrated with our estimated coefficients. Several findings emerge from this analysis. First, there is a high degree of heterogeneity in magnitude under different SSP Scenarios. SSP5-8.5 Scenarios show detrimental impact across states. Second, most states are predicted to have reduced output, but poorer states are adversely impacted in future. Third, Southern and Western states will be worse affected by rising temperatures in the future.

Analysing GSDP growth loss projections over distinct sub-periods within the 2020-2100 time frame reveals nuanced trends. In the initial 2020-2040 phase, the sustainability-focused SSP1-2.6 experiences a moderate decline of -1.3226%, indicating early challenges. In contrast, SSP2-4.5 encounters a significant reduction of -6.1851%, setting the tone for a substantial overall decrease by 2100. The 2040-2060 sub-period sees SSP1-2.6 facing a noteworthy growth loss of -5.0959%, while SSP2-4.5 stabilises with a marginal decrease of -0.389%. However, SSP3-7.0 and SSP5-8.5 continue negative trends, with reductions of -1.9839% and -5.5238%, respectively. Moving to the 2060-2080 sub-period, SSP1-2.6 rebounds with a positive growth of 1.7505%, suggesting potential benefits from sustained sustainability efforts. In contrast, SSP2-4.5, SSP3-7.0, and SSP5-8.5 continue negatively, experiencing declines of -4.279%, -3.8511%, and -8.4024%, respectively. The 2080-2100 period sees SSP1-2.6 facing a modest decline of -0.5835%, SSP2-4.5 and SSP5-8.5 declining further with reductions of -2.2173% and -7.5077%, respectively, and SSP3-7.0 witnessing the most significant reduction of -5.2126%. These numbers underscore the dynamic economic landscape, emphasising the need for adaptive strategies to mitigate the cumulative impact of diverse challenges over time (See online Appendix Table A8).

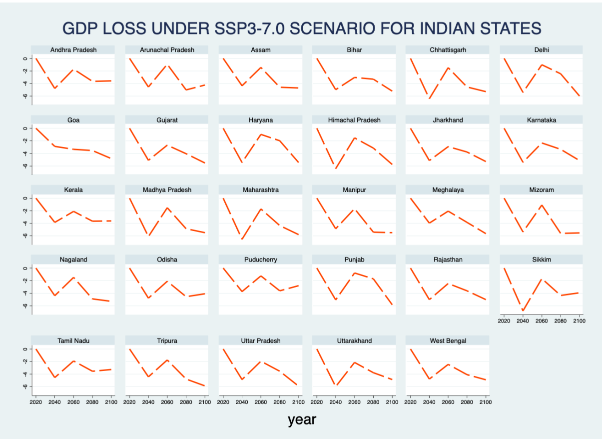
Figure (7) Projected reduction in GDP growth rate - State wise



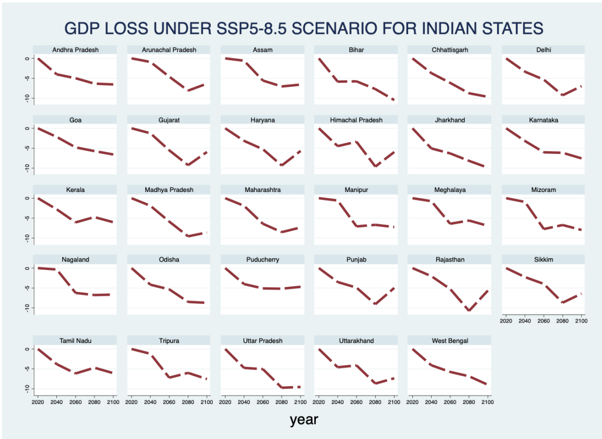
(a) SSP1-2.6



(b) SSP2-4.5



(c) SSP3-7.0



(d) SSP5-8.5

Note: In the context of CMIP6, climate projections are driven by a new set of emissions and land use scenarios known as the Shared Socioeconomic Pathways (SSPs), replacing the previously used Representative Concentration Pathways (RCPs) from CMIP5. These CMIP6 climate projections differ not only due to updated climate models but also because they are based on SSP scenarios generated by updated integrated assessment models (IAMs) and incorporate recent data on emissions trends.

6 Adaptation pathways and policy recommendations

Since the temperature rises exogenously given to an economy that damages the productivity, it is conceptualised that the resource mobilisation from renewable resources can reduce the severity of temperature rise and restrict the productivity damage. The adoption strategy should aim to spend more to sustain the growth. The adaptation finance gap, characterised by the shortfall between the funds needed to achieve adaptation goals and the actual available finance, is a pressing issue. This gap is exacerbated by the limited commitment of developed nations and resource constraints in many developing countries. Traditional public financing sources, including those outlined by the UNFCCC, have been criticised for their inadequate support for Indian adaptation needs. To address this challenge, there is a growing emphasis on identifying new private sources of finance to complement public funding. Remittances have emerged as a prominent private finance tool for adaptation, particularly at the household level. Remittances have gained prominence due to their increasing volume in developing countries, surpassing other financial sources. They offer attributes like predictability, lower volatility, and the ability to directly benefit the most vulnerable populations (Musah-Surugu and Anuga, 2023).

Remittances emerge as a significant adaptation tool to counter the impact of temperature fluctuations on economic growth in Indian states. We found that a state having low remittance inflow has a worse impact of temperature on economic growth than high remittance in India (See columns 1 and 2 in 9). In states with higher remittance levels, households have greater financial resilience to cope with the economic shocks stemming from extreme temperatures. These funds can be invested in climate-resilient practices, diversified income sources, and improved infrastructure to mitigate temperature-related challenges. However, states characterized by low remittance inflows face constraints in terms of funds available for adaptation measures. Households in these regions may lack the financial resources required to invest in climate-resilient practices or infrastructure, resulting in a heightened susceptibility to the economic impact of rising temperatures. In conclusion, remittances play a pivotal role in augmenting the adaptive capacity of states grappling with temperature-related challenges, with higher remittance inflows contributing to increased financial resilience, diversified income sources, and investments in adaptive infrastructure that collectively reduce vulnerability to temperature fluctuations. Conversely, states with limited remittance inflows confront greater challenges in funding adaptation measures, magnifying the economic repercussions of temperature extremes.

In India, states with higher fiscal sustainability, indicated by higher own tax revenue, experience less negative impacts of temperature on economic growth compared to states with lower own tax revenue. This suggests that fiscal sustainability plays a crucial role in adaptation policies. States with greater fiscal capacity have more resources and flexibility to invest in climate resilience, allocate funds to adaptation measures, and prioritise climate-related initiatives. Their ability to generate revenue through taxation contributes to their capacity to fund adaptation, reducing their vulnerability to climate-induced economic shocks. This highlights the importance of fiscal space and resource allocation in effective adaptation policies and suggests that managing fiscal sustainability is crucial for climate resilience, potentially reducing the need for additional debt. A recent paper by Fuje et al. (2023) found a substantial negative impact of droughts and storms on output growth and fiscal positions in EMDEs.

The significant negative impact of temperature on economic growth in high-debt states in India raises crucial concerns about the intersection of debt management and climate adaptation policies (Column 5-6, 9). These states face resource constraints due to their debt obligations, limiting their ability to allocate funds for climate resilience initiatives. Their fiscal space is constrained, making it challenging to respond effectively to climate-related challenges that require substantial investments. Furthermore, the interplay between debt and economic growth becomes intricate as reduced growth hampers revenue generation, potentially leading to a cycle of increasing debt and decreased flexibility for adaptation efforts. High-debt states must navigate difficult choices in prioritizing adaptation measures, often leading to delayed or insufficient investments in climate resilience. This situation underscores the need for innovative financing solutions, international assistance, and strategies to enhance fiscal capacity, enabling these states to address the urgent challenges posed by Climate Change while managing their debt burdens effectively.

Ecological fiscal transfers (EFTs) have emerged as innovative policy instruments with the potential to play a vital role in climate change adaptation in India. These fiscal transfer schemes aim to redistribute public revenues, primarily derived from taxes, from national and regional governments to local governments. One of the primary objectives is to address fiscal imbalances across decentralized governments, but EFTs go further by compensating local governments for the expenditures associated with providing ecological public goods and services(Ring et al., 2010). In many developing countries, including India, there exists a mismatch between the costs and benefits of conservation efforts, often leading to inadequate engagement in conservation activities by local actors. This not only addresses the fiscal imbalances but also encourages local engagement in conservation activities. In India, the introduction of EFTs, which include forest cover as an ecological indicator, is a significant step toward incentivizing states to protect and restore forests.

Table (9) SUBSAMPLE ESTIMATE: EFFECTS OF ANNUAL TEMPERATURES ON GDP GROWTH BASED ON REMITTANCES, DEBT AND FISCAL SPACE

	(1)	(2)	(3)	(4)	(5)	(6)
	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL
	GSDP Growth	GSDP Growth	GSDP Growth	GSDP Growth	GSDP Growth	GSDP Growth
VARIABLES	Low Remittance	High remittances	Low Fiscal Sustainable	Hiigh Fiscal	Low Debt	High Debt
D.MeanTemp	-0.0518*	-0.0364**	-0.0556*	-0.0371**	-0.0288*	-0.0697**
	(0.0248)	(0.0193)	(0.0310)	(0.0166)	(0.0174)	(0.0265)
CADF Statistics	-7.564***	-8.267***	-7.282***	-10.279***	-5.799***	-9.936***
R-Squared	0.81	0.77	0.75	0.78	0.79	0.72
Number of observation	636	440	489	587	361	715
Number of States	18	11	14	15	10	19

Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature. CS-ARDL: Cross-sectional auto-regressive distributed lag of (Chudik and Pesaran, 2015; Ditzen, 2021). CD: Cross-sectional dependence test of Pesaran (2021) - The CD statistics have a null hypothesis of no cross-sectional independence in the residual of the estimated model. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

7 Conclusion

This paper investigated how the temperature rise dampens the total productivity growth by damaging the efficiency of labour, capital and ecology that are responsible for growth deceleration using the aggregate and dis-aggregate level of India data and how the resource abundance, climatic exposure and the state capacity to mobilise resource for renewable sources can minimise the deceleration but at differential rate across the regions. Furthermore, this study utilises the CS-ARDL econometric model(Ditzen, 2021) to explore long-term relationships, incorporating diverse datasets to address potential omitted variables. We find that one Degree Celcius temperature variation leads to a -3.89% reduction in economic growth in India. We find seasonal temperature to be a key determinant in elucidating the economic repercussions of climate change. To the best of our knowledge, Our Study is the first to unveil the impact of seasonal temperature variations in driving seasonal economic cycles across diverse sectors in India. Based on the work of Xiao et al. (2022); Juodis et al. (2021), This paper is the first to empirically establish bidirectional causality between temperature and GDP growth rate in the short run, providing strong evidence of reverse causality. The paper's conclusions are robust at district-level data in India. Additionally, our findings remain robust across various alternative proxies for climate change, estimation techniques, data sources, and regional labor regulations. This study improves existing IAM damage functions by addressing their static nature, which overlooks the dynamic causal impact of temperature fluctuations on macroeconomic growth. Incorporating long-run estimates into IAMs can improve understanding of the long-term impacts of climate change on welfare (Chang et al., 2023; Tol, 2022).

Our paper is the first to examine the effects of temperature rise on the output growth of a panel of industries across states in India. By analyzing sector-specific data, we unveil significant negative effects across agriculture, manufacturing, construction, electricity, and tourism. By prioritizing sectors with significant emissions and potential for mitigation, policymakers can minimize trade-off costs and effectively mitigate climate risks while enhancing economic resilience. Construction, mining, electricity, and tourism sectors also face significant risks, with extreme heat posing health hazards and disrupting operations. This paper also examines how temperature fluctuations affect economic growth in different regions of India, exposing a greater degree of the vulnerability of poorer and agriculture-dominated states, particularly in the Southern and Eastern regions. Extremely hot areas experience more significant GDP growth losses, suggesting non-linear effects. These findings highlight the need for tailored climate adaptation strategies. Additionally, this paper adds to the discussion on the long-term economic consequences of global temperature rise. We incorporate future temperature projections under various scenarios, revealing that ambitious climate policies, such as achieving net-zero emissions by 2050, can significantly reduce vulnerability and position India as a leader in sustainable growth.

At COP26, the Government of India voiced concerns for developing countries and presented its climate action plan. India plans to reduce carbon emissions by one billion tonnes and decrease the carbon intensity of its economy by 45% by 2030, aiming for net zero emissions by 2070.The LIFE mantra (Lifestyle for Environment) was introduced as a campaign for eco-conscious living. The announced climate action has the potential to attract investment and new technologies to support India's transition to a cleaner and climate-resilient economy. While policies like market-based carbon taxes, cap and trade mechanisms, and emission trading schemes are commendable policy instruments for addressing climate change, their implementation may require considerable time. In light of this, there is a growing need to prioritise conventional adaptation policies such as remittances and Ecological Fiscal Transfers in the Indian context. Remittances, which involve funds sent by overseas Indians to their families in India, can play a significant role in helping communities adapt to changing climate conditions. Ecological Fiscal Transfers, which allocate financial resources to states and regions based on their environmental performance, can incentivise local governments to adopt sustainable practices and invest in climate resilience. These adaptation strategies can offer more immediate relief and protection to vulnerable populations in India, complementing longer-term mitigation efforts and fostering greater resilience in the face of climate change-induced challenges.

However, it is essential to discuss and elucidate the various limitations, constraints, and potential biases that may affect the outcomes and interpretations of this study. Since GDP does not account for the monetized effects of temperature change on non-market sectors, future research should further enrich this limitation by exploring empirical links between climate change and biodiversity impacts, health losses, and tipping points, and monetizing these climate impacts(Chang et al., 2023).

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8 Acknowledgements

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9 Declaration of competing interests

We declare that we have no competing interests related to this manuscript.

10 Funding

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11 CRediT authorship contribution statement

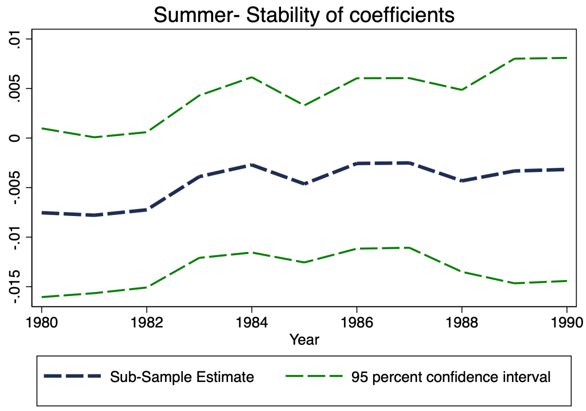
Naveen Kumar: Investigation, Data curation, Methodology, Conceptualization, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.
Dibyendu Maiti: Supervision, Funding acquisition, Validation, Writing – review & editing

12 Data Availability

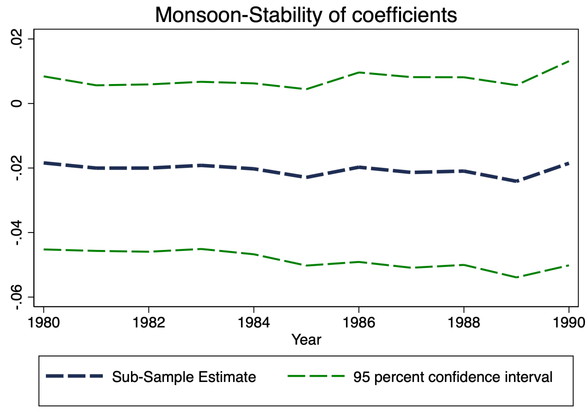
Data are available from the corresponding author on reasonable request

Appendix

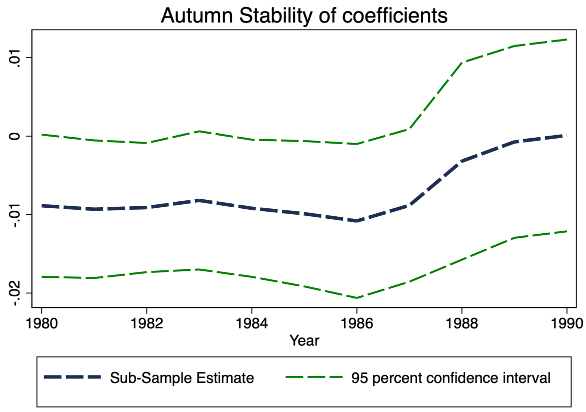
Figure (A1) Stability of coefficients for Seasonal temperature



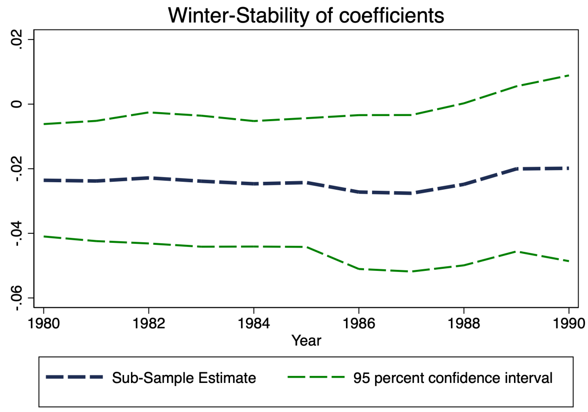
(a) Summer



(b) Monsoon



(c) Autumn



(d) Winter

Note : Summer (Average of month of March , April and May) Monsoon(Average of June, July, August and September) Autumn(October and November) and Winter(Average of December , January and February).Climate research unit weather data is used. Figures show the long-run effect (and their 95% standard error bands) of climate change on GSDP Growth rate on the sub-sample of different windows, using the CS-ARDL specification. We start the estimation with the full sample and then drop one year at a time

Table (A1) Compendium of Variable Definitions and Data Sources: Rationale and Previous Literature

Variables	Definitions	Source of Data	Indicator Justification: Rationale and Prior Literature
Economic Variables			
GSDP Growth rate	State GDP Growth rate in lakhs	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Agriculture Growth rate	agriculture and allied activities(rs lakhs)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Manufacturing Growth rate	manufacturing(rslakhs)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Mining Growth rate	mining and quarrying in (Rslakh)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Construction Growth rate	construction(rslakh)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Electricity Growth rate	electricity gas and water supply (rslakhs)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Hotel and Restaurant Growth rate	trade hotels and restaurants(rslakh)	EPWRF India Time Series	(Colacito et al., 2019; Jain et al., 2020; Kahn et al., 2021)
Labour productivity Growth rate	2004-2019	RBI Handbook of Indian States	(Kahn et al., 2021; Letta and Tol, 2019; Kumar and Khanna, 2019)
Capital productivity Growth rate	2004-2019	RBI Handbook of Indian States	(Kahn et al., 2021)
Forest cover	2004-2019	RBI Handbook of Indian States	(Kahn et al., 2021)
Power consumption	2004-2019	RBI Handbook of Indian States	(Kahn et al., 2021)
Weather Indicators			
Rainfall	Rainfall Precipitation	Climate Change Knowledge Portal (World Bank)	(Kahn et al., 2021; Letta and Tol, 2019; Kumar and Khanna, 2019)
Weather	Max Temperature	Climate Change Knowledge Portal (World Bank)	(Giovanis and Ozdamar, 2022)
Weather	Average Temperature	Climate Change Knowledge Portal (World Bank)	(Kumar and Khanna, 2019; Letta and Tol, 2019)
Weather	Long term temperature anomalies	Author Construction	(Kahn et al., 2021)
Weather	temperature volatility	Author Construction	
Weather	Negative temperature shocks	Author Construction	(Kahn et al., 2021)
Weather	Positive temperature shocks	Author Construction	(Kahn et al., 2021)
Projected Weather Data			
Weather	Projected Temperature RCP 2.6 Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature RCP 4.5 Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature RCP 6.0 Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature RCP 8.5 Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature NGFS Current policy Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature NGFS Delayed Transition Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature NGFS Net Zero 2050 Scenario	NGFS - Climate Analytics	https://climate-impact-explorer.climateanalytics.org/
Weather	Projected Temperature SSP1- 2.6 Scenario	Climate Change Knowledge portal	(Kumar and Khanna, 2019)
Weather	Projected Temperature SSP2- 4.5 Scenario	Climate Change Knowledge portal	(Kumar and Khanna, 2019)
Weather	Projected Temperature SSP3- 7.0 Scenario	Climate Change Knowledge portal	(Kumar and Khanna, 2019)
Weather	Projected Temperature SSP5- 8.5 Scenario	Climate Change Knowledge portal	(Kumar and Khanna, 2019)

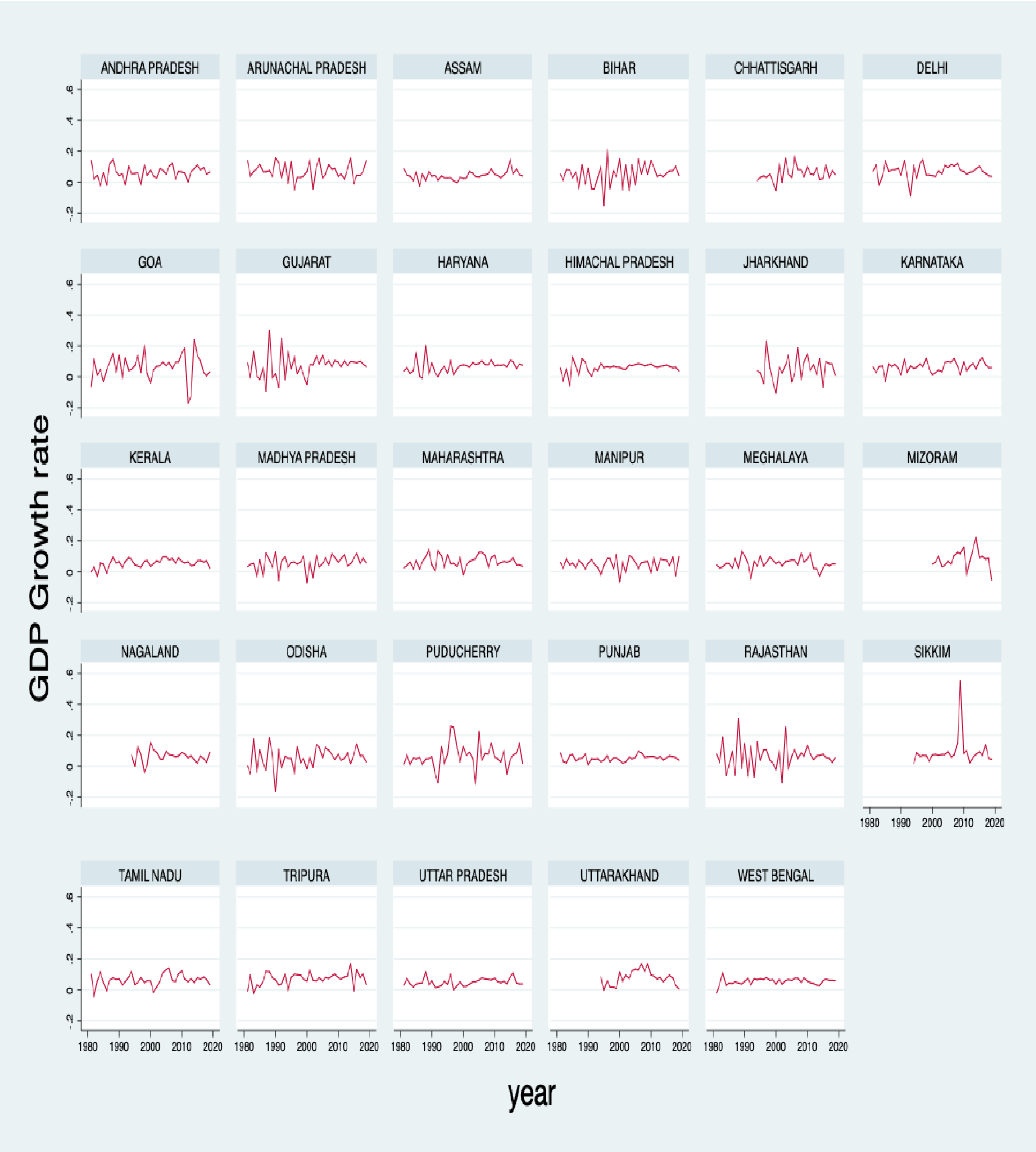
The Dynamic Causal Impact of Climate Change on Economic Activity - A Disaggregated Panel Analysis of India - Online Appendix

Contents

A Data Appendix

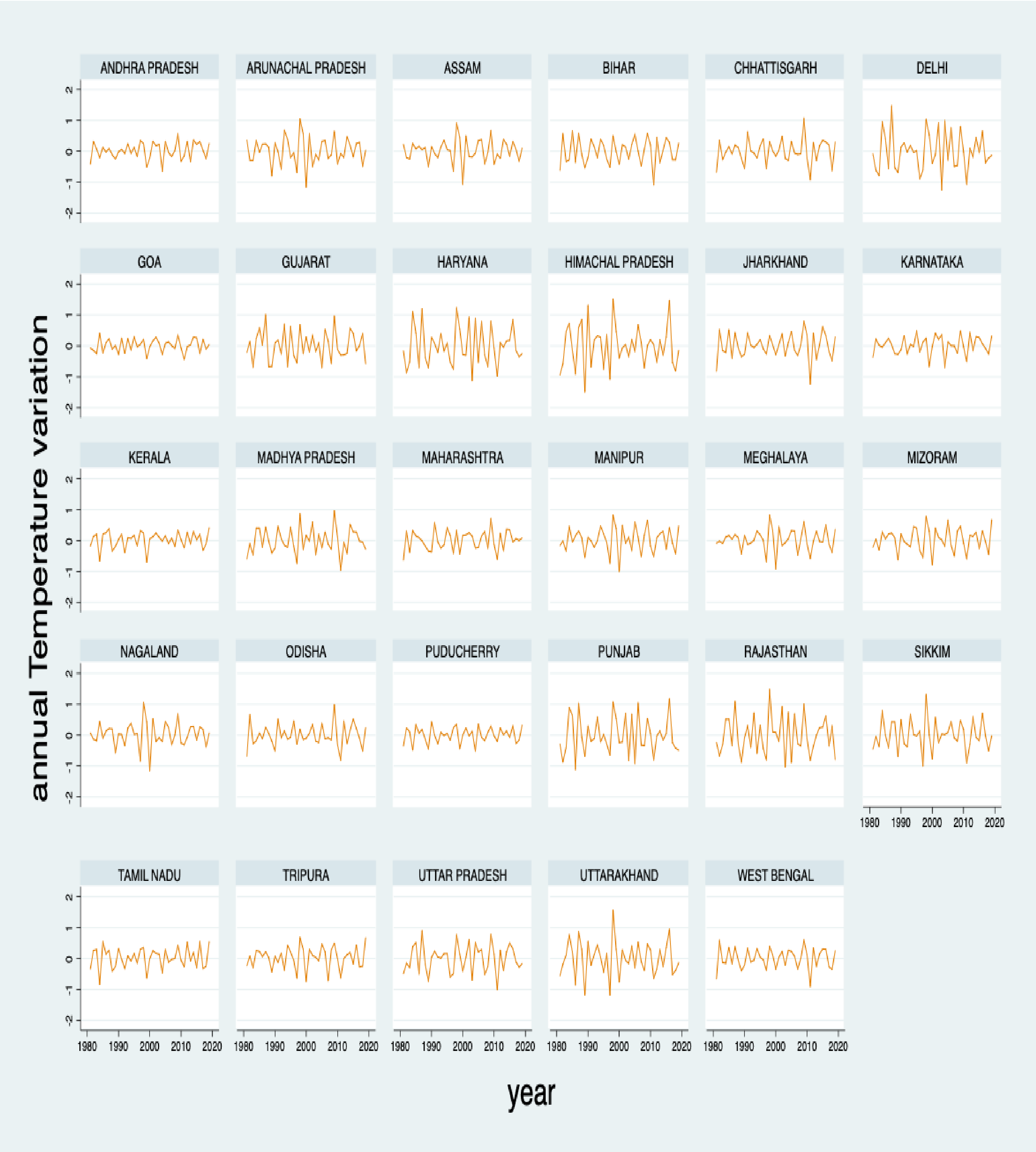
A.1 Trends in GSDP Growth rate- Statewise

Figure (A.1) Trends in GSDP Growth rate- Statewise



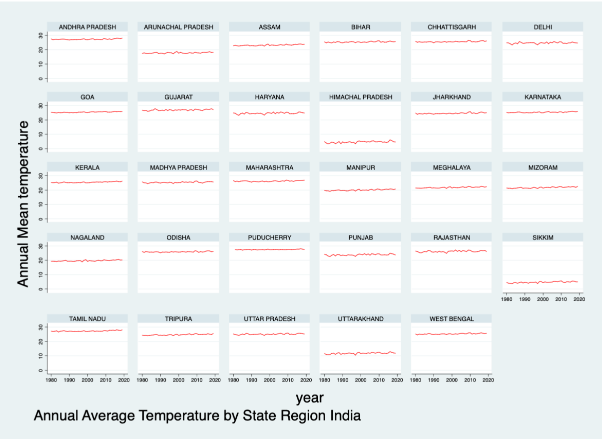
A.2 Trends in annual variation in temperature

Figure (A.2) Trends in annual variation in temperature

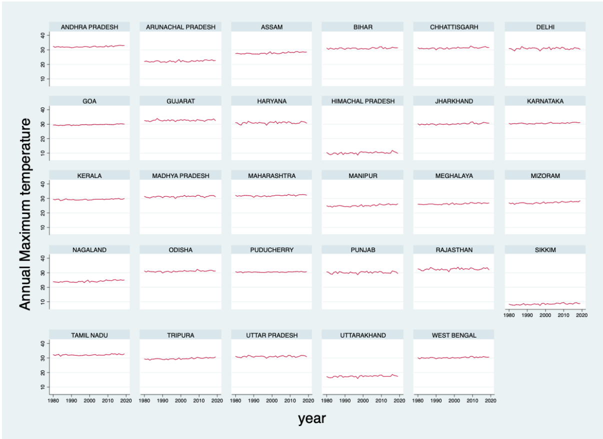


A.3 Climate Indicators Trend by States

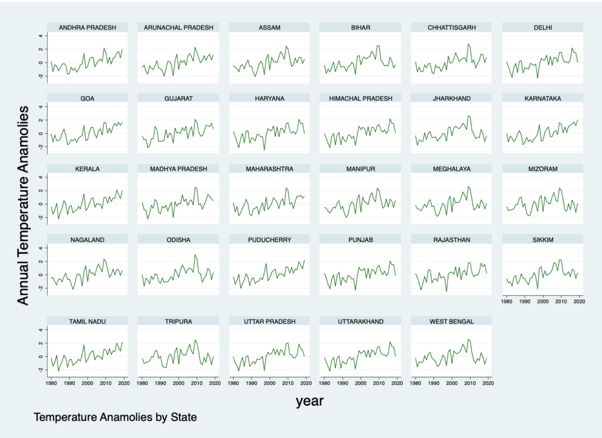
Figure (A.2) Trends in temperature



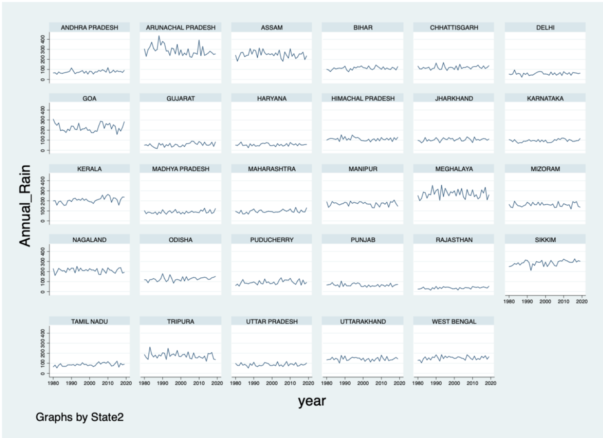
(a) Mean Temperature by States



(b) Maximum Temperature by States



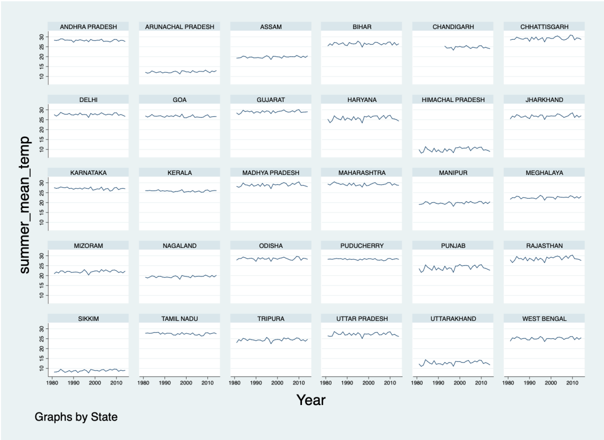
(c) Temperature anomalies by states



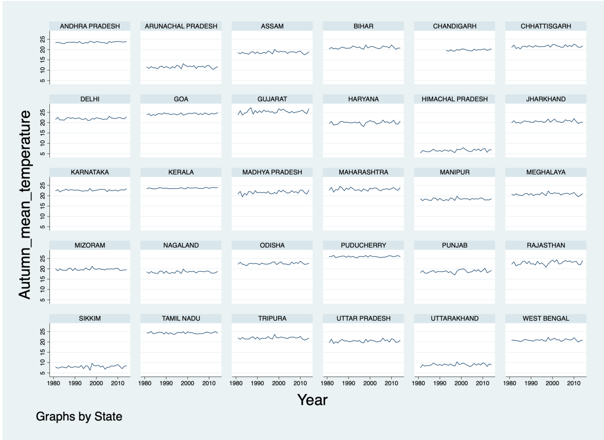
(d) Rainfall by states

A.4 Trends in Seasonal temperature

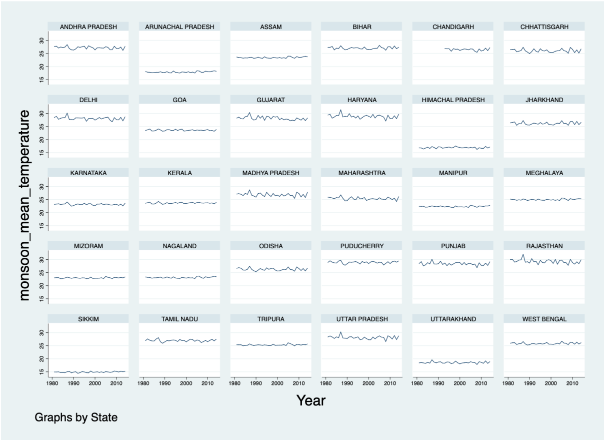
Figure (A.3) Trends in Seasonal temperature



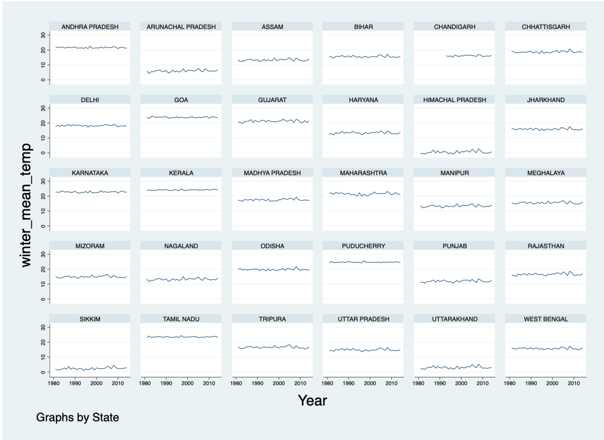
(a) Summer



(b) Autumn



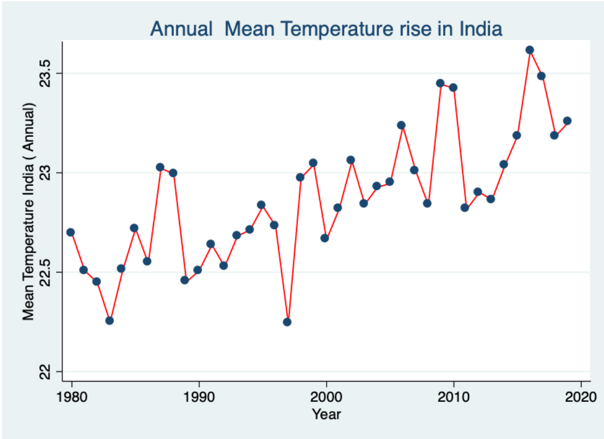
(c) Monsoon



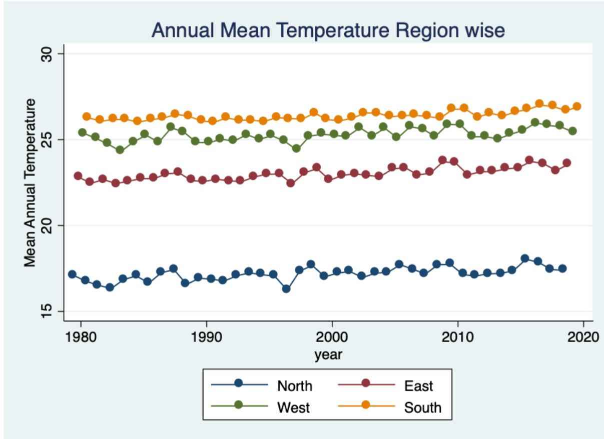
(d) Winter

A.5 Trends in temperature - Different Subsample

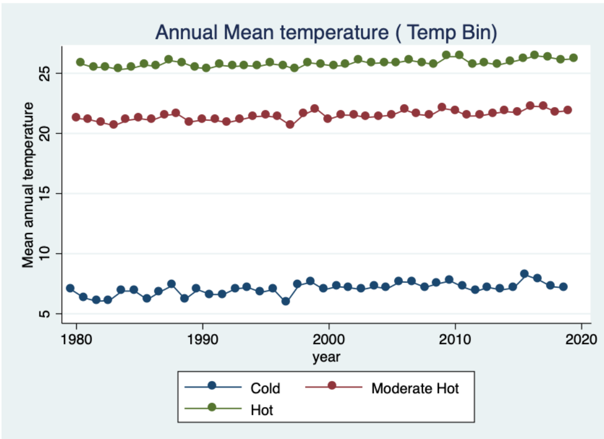
Figure (A.4) Trends in temperature - Different Subsample



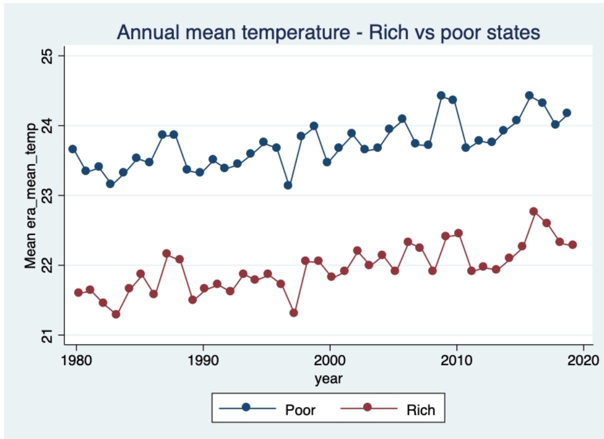
(a) India- Temperature trends



(b) Region wise temperature trends



(c) Temperature trends - Hot Cold and Moderate



(d) Temperature Trends - poor vs Rich states

A.6 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
log(GSDP)	15.7267	1.66239	11.71954	19.13558
log(mining)	11.79664	2.348315	5.170484	15.7463
log(agriallie)d	14.25175	1.687646	10.533	16.94326
log(manufacturing)	13.52719	2.207837	7.438384	17.52647
log(construction)	13.11799	1.7605	8.580168	16.37248
log(electricity)	12.06671	1.783918	2.302585	15.15706
log(tradehotel)	13.3687	1.762959	8.892612	16.64419
population (In Lakhs)	35277.66	39473.82	312	227650
percapita income(In rupees)	59988.21	50247.39	7641	354767
Mean temperature (cru)	23.43577	5.358791	5.09	29.02
Maximum Temperature	28.94434	5.458997	10.79	34.61
Temperature Anamolies	2.49e-07	.9878468	-2.508487	2.991171
Temperature Volatility	10.97449	1.651988	7.400001	15.11
Mean temperature Summer	25.02543	6.13889	2.81	32.66
Mean temperature Monsoon	26.02667	4.772971	10.02	33.0525
Mean temperature Autumn	21.52016	6.037526	.0449998	28.265
Mean temperature Winter	16.84307	7.357157	-7.203333	26.24667
Mean temperature Extended Summer	24.19075	5.434012	5.638333	29.62778
summer Rainfall	272.4909	298.7349	.31	1989.99
monsoon Rainfall	1126.447	590.7984	115.18	3466.58
autumn Rainfall	155.4834	141.8643	.11	895.43
winter Rainfall	95.04365	113.6194	.05	672.99
extended Rainfall	1554.422	867.0657	145.64	4974.52
GDP Growth rate	6.162725	5.321972	-16.70113	55.16443

Table (A1) Summary Statistics

A.7 State wise rank - Annual mean temperature

Table (A2) Rank of States - annual temperature is calculated over the sample 1980–2019 over 29 states

Rank of State	**State Name**	**Average Temp**	**Rank of State**	**State Name**	**Average Temp**
1	HIMACHAL PRADESH	4.59125	16	WEST BENGAL	25.29425
2	SIKKIM	4.731	17	KARNATAKA	25.36375
3	UTTARAKHAND	11.7585	18	MADHYA PRADESH	25.402
4	ARUNACHAL PRADESH	17.81	19	BIHAR	25.41525
5	NAGALAND	19.708	20	GOA	25.438
6	MANIPUR	20.0425	21	KERALA	25.49475
7	MIZORAM	21.77975	22	CHHATTISGARH	25.608
8	MEGHALAYA	21.84875	23	ODISHA	25.89275
9	ASSAM	23.21575	24	RAJASTHAN	26.21225
10	PUNJAB	23.84075	25	MAHARASHTRA	26.2795
11	JHARKHAND	24.62	26	GUJARAT	26.92575
12	HARYANA	24.65875	27	TAMIL NADU	27.2795
13	TRIPURA	24.69225	28	ANDHRA PRADESH	27.34675
14	DELHI	24.74825	29	PUDUCHERRY	27.49051
15	UTTAR PRADESH	25.0832 5			

B Panel unit root test

B.1 CADF unit root test

Table (A3) Panel unit root test result

	Second generation unit root test		
	CADF lag(0)	CADF lag(1)	CADF lag(2)
Variables	p-value	p-value	p-value
log(GSDP)	3.152	5.442	6.497
$\Delta log(GSDP)$	-23.316***	-15.827***	-8.946***
log(mining)	-2.363**	-0.557	2.078
$\Delta log(mining)$	-19.213***	-19.213***	-6.765***
log(agriallied)	0.847	3.052	2.428
$\Delta log(agriallied)$	-23.320***	-16.733***	-10.684***
log(manufacturing)	-1.038	-0.090	0.670
$\Delta log(manufacturing)$	-22.961***	-15.957***	-11.157***
log(constr)	-0.714	1.054	1.465
$\Delta log(constr)$	-23.175***	-15.325***	-9.318***
Log(electricity)	-2.393**	-2.719**	-1.016
$\Delta log(elect)$	-21.012***	-15.088 ***	- -9.058***
Log(Trade hotel)	1.641	3.275	3.874
$\Delta log(tradehotel)$	-22.649***	-15.203***	-8.862***
Population in lakhs	8.339	7.401	7.110
Per capita income(Rupees)	-2.082**	-0.177	2.250
Gross State Value Added(RS lakhs)	0.736	2.350	3.556
meantemperature(CRU)	23.55377	5.224395	5.09
maxtemperature(CRU)	-16.190***	-9.715***	-6.729***
Mean Temperature(ERA)	-19.353***	-10.308***	-6.736***
Precipitation(Annual)	-19.269***	-9.437***	-4.515***
Power	-2.050**	-1.359*	2.757
Forest cover	3.608	10.201	10.484

Notes: Large negative values lead to the rejection of a unit root in favour of (trend) stationarity. We tested second generation unit root test which assumes cross-sectional dependence. **(***)(*) (**)Indicate rejection of the null hypothesis of a unit root at the(1%) (5%) level (10%) level**

C Panel cointegration approach

Table (A4) Westurlund Panel cointegration test

Westurlund Panel cointegration test			
Statistic	Value	Z-value	P-value
Gt	-4.537	-15.119	0.000
Ga	-34.433	-18.862	0.000
Pt	-26.396	-17.043	0.000
Pa	-36.801	-25.957	0.000

Notes: In this table, we present cross-sectional dependence robust p-values obtained from Westerlund's (2007) panel cointegration tests, which were conducted with one lead and one lag. The dependent variable in these tests is GDP Growth Rate.The null hypothesis is that the variables are not cointegrated. p-values indicate that the null hypothesis of no cointegration can be rejected at standard significance levels. We use stata xtwest command for our analysis.
(*)(**) (*) indicate the level of signifance at the (1%) (5%) level (10%) level**

D Additional Robustness Results - State Level Data

D.1 EFFECTS OF ANNUAL AND SEASONAL TEMPERATURES ON GDP GROWTH WITH ADDITIONAL COVARIATES

Table (A5) EFFECTS OF ANNUAL AND SEASONAL TEMPERATURES ON GDP GROWTH WITH ADDITIONAL COVARIATES

Variables	(1) CS-ARDL GSDP Growth	(2) CS-ARDL GSDP Growth	(3) CS-ARDL GSDP Growth	(4) CS-ARDL GSDP Growth	(5) CS-ARDL GSDP Growth
d.Annual Temperature	-0.0170				
	(0.0334)				
d.Summer Temperature		-0.0023			
		(0.0096)			
d.Monsoon Temperature			-0.0163		
			(0.0151)		
d.Autumn Temperature			-	-0.0569**	
				(0.0245)	
d.Winter Temperature					-0.0145
					(0.0115)
CADF Statistics	-9.139***	-12.396***	-10.042***	-10.317***	-11.298
Cointegration	Yes	Yes	Yes	Yes	Yes
CD Statistics	-2.38*	-1.76*	-2.10*	-0.98	-0.55
Rainfall	✓	✓	✓	✓	✓
Population	✓	✓	✓	✓	✓
R Squared	0.61	0.60	0.63	0.57	0.65
Number of observation	1160	1160	1160	1160	1160
Number of States	29	29	29	29	29

Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

D.2 ADDITIONAL RESULTS: EFFECTS OF ANNUAL AND SEASONAL TEMPERATURES ON GDP GROWTH WITH DIFFERENT SOURCE OF DATA

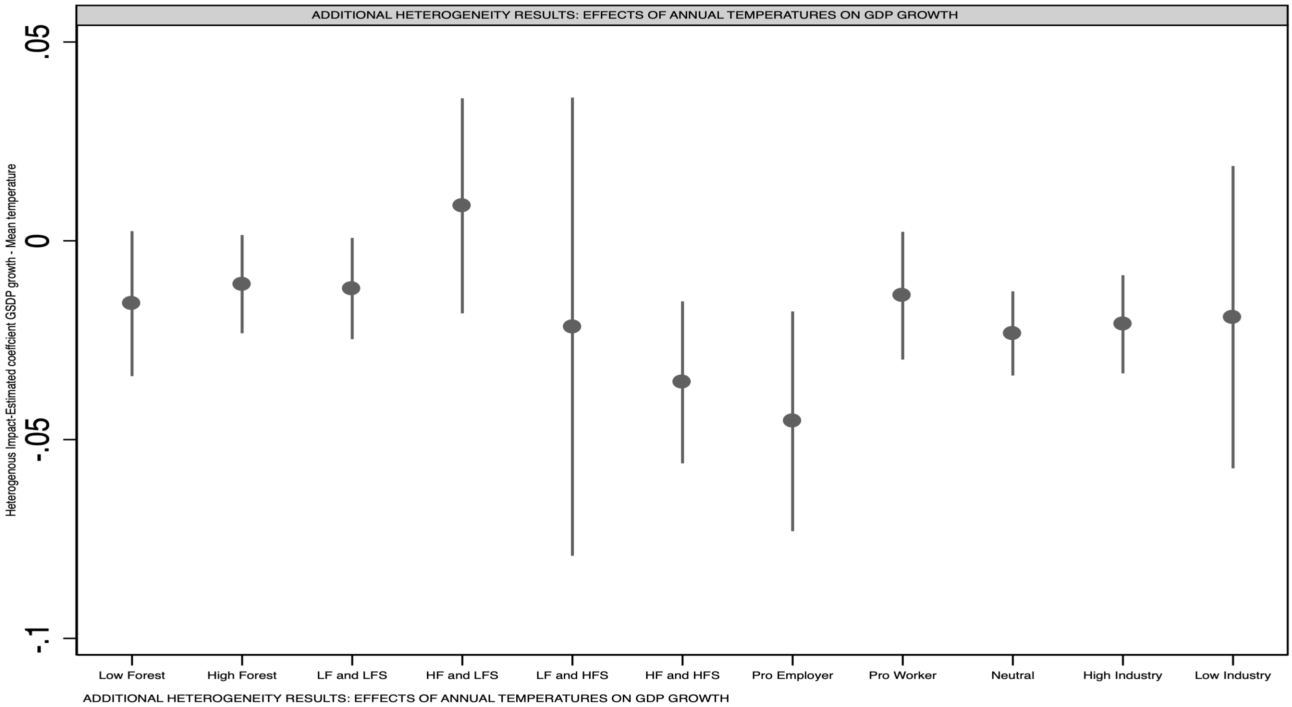
Table (A6) ADDITIONAL RESULTS: EFFECTS OF ANNUAL AND SEASONAL TEMPERATURES ON GDP GROWTH WITH DIFFERENT SOURCE OF DATA

Variables	(1) CS-ARDL Annual	(2) CS-ARDL Summer	(3) CS-ARDL Monsoon	(4) CS-ARDL Autumn	(5) CS-ARDL Winter
GSDP Growth	-0.0237	-0.0105	-0.0070	-0.0228*	-0.0071
	(0.0167)	(0.0066)	(0.0173)	(0.0126)	(0.0099)
CADF Statistics	-12.207***	-10.935***	-10.798***	-11.963***	-13.934***
Cointegration	Yes	Yes	Yes	Yes	Yes
R-Squared	0.80	0.82	0.78	0.78	0.82
Number of observation	1076	1076	1076	1076	1076
Number of States	29	29	29	29	29

Notes: The dependent variable is GSDP Growth. Independent variable is Mean temperature. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

D.3 ADDITIONAL HETEROGENEITY RESULTS: EFFECTS OF ANNUAL TEMPERATURES ON GDP GROWTH BASED ON FOREST COVER, FISCAL SUSTAINABLE AND FOREST COVER, LABOUR LAWS AND INDUSTRIALISATI

Figure (A6) ADDITIONAL HETEROGENEITY RESULTS: EFFECTS OF ANNUAL TEMPERATURES ON GDP GROWTH BASED ON FOREST COVER, FISCAL SUSTAINABLE AND FOREST COVER, LABOUR LAWS AND INDUSTRIALISATION



Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature.

D.4 ROBUSTNESS: EFFECTS OF ANNUAL TEMPERATURES ON GSP GROWTH , PER CAPITA GROWTH AND QUADRATIC SQUARED TEMPERATURE INDICATOR

Table (A7) ROBUSTNESS: EFFECTS OF ANNUAL TEMPERATURES ON GSP GROWTH, PER CAPITA GROWTH AND QUADRATIC SQUARED TEMPERATURE INDICATOR

Variables	(1) CS-ARDL Per capita income(In rupees)	(2) CS-ARDL GSVA Growth	(3) CS-ARDL GSDP Growt
d.Annual mean temperature	-3285.8**	-0.0376**	-0.0382**
	(1600.521)	(0.0150)	(0.0199)
d.Annual squared mean temperature			0.0725
			(0.0369)
CADF Statistics	-11.083***	-11.838 ***	-9.259***
Number of observation	1076	1076	1076
Number of States	29	29	29

Notes: The dependent variable is GSDP Growth. Independent variable is Mean temperature. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

D.5 Projected reduction in GDP growth rate in different SSP Scenarios

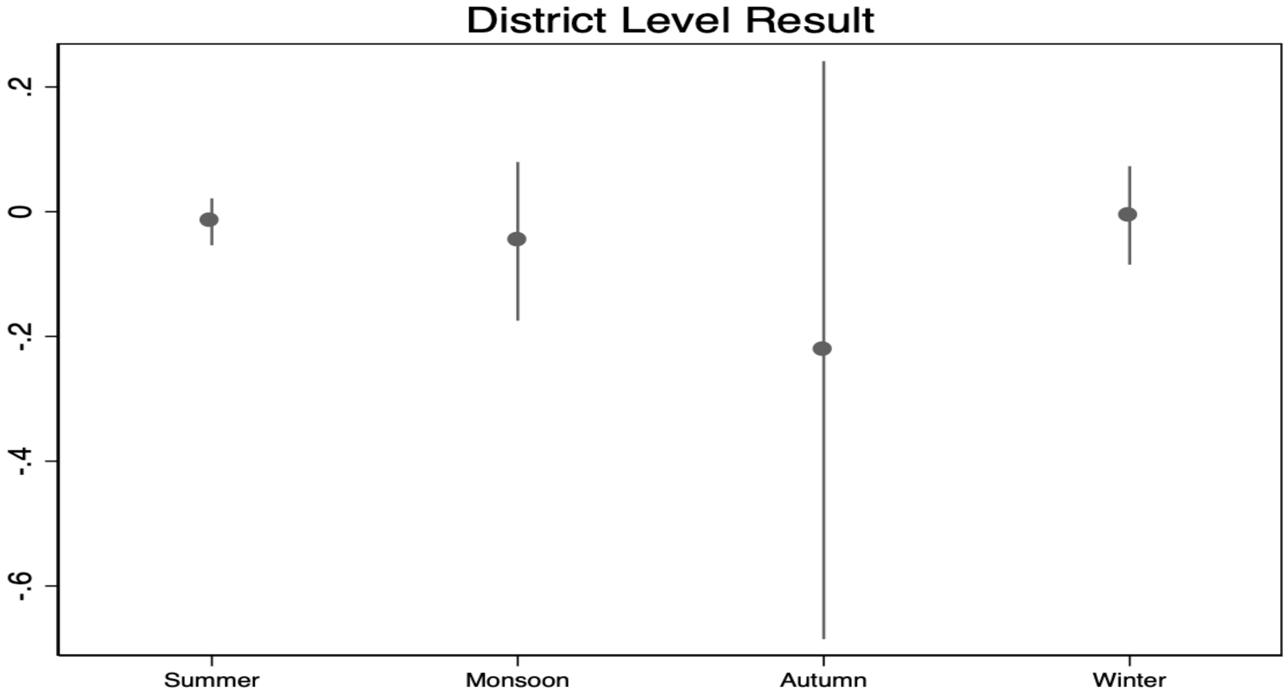
Table (A8) GSDP Growth loss projections (%) over the period 2020–2099

Scenario Growth of GSDP	2020-2040	2040-2060	2060-2080	2080-2100	2020-2100
SSP1-2.6	-1.3226	-5.0959	1.7505	-0.5835	-5.2515
SSP2- 4.5	-6.1851	-0.389	-4.279	-2.2173	-13.0704
SSP3 - 7.0	-5.3682	-1.9839	-3.8511	-5.2126	-16.4158
SSP5- 8.5	-3.0731	-5.5238	-8.4024	-7.5077	-24.507

Source: Authors' calculation based on data drawn from CCKP World Bank

E Additional Robustness Results - District Level Data

Figure (A7) Additional Robustness Results - District Level Data



Notes: The dependent variable is GSDP Growth. The Independent variable is the annual variation in mean temperature.