WP-2024-021

Weather shocks, economic growth and damage function for India: A varying coefficient semi-parametric approach

Pratik Thakkar and Kausik Gangopadhyay

Indira Gandhi Institute of Development Research, Mumbai
October 2024

Weather shocks, economic growth and damage function for India: A varying coefficient semi-parametric approach

Pratik Thakkar and Kausik Gangopadhyay

Email(corresponding author): pratikt@igidr.ac.in

Abstract

Weather shocks associated with global climate change engender substantial damages, in the order of multi-billion dollars annually, to the Indian economy. Using data from 33 states during 1981--2022, we explore the effect of weather shock on India's economic growth, in the presence of interplay of temperature and precipitation levels. To avoid arbitrary assumptions of parametric estimation, we estimate the economic damages resulting from weather shocks using semi-parametric varying coefficient generalised additive models (VC-GAM). We select the optimal class of VC-GAM among 29 possible classes based on four relevant criteria. From the optimal class, out of 84 possible specifications, we determine the optimal damage specification using the out-of-sample and in-sample performance. We find that the contemporaneous year-on-year weather change and lagged year-on-year precipitation change have an impact on the per capita economic growth through total factor productivity channel, whereas only contemporaneous precipitation level have an impact on the per capita economic growth through labour productivity channel. We observe that the marginal effect of a contemporaneous weather change varies with the level of lagged precipitation level, whereas high lagged precipitation level combined with a low to moderate lagged temperature level exacerbates the detrimental impact of a positive lagged precipitation change on the per capita economic growth for India. One potential mechanism through which contemporaneous and lagged weather variables could have an impact on the per capita economic growth, is based on the impact of soil moisture quality. We have demonstrated our results to be considerably robust.

Keywords: Weather, Damage function, Varying coefficient generalized additive models, Economic growth, India

JEL Code: C14, O44, O53, Q54

Weather shocks, economic growth and damage function for India: A varying coefficient semi-parametric approach

Pratik Thakkar*

Kausik Gangopadhyay†

Abstract

Weather shocks associated with global climate change engender substantial damages, in the order of multi-billion dollars annually, to the Indian economy. Using data from 33 states during 1981–2022, we explore the effect of weather shock on India's economic growth, in the presence of interplay of temperature and precipitation levels. To avoid arbitrary assumptions of parametric estimation, we estimate the economic damages resulting from weather shocks using semi-parametric varying coefficient generalised additive models (VC-GAM). We select the optimal class of VC-GAM among 29 possible classes based on four relevant criteria. From the optimal class, out of 84 possible specifications, we determine the optimal damage specification using the out-of-sample and in-sample performance. We find that the contemporaneous year-on-year weather change and lagged year-on-year precipitation change have an impact on the per capita economic growth through total factor productivity channel, whereas only contemporaneous precipitation level have an impact on the per capita economic growth through labour productivity channel. We observe that the marginal effect of a contemporaneous weather change varies with the level of lagged precipitation level, whereas high lagged precipitation level combined with a low to moderate lagged temperature level exacerbates the detrimental impact of a positive lagged precipitation change on the per capita economic growth for India. One potential mechanism through which contemporaneous and lagged weather variables could have an impact on the per capita economic growth, is based on the impact of soil moisture quality. We have demonstrated our results to be considerably robust.

Keywords: Weather, Damage function, Varying coefficient generalized additive models, Economic growth, India

JEL classification: C14, O44, O53, Q54

*Corresponding author. Indira Gandhi Institute of Development Research, Gen. AK Vaidya Marg, Mumbai, 400065, Maharashtra, India. Email: pratikt@igidr.ac.in

†Indian Institute of Management Kozhikode, IIMK Campus P.O., Kozhikode, 673570, Kerala, India. Email: kausik@iimk.ac.in

1. Introduction

India—the fifth largest economy with diverse climatic conditions—has faced repercussions of the global climate change with a rise in weather shocks such as extreme temperature event, decline in monsoon precipitation, increase in average temperature, flood and drought (Krishnan et al., 2020). Consequently, the Indian economic growth, averaging approximately 6% *per annum* during 1981–2023 as per the World Bank data[1], has suffered from these weather shocks. For example, in 2021 alone, weather-related hazards caused an estimated US$ 7.6 billion damage to the Indian economy (WMO, 2022). With the rising mean global temperature, the frequency and intensity of these weather shocks may increase for India in the coming years with arguably different magnitudes of economic damages for the growing Indian economy. Policymakers need to understand the magnitude of these weather shock-induced economic damages in order to formulate adaptation policies.

Policymakers commonly utilize Integrated Assessment Models to evaluate the weather shock-induced economic damages. However, these models' damage functions, along with the choice of values for the underlying damage parameters, are quite arbitrary (Dell et al., 2014; Nordhaus, 2018; Pindyck, 2013). Although the existing empirical literature, in the Indian context, has attempted to estimate the appropriate weather damage specification to capture the impact of damages due to weather shocks, these studies, however, do not shed any light on the impact of the *interplay* of temperature and precipitation variables on economic growth. This *interplay* captures the joint behaviour of temperature and precipitation and is used for the impact analysis of drought, flood, and agriculture production (Rana et al., 2017). Understanding this *interplay* is also critical for developing suitable adaptation policies towards the weather shocks.

Our estimation of this *interplay* highlights the potential mechanism of the effect of temperature and precipitation on the economic growth through the soil moisture quality which can be an important parameter while deciding an adaptation policy for the future weather shocks. Our empirical approach, furthermore, suggests a fresh perspective to understand how contemporaneous and lagged weather variables have an impact on the economic growth, prompting policymakers to consider the dynamic nature of impact of weather shocks in the interest of medium-run planning. This strategy has resulted into a substantially different specification than those considered in the existing literature for India allowing for more diverse computation of the social cost of carbon for the Indian economy. Finally, our estimated weather damages can be used as base data to assess the value of damage parameters in integrated assessment models or General Equilibrium Models providing more robust findings for policy-making.

We develop our theoretical foundation in line with Kalkuhl and Wenz (2020) who have considered a Ramsay-style growth model with constant returns to scale. Their framework assumes that a

[1] https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=IN

temperature (precipitation) change[2] has a marginal effect on the economic growth through the total factor productivity growth channel and these marginal effects vary with temperature (precipitation) level. Their model implies that an additive non-linear form of temperature and precipitation level have an impact on the economic growth via the labour productivity growth channel too. We relax the assumption of constant returns to scale, since it is often considered restrictive for an emerging economy. We introduce the *interplay* of weather variables by assuming that the marginal effect of weather change is a function of both temperature and precipitation levels. Moreover, we consider a broader class of models in which temperature and precipitation levels may even have a non-additive effect on economic growth.

We utilise the state-level Indian data for the fiscal years 1980–1981 to 2021–2022. We use a semi-parametric econometric technique of Varying Coefficient Generalised Additive Model (VC-GAM) departing from Kalkuhl and Wenz (2020)'s parametric approach to empirically implement our generalized theoretical framework. We select *the* optimal class of VC-GAM to estimate the impact of weather variables on the economic growth by evaluating 29 possible classes of VC-GAMs based on the four criteria of (i) parsimony, (ii) low concurvity, (iii) avoidance of over-fitting, and (iv) balancing goodness-of-fit with model complexity.

We observe a strong evidence in favour of the *interplay* of weather variables on the economic growth. For example, a positive temperature (precipitation) change has an adverse marginal effect on the per capita economic growth when the preceding year's precipitation level is low (high). It is also observed that the negative effects of a positive lagged precipitation change on the per capita economic growth of India are amplified when there is a high lagged level of precipitation paired with a low to moderate lagged temperature level.

Next, we estimate the optimal damage specification by fitting the predicted values of *the* optimal VC-GAM on the 84 relevant specifications of weather variables. Methodologically, we follow Newell et al. (2021) who have implemented the cross-validation and the model confidence set technique to compare the models with different parametric specifications based on their forecasting abilities. We augment their method of cross-validation technique with the ridge regression and then, obtain 55 specifications in the superior set of models from the considered specifications based on out-of-sample performance metrics. In the next step, we select the damage specifications from the superior set of models (55 specifications considered) by employing in-sample performance metric of adjusted generalized variance inflation factor to address the concern of multicollinearity and hence, end up with six specifications. Finally, we select the optimal damage specification (out of these six specifications) by implementing Bayes factor and ensuring the goodness of fit.

[2]We term year-on-year temperature and precipitation level variations as temperature and precipitation change, respectively.

We find that the marginal effect of contemporaneous temperature change is an inverted U-shaped function of lagged precipitation level whereas the marginal effect of a lagged precipitation change is a linear interaction of lagged temperature and precipitation levels. These findings conclusively demonstrate the interplay of contemporaneous temperature change, lagged precipitation change and lagged weather level, unaddressed in the existing literature (Kalkuhl and Wenz, 2020; Kumar and Maiti, 2024a; Letta and Tol, 2019). We also find that the marginal effect of contemporaneous precipitation change is a decreasing linear function of lagged precipitation level. This result indicates the significance of precipitation change in the Indian context which has been found to be globally insignificant by Kalkuhl and Wenz (2020). Finally, we find that the marginal effect of contemporaneous precipitation level on the economic growth yields a U-shape curve indicating a cubic relationship instead of quadratic one (Damania et al., 2020; Kotz et al., 2022) between precipitation level and the economic growth.

This paper proceeds as follows. Section 2 discusses the related literature on the impact of weather on the economic growth. Section 3 narrates the theoretical framework for our empirical analysis. Section 4 describes the data, conducts a preliminary analysis, and formulates our hypothesis for further probing. Section 5 elaborates on the empirical strategy and the model selection approach employed for the study. Section 6 presents the results. Section 7 discusses the results and concludes the paper.

2. Related literature

2.1. Weather effects on Indian economy

A growing research looks into how varied weather patterns affect numerous aspects of the Indian economy. To arrange our review, we divide the literature into two categories based on its focus: studies investigating the impacts of temperature (Section 2.1.1) and those studying the impact of precipitation (Section 2.1.2).

2.1.1. Temperature impact

Studies using global-level data find that a rising temperature significantly hinders economic growth, including for economies like India (Acevedo et al., 2020; Burke et al., 2015; Dell et al., 2012; Kahn et al., 2021; Kalkuhl and Wenz, 2020; Kotz et al., 2021; Letta and Tol, 2019). These studies link these negative effects to less investment, lower labour productivity, deteriorating human health, and decreasing agricultural and industrial output. Regional-level studies find that a temperature shock has a detrimental impact on Indian agriculture output (Mendelsohn, 2014, study for Asian countries), total factor productivity (Kumar and Maiti, 2024b, study for emerging economies), and economic growth (Zhao, 2018, study for China and India).

The India-specific studies too conclude that a temperature shock has an adverse impact on the overall economic growth. Using the specification of Burke et al. (2015) and state-level data, Jain et al. (2020) find that a 1°C increase in temperature reduces the economic growth by 2.5 percentage points (pp), disproportionately affecting poorer states and the agriculture sector. Similarly, Sandhani et al. (2023), using specification of Dell et al. (2012) and district-level data, estimate that a 1°C increase in temperature leads to a 4.7 pp drop in the economic growth. According to Kumar and Maiti (2024a), rising temperatures have a cumulative effect on ecosystem services, labour productivity, and capital productivity, leading to a 3.89 pp loss in the economic growth.

Many studies have explored the impact of temperature on specific aspects of the Indian economy that may influence its economic growth. Taraz (2018) confirms that temperature shocks significantly affect the agricultural yields in India, although high heat-prone districts face less damage due to their better adaptability. According to Pattanayak et al. (2021), a 1°C increase in temperature affects the agricultural production efficiency by 4.7 pp across regions. A heat wave or an extreme temperature has a negative effect on the agricultural productivity (Birthal et al., 2021). Carleton (2017) indicates that a higher temperature decreases the yield of crops and associated suicides of distressed farmers to a higher temperature (around 70 suicides per 1°C increase).

Somanathan et al. (2021) study how temperature impacts labour productivity and supply in manufacturing facilities. A temperature shock of 1°C reduces manufacturing output by 2 pp, primarily due to reduced worker productivity and higher absenteeism. According to Colmer (2021), temperature shocks impact labour markets in various sectors in India, including agricultural production and labour demand. His findings reveal that when there is a temperature shock, labour law-regulated firms suffer, whereas small businesses profit.

2.1.2. Precipitation impact

The majority of the works described above account for precipitation shocks and conclude that their overall impact on economic indicators is insignificant. Damania (2020) examines how a precipitation shock affects agricultural production, conflicts, human capital, and economic progress. According to Acevedo et al. (2020), a higher precipitation has a negative impact on economic growth, whereas Mohaddes et al. (2023) demonstrates that a below-normal precipitation reduces economic growth, labour productivity, and employment, especially for the United States.

Additionally, Damania et al. (2020) and Kotz et al. (2022) show that a precipitation shock significantly affects the overall economic growth. They derive a non-linear inverted-U shaped relationship between precipitation and the economic growth. Notably, the negative effects of weather shocks on poor countries are manifested through the agriculture sector, whereas developed countries are affected through the manufacturing and services sectors.

Gilmont et al. (2018) investigate the relationship between precipitation and economic growth in several Indian states and note that states with a higher precipitation are less sensitive to precipitation shocks due to irrigation practice adaption. According to Auffhammer et al. (2006), additional precipitation during the harvest season increases rice yields in India. Moreover, Pattanayak et al. (2021) conclude that a positive precipitation shock has a favourable effect, but higher precipitation volatility reduces the total factor productivity of the Indian agriculture sector.

Mitra (2014) reports that a one-standard deviation shock from the mean precipitation level favours crop production elasticity for a lower precipitation level compared to its higher counterparts. Lastly, Birthal et al. (2021) find that an unusually high rainfall or a flood has no significant effect on the agricultural productivity, but an abnormally low rainfall or a drought has a negative effect.

2.2. Choice of the weather variables

The above-mentioned literature, with the few exceptions noted below, mostly considers linear or non-linear weather levels while estimating the marginal impact of weather on the economic growth. Notably, some studies consider weather changes instead of weather levels to estimate the constant marginal impact on the economic growth (Kahn et al., 2021; Kumar and Maiti, 2024a, 2024b; Mohaddes et al., 2023). Studies have also considered the interaction of weather levels with their corresponding weather changes for estimation purposes (Kalkuhl and Wenz, 2020; Kotz et al., 2021; Letta and Tol, 2019). The inclusion of interactions exemplifies the potential differential impact of weather on economic growth in hot and cold regions.

These existing studies consider the impact of weather variables in isolation, neglecting the *interplay* of temperature and precipitation while studying the impact of weather on economic growth. Our paper presents an alternative perspective on the interaction of weather levels and changes. We consider the interaction of weather changes with the temperature and precipitation levels (rather than only the associated weather level). Our approach calculates the marginal effect of weather on the economic growth while adapting for regional weather features, drawing on the research on the effects of temperature and precipitation on the economic growth.

2.3. Estimation specification

Empirical technique, in this field, has advanced from cross-sectional regression to fixed-effect panel regression to a 'hybrid' regression model (Chang et al., 2023; Dell et al., 2014; Kolstad and Moore, 2020; Tol, 2024). While cross-section regressions and fixed-effect panel regression models are employed to investigate the short-run link between weather and economic growth, the 'hybrid' approach or long-difference regression model investigates the medium- to long-term impact of temperature and precipitation on the economic growth. Recently, studies have employed the cross-sectional augmented autoregressive distributed lag model to estimate the long-run impact in the presence of feedback effects (Kumar and Maiti, 2024a, 2024b). All these studies assume a linear or non-linear parametric specification for estimation.

However, Newell et al. (2021) implement an extensive comparison of different specifications for estimating the weather effects on economic growth. Their specifications include 800 combinations of different orders of weather variables and higher lags of dependent variables. They highlight the significant model uncertainty in forecasting climate change implications due to parametric specification.

Given the uncertainty regarding the predetermined parametric specification, our study employs an innovative semi-parametric technique whereby the non-linear impacts of weather on the economic growth (if any) are endogenously determined based on the data. We couple this semi-parametric technique with panel regressions to estimate the damage specification for the effect of weather on economic growth.

3. A generalized conceptual framework

3.1. Theoretical Framework

We consider a stylized Ramsey-type growth model where changes in weather variables alter the productivity level of the entire economy and the growth rate of labour-augmented productivity. In particular, we assume that economic output, $Y_t = \Theta(T_t, P_t, t) \cdot F_t(K_t, A_t L_t)$, where K_t, L_t and A_t are capital stock, labour quantity and labour-augmented productivity (henceforth, LP), respectively, for the production function $F_t(.)$ producing economic output (Y_t) for an economy. In our theoretical framework, "labour quantity" corresponds to the entire population.

$F_t(.)$ is a homogeneous function with degree τ_t, where $\tau_t > 0$. Understandably, $\tau_t = 1$ represents the case of constant returns to scale for that economy. The other two cases are that of $\tau_t > 1$ (increasing returns to scale) and $\tau_t < 1$ (decreasing returns to scale). By appealing to the Euler's theorem, we observe the following identity:

$$\frac{\partial F_t(.)}{\partial A_t L_t} = \frac{\tau_t F_t(.) - \frac{\partial F_t(.)}{\partial K_t} K_t}{A_t L_t} \tag{1}$$

$\Theta(T_t, P_t, t)$ is the total factor productivity (henceforth, TFP) function dependent on weather[3]—temperature (T_t) and precipitation (P_t) levels—and other non-weather factors that varies with year 't'. Let $g_{\chi_t} = \frac{1}{\chi_t}\frac{d\chi_t}{dt}$ denote growth rate of variable χ_t. Taking log and differentiating Y_t with respect

[3]Undoubtedly, there are other weather factors which could potentially affect economic growth. To estimate the economic damage function for India, we follow the existing literature (Tol, 2024), which has generally defined damage function either in terms of temperature only or in terms of GHG emissions alone. Here, we pursue the former avenue but extend the arguments for the damage function to include precipitation along with temperature.

to t, we obtain:

$$\frac{dln(Y_t)}{dt} = \frac{dln\Theta(.)}{dt} + \frac{dlnF_t(.)}{dt}$$

$$\frac{dln(Y_t)}{dt} = \frac{\partial ln\Theta(.)}{\partial T_t}\frac{dT_t}{dt} + \frac{\partial ln\Theta(.)}{\partial P_t}\frac{dP_t}{dt} + \frac{\partial ln\Theta(.)}{\partial t} + \frac{1}{F_t(.)}\left[\frac{\partial F_t(.)}{\partial K_t}\frac{dK_t}{dt} + \frac{\partial F_t(.)}{\partial A_t L_t}\frac{dA_t L_t}{dt}\right]$$

Imposing Equation (1) on the above equation, we obtain the following result:

$$\begin{aligned}\frac{dln(Y_t)}{dt} &= g_{\Theta_T}(T_t, P_t) \times \frac{dT_t}{dt} + g_{\Theta_P}(T_t, P_t) \times \frac{dP_t}{dt} + g_{\Theta_O}(t) \\ &\quad + \eta_{K_t} \times g_{K_t} + (\tau_t - \eta_{K_t}) \times [g_{A_t} + g_{L_t}]\end{aligned} \tag{2}$$

where $\eta_{K_t} = \frac{K_t}{F(.)}\frac{\partial F(.)}{\partial K_t}$ is the elasticity of input K in production function $F(.)$. $g_{\Theta_T}(T_t, P_t) = \frac{\partial ln\Theta(.)}{\partial T_t}$ and $g_{\Theta_P}(T_t, P_t) = \frac{\partial ln\Theta(.)}{\partial P_t}$ are interpreted as marginal effect of changes in temperature ($\frac{dT_t}{dt}$) and precipitation ($\frac{dP_t}{dt}$), respectively. $g_{\Theta_O}(t) = \frac{\partial ln\Theta(.)}{\partial t}$ is the TFP growth rate due to other non-weather factors varying with time.

Our paradigm, like Kalkuhl and Wenz (2020), ignores the effect of adaptation choices[4], capital productivity damages[5], and labour supply responses because these effects cannot be identified in our framework, given the limitations of the data. Somanathan et al. (2021) have found that a temperature change has a negative impact on labour supply. However, no macro-level statistics on worker absenteeism are available for India. As a result, we are unable to empirically distinguish the effect of weather on economic growth through the labour supply channel. Even then, our approach is useful to distinguish between the effects of weather on economic growth through the TFP channel and its counterpart through the LP channel, as we focus on estimating the functional form for the damage function for each channel.

Empirical studies such as Burke et al. (2015), Dell et al. (2012), Jain et al. (2020), Kalkuhl and Wenz (2020), and Kumar and Maiti (2024b) suggest that weather levels have an impact on the LP growth rate. Accordingly, the model assumes that the LP growth rate depends upon temperature and precipitation levels. Furthermore, any assumption towards the effect of weather level on the LP at level (rather than on the LP growth rate) in our model would be ineffective in identifying the effect of weather changes on the TFP and the LP growth channels separately (demonstrated in

[4]While year fixed effects are used to control short-term adaptation decisions at the India level and state fixed effects to control long-run adaptations, we are unable to clearly assess the influence of adaptation choices on weather-related economic growth.

[5]Kumar and Maiti (2024b) have found that a temperature shock negatively affects overall productivity, wherein the reduction in capital productivity also plays a role. Accordingly, the exclusion of capital productivity effect in the model produces modest estimates of economic damages since it does not explicitly account for capital stock damages. Any damages to capital stock are assumed to have been captured by total factor productivity as in Burke et al. (2015).

Appendix A). Accordingly, we assume that $g_{A_t} \equiv g_{A_W}(T_t, P_t) + g_{A_O}(t)$ where, $g_{A_W}(T_t, P_t)$ is the growth rate of LP explained by weather levels, and $g_{A_O}(t)$ is the growth rate explained by other non-weather factors.

We add this assumption mentioned above in Equation (2) and also define variables in per capita terms: $y \equiv \frac{Y}{L}$ and $k \equiv \frac{K}{L}$. Lastly, we convert the derivatives with respect to t to their discrete-time analogues. We formulate the following key equation for empirical estimation:

$$\begin{aligned} g_{y_t} = &\overbrace{g_{\Theta_T}(T_t, P_t) \times \Delta T_t + g_{\Theta_P}(T_t, P_t) \times \Delta P_t}^{\text{Weather induced TFP growth (WI-TFPG)}} + \overbrace{(\tau_t - \eta_{K_t}) \times g_{A_W}(T_t, P_t)}^{\text{Weather induced LP growth (WI-LPG)}} \\ &+ \underbrace{\eta_{K_t} \times g_{k_t} + (\tau_t - 1) \times g_{L_t} + \rho(t)}_{\text{Other economic factors}} \end{aligned} \tag{3}$$

where $\rho(t) = g_{\Theta_O}(t) + (\tau_t - \eta_{K_t}) \times g_{A_O}(t)$.

We note that the variation in weather level and changes impact the per-capita economic growth through *Weather induced TFP growth (WI-TFPG)* channel. In contrast, only weather variations have an effect through *Weather induced LP growth (WI-LPG)* channel. Changes in economic growth due to other economic shocks are channelled through capital growth, labour growth, and other economic factors. As per our model, following the law of motion of capital, households decide the level of capital based on lagged economic output and hence, $\eta_{K_t} \times g_{k_t}$ captures the transitory effect of any shock on an economy. Similarly, $(\tau_t - 1) \times g_{L_t}$ captures immediate effect due to labour growth and $\rho(t)$ represent other economic variables effect.

3.2. Comparison with previous literature

3.2.1. Generalization over the previous literature

Our assumption of any $\tau_t > 0$ is a more general formulation compared to the previous literature such as Burke et al. (2015) and Kalkuhl and Wenz (2020)[6] . Our assumption of a homogeneous function may be considered as more general compared to the case of the Cobb-Douglas function as used by previous literature (Burke et al., 2015; Dell et al., 2012; Kumar and Maiti, 2024a, 2024b).

Secondly, empirical studies (Bardhan, 1973; Sankar, 1970) suggest that agriculture and industrial sectors retain heterogeneous returns to scale for their production function across Indian firms. Our relaxation of the assumption of constant returns-to-scale helps us capture the heterogeneity in the production functions across different states in India.

Finally, studies about the impact of temperature/precipitation change on the economic growth

[6] Kalkuhl and Wenz (2020) implement this theoretical framework for their empirical analysis of impact of weather on the economic growth using global level sub-national data.

have considered either constant coefficient (Kahn et al., 2021; Kotz et al., 2022) or temperature/-precipitation levels-varying coefficient (Kalkuhl and Wenz, 2020; Kotz et al., 2021; Letta and Tol, 2019) in their analysis. Our framework allows for the incorporation of the joint effect of temperature and precipitation levels. Therefore, we allow for the marginal effect of temperature and precipitation changes to vary with the joint effect of temperature and precipitation levels.

3.2.2. A different decomposition

We differ from the theoretical framework of Kalkuhl and Wenz (2020) in the decomposition. They have split weather effects on the per capita economic growth into immediate, transitory, and balanced growth path consequences. According to their model, weather has an immediate impact on economic growth via WI-TFPG channel, whereas transitory and balanced growth path effects are mediated by WI-LPG $+ \eta_{K_t} \times g_{k_t} + (\tau_t - 1) \times g_{L_t} + \rho(t)$.

However, empirical studies, such as Letta and Tol (2019) and Kumar and Maiti (2024b), consistently show that temperature has a negative long-run effect on the TFP growth. Given this piece of evidence, we do not pursue Kalkuhl and Wenz (2020)'s breakdown of short- and long-run implications. Instead, we concentrate on decomposing the weather effects, highlighting their transmission via the WI-TFPG and WI-LPG channels. Our method is more consistent with empirical results on the negative long-term consequences of temperature, allowing for a more detailed investigation of the various mechanisms by which weather influences the per capita economic growth.

4. Data and preliminary results

4.1. Data

We utilize back-series data on Gross State Domestic Product (GSDP) in 2011-12 prices from the Economic and Political Weekly Research Foundation (EPWRF) India time series portal (EPWRF, 2011). Our dataset includes 30 Indian states and three centrally governed regions (called Union Territories) of India. We use state-level population statistics to calculate GSDP per capita. We calculate year-on-year growth rates of per capita GSDP (henceforth, the per capita economic growth).

Additionally, we obtain monthly temperature and precipitation data from the Climate Change Knowledge Portal (World Bank Group, 2024) on the Indian states and Union Territories, listed as Indian sub-national units. Since our GSDP data is accounted for India's fiscal year (April 1–March 31), we create annual average weather data for Indian states for the corresponding fiscal years based on the available monthly data.

We have considered the fiscal years 1980-81 to 2021-22 based on the availability of the GSDP data. For the years prior to 1980-81, only Net State Domestic Product (NSDP) data is available.

We have no option but to make a call to choose either the NSDP data or restrict ourselves to the last 42 years of data. The existing literature on India (Jain et al., 2020; Kumar and Maiti, 2024a; Sandhani et al., 2023) has looked into GSDP without exception. Moreover, the literature using cross-country data studies Gross Domestic Product instead of its Net counterpart; we have chosen to go with the available GSDP data. We have done a robustness check with the NSDP data for an extended period and found qualitatively similar results (Appendix D). Our panel data is an unbalanced one with a total of 1243 data points. We report summary statistics in Appendix B.

4.2. Preliminary analysis

We use our panel data to estimate Equation (3) empirically. To that end, we add a new subscript i to all the variables in that equation reflecting each Indian state. For example, $g_{y_{it}}$, T_{it} and P_{it} stand for the per capita economic growth, temperature, and precipitation levels, for the i^{th} Indian state for the year t.

The literature assumes no joint effect of temperature and precipitation levels while estimating the economic damages from weather variables. Moreover, in the case of varying marginal effects of weather changes, the existing studies only consider linear interaction of weather changes with their corresponding levels in their specifications. However, Hainmueller et al. (2019), have observed that the assumption of linear multiplicative interaction terms results in biased and inconsistent estimates if the assumption does not hold true. Following their suggestion, we perform a bin regression to detect any non-linearity in the interaction effect. Moreover, this regression helps us to assess the joint effects of weather levels.

We propose the following bin regression:

$$\begin{aligned} g_{y_{it}} = & \sum_{k=1}^{K^{bin}} \phi_k^T Q_{k,it} \times \Delta T_{it} + \sum_{k=1}^{K^{bin}} \phi_k^P Q_{k,it} \times \Delta P_{it} + \sum_{k=1}^{K^{bin}} \zeta_{1k}^T Q_{k,it} \times T_{it} \\ & + \sum_{k=1}^{K^{bin}} \zeta_{2k}^T Q_{k,it} \times T_{it}^2 + \sum_{k=1}^{K^{bin}} \zeta_{1k}^P Q_{k,it} \times P_{it} + \sum_{k=1}^{K^{bin}} \zeta_{2k}^P Q_{k,it} \times P_{it}^2 \\ & + \psi_1 g_{y_{it-1}} + \psi_2 g_{L_{it}} + \delta_i + \mu_t + \rho_i(t) + \epsilon_{it} \end{aligned} \tag{4}$$

where, ϕ_k^T and ϕ_k^P are the marginal effects of temperature and precipitation changes, respectively, on the per capita economic growth in the k^{th} bin. Likewise, ζ_{1k}^T and ζ_{2k}^T represent the marginal effects of linear and squared terms of temperature levels, respectively, on the per capita economic growth for each bin k. Similarly, ζ_{1k}^P and ζ_{2k}^P are the marginal effects of linear and squared precipitation levels, respectively. We consider the quadratic terms for temperature and precipitation levels as per Burke et al. (2015) and Kalkuhl and Wenz (2020). The lagged per capita economic growth ($g_{y_{it-1}}$) captures the transitory effect through $g_{k_{it}}$. $g_{L_{it}}$ represents the population growth rate of the state i

in the year t to capture labour supply growth. State-specific quadratic time trends $[\rho_i(t)]$ control for various possible state changes that affect the per capita economic growth. δ_i are state-fixed effects, and μ_t are year-fixed effects that account for the national and global shocks in a given year t. ϵ_{it}s are the error terms assumed to be independent and identically distributed.

The bins need to be constructed based on temperature and precipitation levels. Following the bin construction of Kalkuhl and Wenz (2020), we choose the number of bins and their construction to ensure an adequate number of observations in each bin, along with the leeway to capture the joint effects of weather levels. We create the following four bins ($K^{bin} = 4$) partitioned by India's median temperature and precipitation levels. Data with weather levels below the median are placed in the Q_1 ('Low-Low') bin. The Q_2 ('Low-High') bin includes observations with above-median precipitation but below-median temperature. Observations with above-median temperature but below-median precipitation are included in the Q_3 ('High-Low') bin. Lastly, data with above-median weather levels are placed in the Q_4 ('High-High') bin. The variable $Q_{k,it}$ is a dummy variable that assumes the value of unity if the given it^{th} observation falls in the k^{th} bin.

In Equation (4), we represent the two channels denoted as the *WI-TFPG* and *WI-LPG* as given below:

$$\text{WI-TFPG}_{it} = \sum_{k=1}^{4} \phi_k^T Q_{k,it} \times \Delta T_{it} + \sum_{k=1}^{4} \phi_k^P Q_{k,it} \times \Delta P_{it}$$

$$\text{WI-LPG}_{it} = \sum_{k=1}^{4} \zeta_{1k}^T Q_{k,it} \times T_{it} + \sum_{k=1}^{4} \zeta_{2k}^T Q_{k,it} \times T_{it}^2 + \sum_{k=1}^{4} \zeta_{1k}^P Q_{k,it} \times P_{it} + \sum_{k=1}^{4} \zeta_{2k}^P Q_{k,it} \times P_{it}^2$$

Table 1 tabulates the estimated coefficients of weather variables for each bin based on regression Equation (4). We observe that temperature change has an adverse marginal effect on the per capita economic growth through the *WI-TFPG* channel. Moreover, this adverse effect is definitely more significant in regions with low precipitation levels, irrespective of the temperature levels (Bin 1 and Bin 3). We also find that precipitation change has a negative marginal impact on the per capita economic growth in regions only with high temperature and precipitation levels (Bin 4).

Furthermore, a variation in temperature level has a significant non-linear impact on the per capita economic growth through the *WI-LPG* channel in Bin 1 and Bin 2 (low-temperature regions) only. Variations in precipitation levels indicate non-linear impact on the per capita economic growth in regions with low precipitation and high temperature levels (Bin 3). We estimate the marginal effect of weather level on the per capita economic growth from Equation (4). That marginal effect entails an inverted U-shaped association with the per capita economic growth against both the temperature and precipitation levels, for certain bins.

Table 1: **Bin regression results**

	(1)	(2)	(3)	(4)
	Dependent variable: Per capita economic growth rate			
	Bin 1	**Bin 2**	**Bin 3**	**Bin 4**
	Low-Low	**Low-High**	**High-Low**	**High-High**
	(Q_4)	(Q_3)	(Q_2)	(Q_1)
Weather induced TFP growth (WI-TFPG)				
Temperature change (ΔT)	-1.666**	-1.0260	-2.695**	-1.3310
	(1.017)	(1.042)	(1.141)	(1.215)
Precipitation change (ΔP)	-0.0413	-0.0028	0.0221	-0.0228**
	(0.025)	(0.012)	(0.020)	(0.011)
Weather induced LP growth (WI-LPG)				
Linear Temperature level (T)	5.683***	5.929**	2.3360	3.8210
	(2.201)	(2.317)	(2.611)	(2.654)
Squared Temperature level (T^2)	-0.1031***	-0.1026**	-0.0044	-0.0258
	(0.050)	(0.052)	(0.062)	(0.063)
Linear Precipitation level (P)	0.0025	0.0232	0.6543***	0.0508
	(0.127)	(0.037)	(0.127)	(0.053)
Squared Precipitation level (P^2)	0.0008	-0.00002	-0.0038***	-0.0001
	(0.0009)	(0.0001)	(0.0009)	(0.0001)
Observations	283	322	322	283
Fixed effects	State, Year			
State-trend	Quadratic			
Controls	lagged economic growth rate, population growth rate			
Adjusted R^2	0.572			

This table displays estimated coefficients from the the bin regression in Equation (4). The bins are constructed based on India's median temperature and precipitation levels. Bin 1 (Low-Low) takes value one if the observation has below median temperature and precipitation levels. Bin 2 (Low-High) takes value one if the observation has a temperature below the median temperature and precipitation above median precipitation levels. Above-median temperature but below-median precipitation measurements are included in Bin 3 ('High-Low'), whereas above-median weather levels are taken into consideration in Bin 4 ('High-High').

The specification considers state, year fixed effects, and state-specific quadratic trends. Other controls include lagged economic growth rate ($g_{y_{it-1}}$) and population growth ($g_{L_{it}}$). Standard errors are in parentheses. Significance levels: * 10%, ** 5%, and *** 1%.

4.3. Formulation of the hypotheses

We use the findings from Table 1 to formulate hypotheses for deeper investigation. These findings confirm the usefulness of the classification of regions based on climatic zones (Gallup et al., 1999) for studying the impact of weather variables on economic damages. They also second the understanding given by the literature (Burke et al., 2015; Kalkuhl and Wenz, 2020) that weather variables cause changes in the per capita economic growth in a non-linear fashion.

We gain additional insights from the above bin regression results. Not only do weather changes affect the per capita economic growth, but these negative effects also depend conditionally upon weather levels. More specifically, temperature changes have varying marginal consequences depending on precipitation levels. Furthermore, on considering the joint effect of temperature and precipitation levels, we observe significant adverse effects of precipitation changes for Bin 4 only, which indicates a dependency of the marginal consequence of a precipitation change with the temperature and precipitation levels.

These findings justify the choice of our theoretical framework in Equation (3), in which we consider a joint effect of weather levels on the marginal effect of weather change on the per capita economic growth via the *WI-TFPG* channel. We posit the following two hypotheses based on the above insights gained from the bin regression.

Hypothesis 1: The adverse marginal effects of a temperature change on the per capita economic growth depends upon the precipitation level in-question.

Hypothesis 2: The marginal effect of a precipitation change on the per capita economic growth jointly depends upon the temperature and precipitation level in-question.

In line with the earlier research (Kahn et al., 2021; Kalkuhl and Wenz, 2020; Kotz et al., 2021; Kumar and Maiti, 2024a), Hypothesis 1 draws attention to the detrimental effects of temperature change on the economic growth. However, these studies typically use constant-coefficient models or models in which the effect of a temperature change varies with the temperature level. In contrast to them, Hypothesis 1 highlights the possibility of dependency of the impact of a temperature change (on the per capita economic growth) with the precipitation level. More specifically speaking, we posit that low precipitation levels may increase the negative impact of a temperature change on the per capita economic growth. This position of ours is an addition to the literature.

In a global study, Kalkuhl and Wenz (2020) have concluded that a precipitation change does not significantly affect the per capita economic growth. However, through a different approach, Kotz et al. (2022) find a significant impact of a precipitation change on the per capita economic growth. These two works are based on the assumption that the marginal effect of a precipitation change only varies with the precipitation level. Our Hypothesis 2 considers a more general position with the potential interactive effect between weather levels.

We sum up here that our preliminary findings using the Indian data are in contrast with certain conceptualizations of the existing literature. This contrast warrants further investigation for a better understanding.

5. Empirical methodology

Notably, there are two important drawbacks to bin regressions. Firstly, there is inherent arbitrariness in the bin selection process, and the estimates of coefficients depend on the choice of the particular bin selection process. Secondly, and perhaps more importantly, bin regression does not consider non-linearity within a particular bin when weather levels—the foundation for constructing a bin—are associated with weather changes. This can result in an omitted variable bias, as highlighted by Simonsohn (2023), who suggests using a generalized additive model approach to overcome the drawbacks of bin regression.

5.1. The Overall Methodology

We implement the Varying Coefficient Generalized Additive Model (VC-GAM) to test the hypotheses mentioned in Section 4.3. Thereafter, we compute the magnitude of economic damage due to weather variables for the available data-points. We estimate the corresponding damage function for India using our computed damages for the data-points. We describe the overall methodology first before taking up a detailed discussion on each of the constituents in our methodology.

5.1.1. Hypothesis Testing

We employ the semi-parametric technique of VC-GAM to estimate an empirical version of Equation (3) by introducing a new subscript i to all the variables reflecting each Indian state. The advantage of VC-GAM is that the functional forms for $g_{\Theta_T}(T_{it}, P_{it})$, $g_{\Theta_P}(T_{it}, P_{it})$ and $(\tau_{it} - \eta_{K_{it}}) \times g_{A_W}(T_{it}, P_{it})$ are not subjectively defined but objectively fitted based on the data available. We recast Equation (3) for the purpose of VC-GAM regression to below:

$$\begin{aligned} g_{y_{it}} = & \overbrace{g_{\Theta_T}(T_{it}, P_{it}) \times \Delta T_{it} + g_{\Theta_P}(T_{it}, P_{it}) \times \Delta P_{it}}^{\text{WI-TFPG}} + \overbrace{M(T_{it}, P_{it})}^{\text{WI-LPG}} \\ & + \underbrace{f(g_{y_{it-1}}) + h(g_{L_{it}}) + \rho_i(t) + \mu_t + \delta_i}_{\text{Other economic factors}} + \underbrace{\epsilon_{it}}_{\text{error term}} \end{aligned} \tag{5}$$

where, $g_{\Theta_T}(.)$, $g_{\Theta_P}(.)$, $M(.)$, $f(.)$ and $g(.)$ are smooth terms of their respective arguments. Evidently, the smooth term $M(T_{it}, P_{it})$ represents the total effect through the *WI-LPG* channel. Similarly, $g_{\Theta_T}(T_{it}, P_{it})$ and $g_{\Theta_P}(T_{it}, P_{it})$ are smooth terms for marginal effects of a temperature and precipitation change, respectively, for the *WI-TFPG* channel. Finally, $f(.)$, and $h(.)$ are smooth terms for the lagged per capita economic growth and population growth, respectively, replacing the corresponding linear terms used in Equation (4). Other terms [$\rho_i(t)$, μ_t, δ_i, and ϵ_{it}] are defined as in Equation (4).

The VC-GAM estimations are useful as a visual tool for hypothesis testing. Furthermore, VC-GAM uses a Bayesian approach to estimate variance, facilitating the generation of confidence intervals for smooth terms. We use these confidence intervals to test our hypotheses.

5.1.2. Estimation of damage function

We compute the predicted values for each smooth term for each observation as provided by the VC-GAM. Consequently, we calculate the predicted values of the two channels—*WI-TFPG* and *WI-LPG*—as noted in Equation (5). Mathematically speaking,

$$\widehat{\text{WI-TFPG}}_{it} = \hat{g}_{\Theta_T}(T_{it}, P_{it}) \times \Delta T_{it} + \hat{g}_{\Theta_P}(T_{it}, P_{it}) \times \Delta P_{it} \tag{6}$$

$$\widehat{\text{WI-LPG}}_{it} = \hat{M}(T_{it}, P_{it}) \tag{7}$$

Equations (6) and (7) represent the predicted changes in weather-induced TFP and LP growth, respectively. Notably, joint smooth terms defined in Equations (6) and (7) have a common set of weather levels. Hence, weather level, say temperature (T_{it}), not only governs WI-TFPG$_{it}$ channel through terms like $\hat{g}_{\theta_T}(.)$ and $\hat{g}_{\Theta_P}(.)$ but also have an impact on the WI-LPG$_{it}$ channel through the term $\hat{M}(.)$. This approach has been considered by Gawande (1997) for linear and non-linear estimations. Therefore, we estimate for the corresponding damage function, wherein we define the predicted values of the Weather induced per capita economic growth ($\widehat{\text{WI-EG}}_{it}$) as the sum of $\widehat{\text{WI-TFPG}}_{it}$ and $\widehat{\text{WI-LPG}}_{it}$.

We implement a variety of parametric specifications for the damage function. We select the best parametric model based on both out-of-sample and in-sample performance metrics. For out-of-sample performance metrics, we consider ridge regression to reduce multicollinearity, followed by K-Fold cross-validation and model confidence sets as recommended by Newell et al. (2021). The in-sample metrics comprise the adjusted generalized variance inflation factor with a threshold of 4.00 for detecting multicollinearity and the Bayes factor to ensure a balance between goodness-of-fit and model complexity.

In the following sub-sections (Sections 5.2 and 5.3), we expand both constituents of the methodology.

5.2. Hypothesis testing

5.2.1. Varying Coefficient Models:

The VC-GAM (Hastie and Tibshirani, 1993) assumes the following structure:

$$Y = Z^T\alpha + \beta^T(U)X + \epsilon$$

where $\beta^T(U)$ is a vector of unknown function coefficient allowed to vary smoothly over the effect modifiers U. This model considers a parametric estimation of linear predictors Z while permitting non-linear interaction between U and X and assuming non-normal error distribution ϵ.

There are various smoothing splines (Wood, 2017) to estimate the unknown function $\beta(.)$ like cubic regression splines, P-splines, and B-splines. However, one of the disadvantages of these splines is that they estimate functions with only one effect modifier. We employ thin-plate splines (Duchon, 1977) to estimate $\beta(.)$, which allows for the use of more than one effect modifier in a smooth function. We can represent the varying coefficients $\beta(.)$ as linear combinations of thin plate spline basis functions:

$$\beta(U) = \sum_{k=1}^{K^{knots}} \theta_k \phi_k(U)$$

where K^{knots} represents the number of knots in the basis functions used, θ_k are the coefficients to be estimated and $\phi_k(U)$ are the thin plate spline basis functions evaluated at the covariates in U. To estimate α and θ_k, a double penalized regression technique is implied as follows:

$$minimize \left\{ \sum_{i=1}^{n} \left(Y_i - Z^t\alpha + \sum_{k=1}^{K^{knots}} \theta_k \phi_k(U_i) X_i \right)^2 + \lambda_1 \sum_{k=1}^{K^{knots}} \int \left(\frac{\partial^2 \theta_k}{\partial U^2} \right)^2 dU + \lambda_2 \sum_{k=1}^{K^{knots}} \int \theta_k^2 dU \right\}$$

where Y_i is the i-th response variable, Z_i is the i-th row of the matrix Z, U_i is the i-th row of the matrix U, and X_i is the i-th row of the matrix X. The parameter λ_1 penalizes the more complex or "wiggly" part of the smoother, known as the range space. The double-penalty technique goes a step further by imposing an additional penalty, λ_2, on the smoother's simpler half, known as the null space (see Marra and Wood, 2011).

Smoothing parameters (λ_1 and λ_2) balance fit and smoothness and can be chosen by minimizing the generalized Akaike's Information Criterion (AIC)[7], or Restricted (Residual) Maximum Likelihood estimation (henceforth, REML) score. However, Reiss and Ogden (2009) and Wood (2011) demonstrate that AIC is prone to under smoothing and is more likely to create numerous minima. Hence, the REML score is chosen.

[7]Non-parametric modelling uses candidate models to approximate complex true functions. AIC is generally recommended over Bayesian Information Criterion (BIC) as a general method for model selection (Shao, 1997).

The significance of smooth terms is tested under the null hypothesis that $\beta(U) = 0$ for the range of values of U. The null hypothesis posits that the relationship between X and Y does not change with U. To assess this, we use F-test statistics. We compare two distributions describing the error structure to make reliable inferences about model parameters: the Gaussian distribution and the Scaled t-distribution. The Scaled t-distribution is especially beneficial in situations when residuals include heavy tails or outliers because it provides a more robust alternative to the assumption of normality. We compare the model residuals based on diagnostic plots, which include the Quantile-Quantile plot, histogram of residuals, residuals vs linear predictor plot, and response vs fitted value plot. Based on our comparisons, we consider the Scaled-t distribution for our analysis (Refer to Appendix C for details).

5.2.2. Panel Unit root test

Like other regression models, the VC-GAM assumes that the underlying data generation process is stationary. Since the VC-GAM with non-stationary variables captures spurious relationships, estimates for the smooth terms could be biased or inconsistent if the assumption of stationarity does not hold. Consequently, we employ the Cross-Sectionally Augmented IPS (CIPS) unit root test, suggested by Pesaran (2007), to test panel unit roots. This unit root test takes into account the cross-sectional dependence and serial correlation of the error terms.

5.2.3. Model selection for VC-GAM

The usual concerns with VC-GAMs are that they are difficult to interpret and prone to overfitting, particularly when dealing with joint smooth functions. To address these concerns, we evaluate several model designs using the following four criteria: (i) *Parsimonious interpretation*, (ii) *low concurvity* (collinearity) between smooth terms, (iii) *avoidance of over-fitting*, and (iv) *balancing goodness-of-fit with model complexity.* Criteria (i) and (ii) aid in hypothesis testing as outlined in Section 4.3. Criteria (iii) and (iv) are crucial factors in determining reliable predicted values for the damage function.

We use the following classes of models based on their '*complexity*':

I. **Joint model:** It describes Equation (5);

II. **LP decomposed model:** It decomposes the smooth term in the *WI-LPG* channel $[M(.)]$, as below, while retaining the joint smooth term for the *WI-TFPG* channel

$$M(T_{it}, P_{it}) = M_1(T_{it}) + M_2(P_{it}) + M_3(T_{it} \times P_{it})$$

III. **TFP decomposed model:** It dissects the smooth terms $[g_{\Theta_T}(.)$ and $g_{\Theta_P}(.)]$, mentioned below, in the *WI-TFPG* channel while keeping the joint smooth term in *WI-LPG* intact.

$$g_{\Theta_T}(T_{it}, P_{it}) = g_{\Theta_{T,1}}(T_{it}) + g_{\Theta_{T,2}}(P_{it}) + g_{\Theta_{T,3}}(T_{it} \times P_{it})$$
$$g_{\Theta_P}(T_{it}, P_{it}) = g_{\Theta_{P,1}}(T_{it}) + g_{\Theta_{P,2}}(P_{it}) + g_{\Theta_{P,3}}(T_{it} \times P_{it})$$

IV. **Overall decomposed model:** It decomposes smooth terms in both channels, which improves the model's parsimony

V. **Overall decomposed with backward elimination (BE) model:** In this model, to avoid high concurvity, we use backward elimination wherein we remove the insignificant terms in the "Overall decomposed" model and select the model with observed pairwise concurvity less than 0.50. Pairwise concurvity occurs when another smooth term can approximate a smooth term. High concurvity between smooth terms increases the risk of type 1 error (Ramsay et al., 2003) and results in instable estimates (Buja et al., 1989).

With these five classes of models established, we explore the following combinations of weather variables ('*weather combinations*') as follows:

a. Contemporaneous weather levels, contemporaneous weather changes

b. Contemporaneous weather levels, contemporaneous and one-year lagged weather changes

c. One-year lagged weather levels, contemporaneous weather changes

d. One-year lagged weather levels, contemporaneous and one-year lagged weather changes

e. Contemporaneous and one-year lagged weather levels, contemporaneous weather changes

f. Contemporaneous and one-year lagged weather levels, contemporaneous and one-year lagged weather changes

The five classes of models based on *complexity*, 'I–V', each with six of the *weather combinations*, 'a–f', result in a total of 30 specifications. However, the *complexity* of Overall decompose with BE model for contemporaneous and lag weather changes (V-b) is identical to the same complexity with only contemporaneous weather changes (V-a). Therefore, we effectively consider 29 specifications for our analysis.

Balancing goodness-of-fit and model complexity entails assessing the model's fit to the estimation sample while considering the trade-off between bias and variance. In the context of VC-GAM, a smoother is a function or technique that estimates the smooth term in the model using smoothing parameters. As discussed in Section 5.2.1, we employ REML for the estimation of the smooth parameter.

Finally, we implement a double-penalty shrinkage strategy to *reduce overfitting* and increase prediction performance (Marra and Wood, 2011). This double-penalty technique aids in determining the proper level of smoothness, avoiding both overfitting from excessively complex terms and underfitting by the inclusion of redundant simple terms. We further complement this approach with an out-of-sample K-fold cross-validation technique (discussed in detail in Section 5.3.2) and choose the model with the least average root mean square error (average RMSE).

5.3. Estimation of damage function

5.3.1. Damage specifications considered:

We interpret $\widehat{\text{WI-EG}}_{it}$—sum of $\widehat{\text{WI-TFPG}}_{it}$ and $\widehat{\text{WI-LPG}}_{it}$—as total effect of weather variables on the per capita economic growth through the *WI-TFPG* and *WI-LPG* channels. Thus, $\widehat{\text{WI-EG}}_{it}$ provides us with a fresh set of panel data values, which is why it can be a dependent variable for determining the parametric form of the economic damages.

To obtain an damage function, we consider the optimal class of VC-GAM based on four criteria mentioned in Section 5.2.3. We find that the Overall decomposed with BE model (V) with weather combination 'f' as *the* optimal VC-GAM as elaborated in Section 6.1.1. Accordingly, we describe the following generalized regression specification for the damage function:

$$\begin{aligned} \widehat{\text{WI-EG}}_{it} = {} & b_1(P_{it-1}) \times \Delta T_{it} + b_2(P_{it-1}) \times \Delta P_{it} \\ & + b_3(T_{it-1} \times P_{it-1}) \times \Delta P_{it-1} + b_4(P_{it}) + \kappa_i + \nu_{it} \end{aligned} \tag{8}$$

where κ_i presents the state-fixed effects, which control for geo-climatic features of states over the period. We assume that error terms, ν_{it}s, are independent and identically distributed. For the *WI-TFPG* channel, $b_1(.)$, $b_2(.)$, and $b_3(.)$ represent the varying marginal effect on the per capita economic growth, of a temperature change (ΔT_{it}), precipitation change (ΔP_{it}), and one-year lagged precipitation change (ΔP_{it-1}), respectively. For the *WI-LPG* channel, $b_4(.)$ is the total effect of precipitation level (P_{it}) on the per capita economic growth.

Our focus is to determine the approximate parametric (linear or non-linear) functional form for $b_1(.)$, $b_2(.)$, $b_3(.)$, and $b_4(.)$. $b_1(.)$. In total, we evaluate 81 possible specifications resulting from the following parametric restrictions in equation (8):

A. Terms in $b_1(.)$: Marginal effect of temperature change (3 forms)

1. $b_1(P_{it-1}) = b_{11}$
2. $b_1(P_{it-1}) = b_{11} + b_{12}P_{it-1}$
3. $b_1(P_{it-1}) = b_{11} + b_{12}P_{it-1} + b_{13}P_{it-1}^2$

B. Terms in $b_2(.)$: Marginal effect of precipitation change (3 forms)

1. $b_2(P_{it-1}) = b_{21}$
2. $b_2(P_{it-1}) = b_{21} + b_{22}P_{it-1}$
3. $b_2(P_{it-1}) = b_{21} + b_{22}P_{it-1} + b_{23}P_{it-1}^2$

C. Terms in $b_3(.)$: Marginal effect of one-year lagged precipitation change (3 forms)

1. $b_3(T_{it-1} \times P_{it-1}) = b_{31}$
2. $b_3(T_{it-1} \times P_{it-1}) = b_{31} + b_{32}T_{it-1} \times P_{it-1}$
3. $b_3(T_{it-1} \times P_{it-1}) = b_{31} + b_{32}T_{it-1} \times P_{it-1} + b_{33}T_{it-1}^2 \times P_{it-1}^2$

D. Terms in $b_4(.)$: Total effect of precipitation levels (3 forms)

1. $b_4(P_{it}) = b_{41}P_{it}$
2. $b_4(P_{it}) = b_{41}P_{it} + b_{42}P_{it}^2$
3. $b_4(P_{it}) = b_{41}P_{it} + b_{42}P_{it}^2 + b_{43}P_{it}^3$

The above parametric restrictions are determined based on visual estimates provided by *the* optimal VC-GAM. Along with the above 81 specifications, we also include the specification suggested by Dell et al. (2012), Burke et al. (2015), and Kalkuhl and Wenz (2020). Thus, we compare 84 models to determine the parametric form of the damage function based on their goodness-of-fit, complexity, and out-of-sample performance, which we will discuss in detail in the next section.

5.3.2. Model selection procedure

In order to resolve overfitting concerns, it is necessary to consider the out-of-sample prediction features of models (Auffhammer and Steinhauser, 2012; Chatfield, 1996). Lastly, we obtain the final set of damage function parameters using the adjusted generalized variance inflation factor and the Bayesian model selection criteria, which identifies multicollinearity and ensures the balance between goodness-of-fit and complexity, respectively.

Cross-validation and model confidence set

We follow the methodology proposed by Newell et al. (2021) to compare the out-of-sample performance of different specifications. However, 84 specifications (described in Section 5.3.1) contain higher-order terms and interactions, which may raise concerns about multicollinearity. Kalkuhl and Wenz (2020) point out multicollinearity in their paper. In response, we utilize ridge regression, as introduced by Hoerl and Kennard (1970), which adds the squared magnitude of the coefficients to the objective function, imposing a L_2 regularization penalty[8] that reduces multicollinearity and mitigates overfitting.

[8] We consider a penalty of 0.1 in our analysis. We also consider a penalty of 0.05 and 0.15 for sensitivity analysis.

Accordingly, we utilize the K-fold cross-validation technique (CV) to assess the prediction ability of the proposed specifications with the ridge regression. CV divides the data into $K^{CV} = 5$ random groups in our investigation. For each group k^{CV}, the specification is estimated from data of the remaining four groups and tested on the k^{th} group. Next, we compute and compare the average RMSE of specifications, choosing specifications with significantly lower average RMSE than the others.

Subsequently, we use the model confidence set (MCS) procedure proposed by Hansen et al. (2011). The approach generates a set of superior models. This approach tests the null hypothesis of equal predictive ability (EPA) at a 95% confidence level. If the null is rejected, an elimination rule is applied to remove that particular specification from the initial set, and the null hypothesis is tested again. The iterative process continues until the equivalence of model losses can no longer be rejected. The test statistic $T_{max,M}$ assesses the EPA hypothesis, and the loss function in our procedure is the series prediction errors of models obtained from CV[9].

Adjusted generalized variance inflation factor and Bayes factor:

While the ridge regression improves prediction accuracy and addresses multicollinearity, the regularization approach creates biased coefficient estimates for interpretation (Hoerl and Kennard, 1970). Hence, we transit to a linear regression estimation framework for obtaining parametric forms of the coefficient estimate for the superior set of models. We check for multicollinearity for each specification in the superior set by employing an adjusted Generalized Variance Inflation Factor (aGVIF), as recommended by Fox and Monette (1992). In the presence of higher order and interaction terms, aGVIF is a reliable measure of how much the variance of the predicted coefficients is increased due to multicollinearity. Accordingly, we retain only those specifications in the superior set for which aGVIF < 4.00.

Once we reasonably address the concern of multicollinearity, we identify the model specification with the lowest BIC from the superior set of models to ensure simplicity and goodness-of-fit. Although the lowest BIC model is considered, models with a BIC that is marginally higher than the lowest BIC model cannot be disregarded. Consequently, we calculate the following Bayes factor[10] (BF) and contrast the BIC of alternative models [BIC(H_1)] with the null model, which in this case is the specification with the lowest BIC [BIC(H_0)]:

$$BF \approx e^{[BIC(H_1)-BIC(H_0)]/2} \tag{9}$$

The odds favouring the null model against the alternative model are obtained from the ensuing estimate of the Bayes factor. BF may then be translated into the following posterior probability

[9]We use 'MCS' package in R (Bernardi and Catania, 2018).

[10]For details of the Bayes factor, see Masson (2011).

(p_{BIC}), indicating that the data favour the null model:

$$p_{BIC}(H_0|Data) = \frac{BF}{BF+1} \tag{10}$$

Based on values suggested by Raftery (1995) for $p_{BIC}(H_0|Data)$, we consider only those alternative specifications which show weak evidence ($0.50 \leq p_{BIC}(H_0|Data) \leq 0.75$) of BIC($H_0$) < BIC($H_1$).

6. Results

As an initial exercise, we conduct the panel unit root test given by Pesaran (2007) with lag orders of 1, 2, and 3, respectively. The results (refer to Table 2 below) show that the relevant variables are stationary even at 1% level, allowing us to use the VC-GAM.

Table 2: **Panel unit root test results**

	$\tilde{Z}$- statistics		
Variables	**1 Lag**	**2 Lags**	**3 Lags**
Per capita economic growth	-4.2168***	-3.2446***	-3.0145***
Population growth	-3.6442***	-3.0154***	-2.715***
Temperature level	-3.9696***	-3.3356***	-3.2719***
Temperature change	-6.6715***	-4.618***	-4.8114***
Precipitation level	-4.3354***	-3.3771***	-3.2348***
Precipitation change	-7.1671***	-5.0880***	-4.6245***

The $\tilde{Z}$-statistics are computed using a cross-sectionally augmented IPS test proposed by Pesaran (2007) using a lag of one, two and three of relevant variables in VC-GAM. Significant negative values reject the existence of unit root in favour of stationarity. Significance levels: * 10%, ** 5%, and *** 1%.

6.1. Hypothesis testing:

6.1.1. Selection of the optimal VC-GAM

Results for the selection of the classes of VC-GAM based on different criteria (described in Section 5.2.3) are reported in Figure 1. This plot illustrates the estimated REML score for each of the 29 classes of VC-GAMs. The horizontal axis in the plot indicates the corresponding class of model based on *complexity* (I to V) and *weather combinations* (a to f). The green triangles signify an observed pair-wise concurvity of less than 0.50 between the smooth terms (acceptable threshold) for the corresponding class of VC-GAM. All the classes of models satisfy the rest of the three criteria of *parsimonious interpretation*, *avoidance of over-fitting*, and *balancing goodness-of-fit with model complexity*. Thus, the following class of VC-GAMs—'I-a', 'V-a', 'I-b', 'I-c', 'I-d', and 'V-f'—satisfy all the criteria for the selection of optimal VC-GAM and will be the focus of our further analysis.

Table 3 shows the Effective Degrees of Freedom (EDF) for the abovementioned optimal VC-GAMs, highlighting the complexity of a smooth term. A higher EDF suggests that the smooth term has greater flexibility in fitting the data, catching more complicated patterns. Notably, EDF only

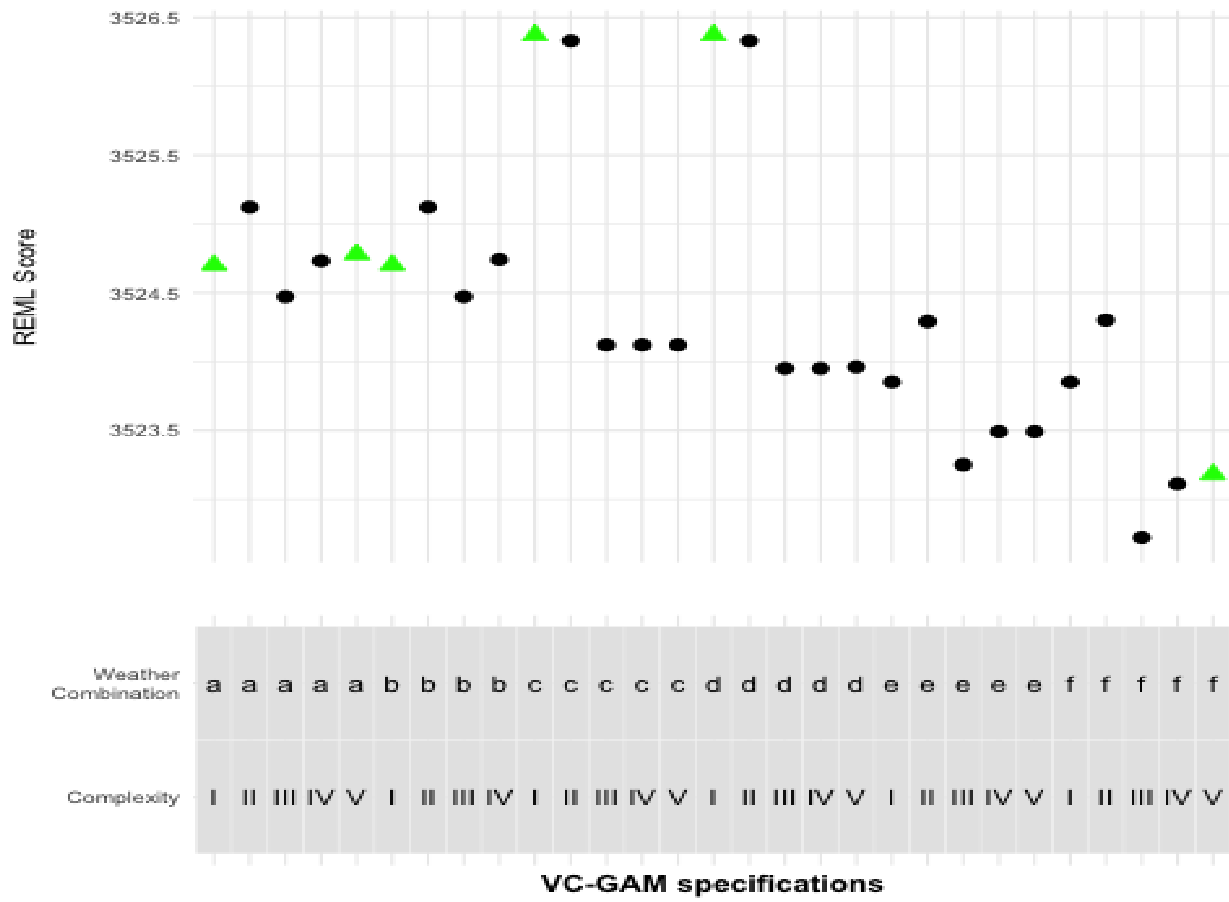

Figure 1: **Model selection for VC-GAM:** This figure depicts REML score for 29 classes of VC-GAMs. Green triangles indicate the REML score for those models with observed pair-wise concurvity less than 0.50. Black dots present the remaining models. For the classes of models in complexity: I - Joint model; II - LP decomposed model; III - TFP decomposed model; IV - Overall decomposed model; and V - Overall decomposed with backward elimination (BE) model.
In case of models with weather combinations: a - Contemporaneous weather levels, contemporaneous weather changes; b - Contemporaneous weather levels, contemporaneous and one-year lagged weather changes; c - One-year lagged weather levels, contemporaneous weather changes; d - One-year lagged weather levels, contemporaneous and one-year lagged weather changes; e - Contemporaneous and one-year lagged weather levels, contemporaneous weather changes; and f - Contemporaneous and one-year lagged weather levels, contemporaneous and one-year lagged weather changes.

indicates the complexity of association of weather variables with the per capita economic growth; it offers no insight into the direction or strength of the influence of their effect on the per capita economic growth. Along with the EDF values, the table displays the significance of each smooth term. This significance reveals whether the flexible relationship recorded by the VC-GAM has sufficient predictive power for the model's performance.

Columns (1), (3), (4), and (5) of Table 3 represent Joint model (I) with *weather combinations* 'a', 'b', 'c', and 'd', respectively. Columns (2) and (6) represent Overall decomposed with BE model (V) with *weather combinations* 'a' and 'f', respectively. The adjusted R^2, AIC and REML score—the in-sample metrics of the model's complexity and goodness-of-fit —pinpoint to the critical observation that the Overall decomposed with BE model combined with the *weather combination* 'f' [Column (6): 'V-f'] is *the* optimal VC-GAM[11].

6.1.2. Hypothesis testing using the optimal VC-GAM

We now shift our attention towards the EDF and significance of smooth terms in Column (6) of Table 3. The EDF of the smooth term in $g_{\Theta_{T,2}}(Lag.P) \times \Delta T$ is 1.21, indicating that the relationship between a temperature change and the per capita economic growth is slightly more flexible than a linear relationship but not highly complex. We observe that the marginal effect of temperature changes significantly impacts the per capita economic growth. Furthermore, this marginal effect is conditional on the lagged precipitation level. Panel (a) of Figure 2 visually represents the estimates of a varying marginal effect of temperature change on the per capita economic growth through the *WI-TFPG* channel. We find that the positive temperature change is associated with an adverse effect on the per capita economic growth *only* when the lagged precipitation level is below a certain threshold (approx. 150 mm), beyond which a temperature change does not have any significant effect. These results confirm our hypothesis 1, posited in Section 4.3.

The EDF (found to be 1.29) and significance of smooth term $[g_{\Theta_{P,2}}(Lag.P)]$ for a contemporaneous precipitation change (Refer to column (6) of Table 3) indicate that the marginal effect of a contemporaneous precipitation change is more flexible than linear and has a significant impact on the per capita economic growth conditional on lagged precipitation level. We find from Panel (b) of Figure 2 that a positive contemporaneous precipitation change adversely affects the per capita economic growth when the lagged precipitation level is above a certain threshold (approx. 225 mm).

On the other hand, we observe an EDF of 0.85 [Column (6) of Table 3] indicating a near linear fit of the interaction of the lagged temperature and precipitation levels $[g_{\Theta_{P,3}}(Lag.T \times Lag.P)]$ for the marginal effect of a positive lagged precipitation change. To investigate this interactive effect of the

[11]While the average RMSE from K-fold cross-validation indicates that model 'V-a' [Column (2)] is having the lowest, the average RMSE of model 'V-f' [Column (6)] is only slightly higher than model 'V-a'. Consequently, we consider the model in Column (6), model 'V-f', as our preferred specification and use it for the hypothesis testing.

Table 3: **Effective degrees of freedom**

	(1) I-a Joint	(2) V-a Overall Decomposed with BE	(3) I-b Joint	(4) I-c Joint	(5) I-d Joint	(6) V-f Overall Decomposed with BE
Weather induced TFP growth (WI-TFPG)						
$g_{\Theta_T}(T, P) \times \Delta T$	0.9111***		0.9113***			
$g_{\Theta_T}(T, P) \times L.\Delta T$			0.0010			
$g_{\Theta_T}(Lag.T, Lag.P) \times \Delta T$				0.9527***	0.9526***	
$g_{\Theta_T}(Lag.T, Lag.P) \times Lag.\Delta T$					0.0011	
$g_{\Theta_{T,2}}(P) \times \Delta T$		1.1424**				
$g_{\Theta_{T,2}}(Lag.P) \times \Delta T$						1.2075**
$g_{\Theta_P}(T, P) \times \Delta P$	1.017*		1.0161*			
$g_{\Theta_P}(T, P) \times L.\Delta P$			0.0019			
$g_{\Theta_P}(Lag.T, Lag.P) \times \Delta P$				2.3035***	2.3035***	
$g_{\Theta_P}(Lag.T, Lag.P) \times Lag.\Delta P$					0.0021	
$g_{\Theta_{P,3}}(T \times P) \times \Delta P$		0.8527**				
$g_{\Theta_{P,2}}(Lag.P) \times \Delta P$						1.2924***
$g_{\Theta_{P,3}}(Lag.T \times Lag.P) \times Lag.\Delta P$						0.8486**
Weather induced LP growth (WI-LPG)						
$M(T, P)$	6.9299***		6.9295***			
$M(Lag.T, Lag.P)$				0.7972**	0.7966**	
$M_2(P)$		3.3505***				2.7768***
Other variables						
$f(g_{Lag.y})$	4.6093***	4.5666***	4.6093***	4.6069***	4.6069***	4.6151***
$f(g_L)$	3.6491***	3.6586***	3.6492***	3.6439***	3.6440***	3.6346***
Weather level	Current	Current	Current	Lag	Lag	Current + Lag
Weather change	Current	Current	Current + Lag	Current	Current + Lag	Current + Lag
State-specific trends	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Fixed effects	State, year	State, year	State, year	State, year	State, year	State, year
Adj R^2	0.354	0.356	0.354	0.352	0.352	0.358
AIC	6973.53	6973.33	6973.54	6974.71	6974.71	6967.49
REML score	3524.70	3524.78	3524.70	3526.37	3526.37	3523.18
average RMSE	5.1633	5.1577	5.1726	5.1860	5.1866	5.1646

This table includes the Effective Degrees of Freedom (EDF) for each smooth term in the VC-GAMs, as well as post-diagnostic tests. The significance of the EDF values for the smooth terms is determined using an F-test. EDF values reflect the complexities of the link between predictor and outcome variables. The Akaike information criterion (AIC) and restricted maximum likelihood (REML) score assess model fit based on in-sample performance and complexity. The average root mean square error (average RMSE) obtained from K-fold cross-validation evaluates the models' out-of-sample performance and helps to prevent overfitting.

Columns (1), (3), (4), and (5) represent Joint model (I) with weather variable combinations 'a', 'b', 'c', and 'd', respectively. Columns (2) and (6) represent the Overall decomposed with BE model (V) with weather variable combinations 'a' and 'f', respectively.

All models have state-fixed effects, year-fixed effects and quadratic state-specific trend terms as controls. Error term follows a the Scaled-t distribution. Significance levels: * 10%, ** 5%, and *** 1%.

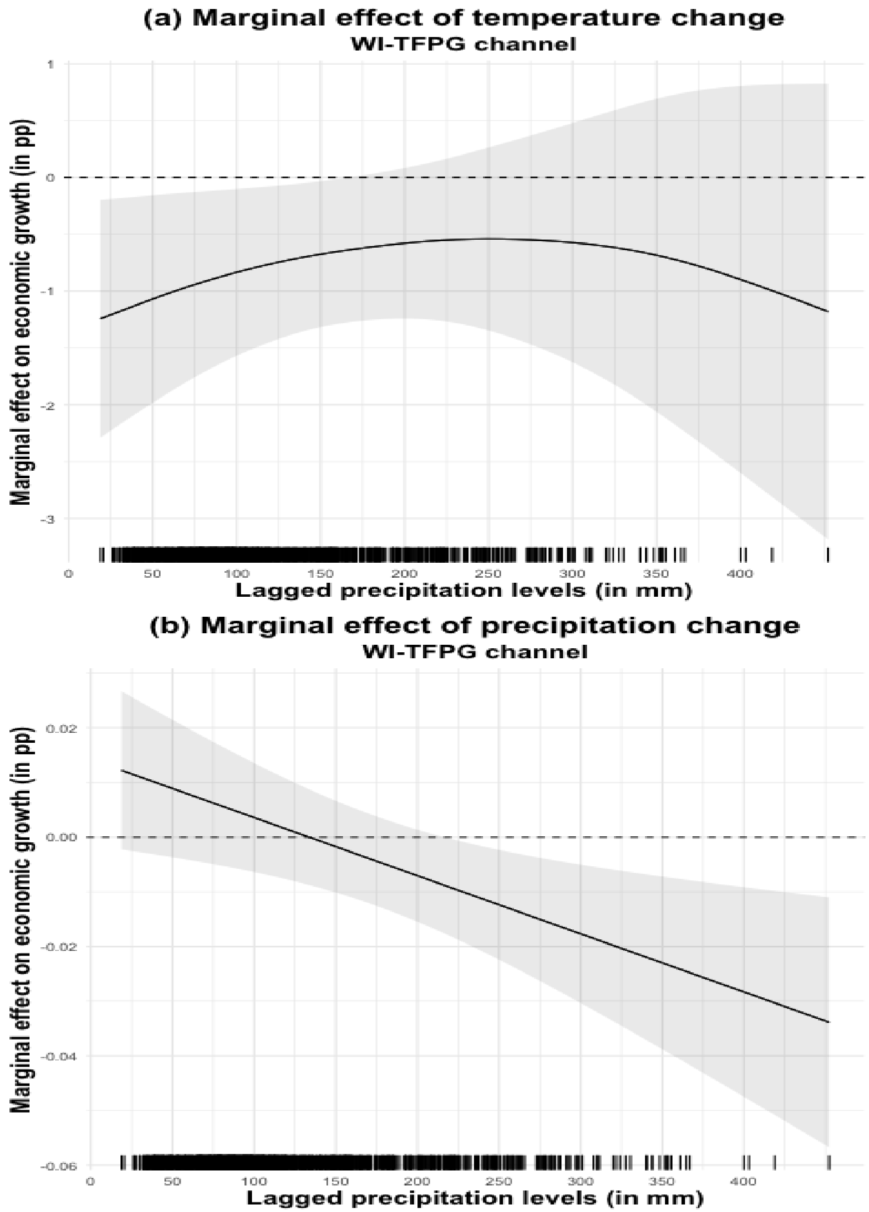

Figure 2: **Plot of the marginal effect of a positive contemporaneous temperature and precipitation change:** Figure represents plots of smooth terms for Model 'V-f' in Column (6) of Table 3. The ticks at the bottom of both panels represent the observed value as per our data. Panels (a) and (b) plot corresponding smooth terms representing the marginal effect of a positive contemporaneous temperature $[g_{\Theta_{T,2}}(Lag.P)]$ and precipitation $[g_{\Theta_{P,2}}(Lag.P)]$ changes, respectively on the per capita economic growth through the *WI-TFPG* channel.

smooth term, we plot the conditional marginal effect of a positive lagged precipitation change on the per capita economic growth at different specific values of lagged temperature and precipitation level. Panel (a) of Figure 3 represents the lagged precipitation-varying marginal effect of a positive lagged precipitation change at a specific level of lagged temperature. We observe that at a lower level of a lagged temperature (15°C and 20°C), the marginal effect of a positive lagged precipitation change on the per capita economic growth is a decreasing function of lagged precipitation level. At higher lagged temperature levels (25°C and 30°C), we get a contrasting result where that marginal effect is an increasing function of lagged precipitation level.

Similarly, in Panel (b), we find a U-shaped curve for the lagged temperature-varying marginal effect of a positive lagged precipitation change at high lagged precipitation levels (220 mm and 320 mm). In contrast, we find an inverted U-shaped curve at a lower lagged precipitation level (50 mm). Thus, these plots demonstrate that while a contemporaneous precipitation change has a lagged precipitation-varying impact on the per capita economic growth, a lagged precipitation change impact varies with both lagged temperature and precipitation level. These pieces of evidence confirm our hypothesis 2, formulated in Section 4.3.

Moreover, we assess the total effect of contemporaneous precipitation level on the per capita economic growth through the *WI-LPG* channel. The EDF of smooth term $M_2(P)$, in Column (6) of Table 3, is 2.78, indicating a significant non-linear relationship between the contemporaneous precipitation level and the per capita economic growth. These results are visually represented in Figure 4. Notably, a lower level of precipitation (below 100 mm) is translated into negative per capita economic growth, while positive per capita economic growth is associated with a precipitation level beyond 100 mm. Consequently, we can observe that the relationship between precipitation level and the per capita economic growth is quite close to a concave function. Our observation is in line with Damania et al. (2020) and Kotz et al. (2022).

In conclusion, we find that a positive change in contemporaneous temperature (precipitation) has an adverse effect on the per capita economic growth at a lower (higher) lagged precipitation level. Furthermore, a positive lagged precipitation change has a negative impact on the per capita economic growth when the lagged precipitation level is high, and the lagged temperature level is moderate. In contrast, a rise in contemporaneous precipitation level registers a positive association with the per capita economic growth through *WI-LPG* channel.

6.2. Estimation of damage function

This section discusses the results pertaining to the selection procedure and estimates of optimal specification for the weather-induced economic damages described in Section 5.3.

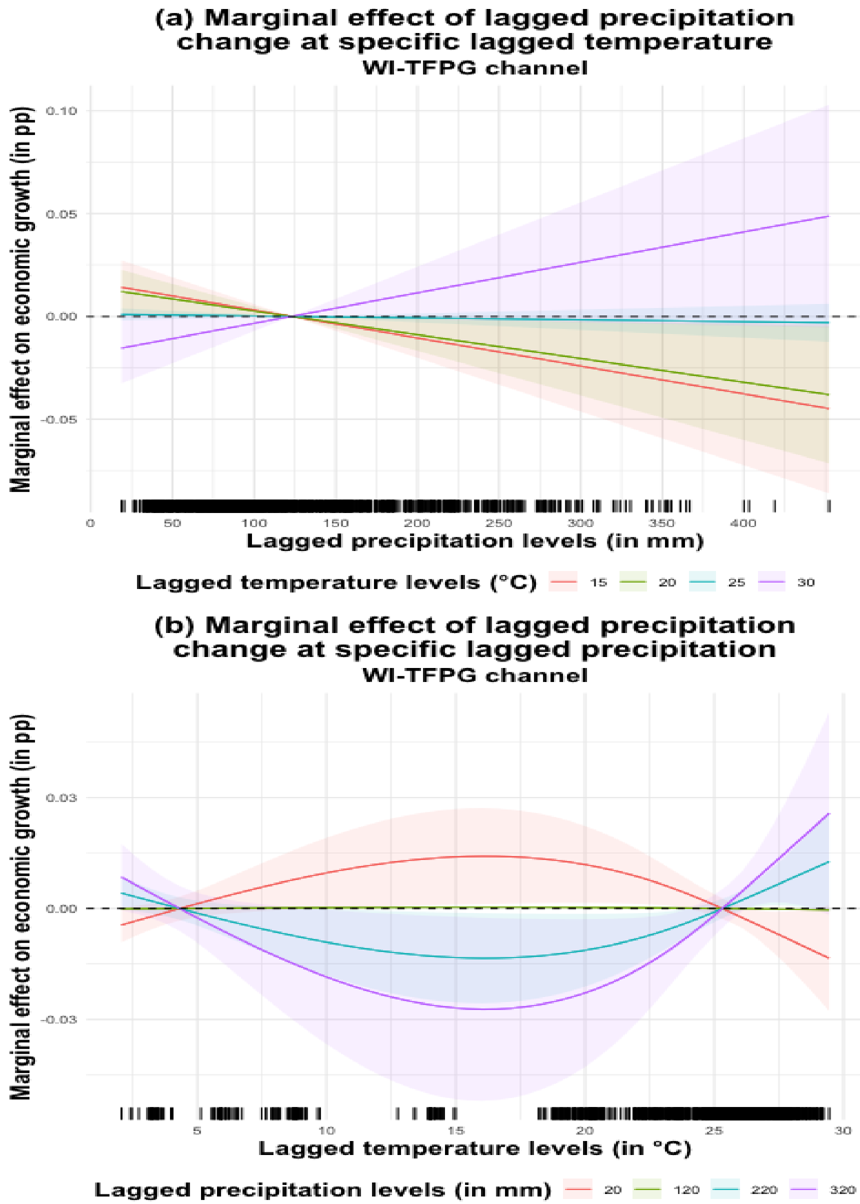

Figure 3: **Plot of the marginal effect of a positive lagged precipitation change:** Figure represents plots of smooth terms for Model 'V-f' in Column (6) of Table 3. The ticks at the bottom of both panels represent the observed value as per our data. Panels (a) and (b) present the marginal effect of a positive lagged precipitation change on the per capita economic growth through the *WI-TFPG* channel. Panel (b) plots $g_{\Theta_{P,3}}(Lag.T, Lag.P)$ at specific values of lagged temperature level. Panel (d) plots $g_{\Theta_{P,3}}(Lag.T, Lag.P)$ at specific values of lagged precipitation level.

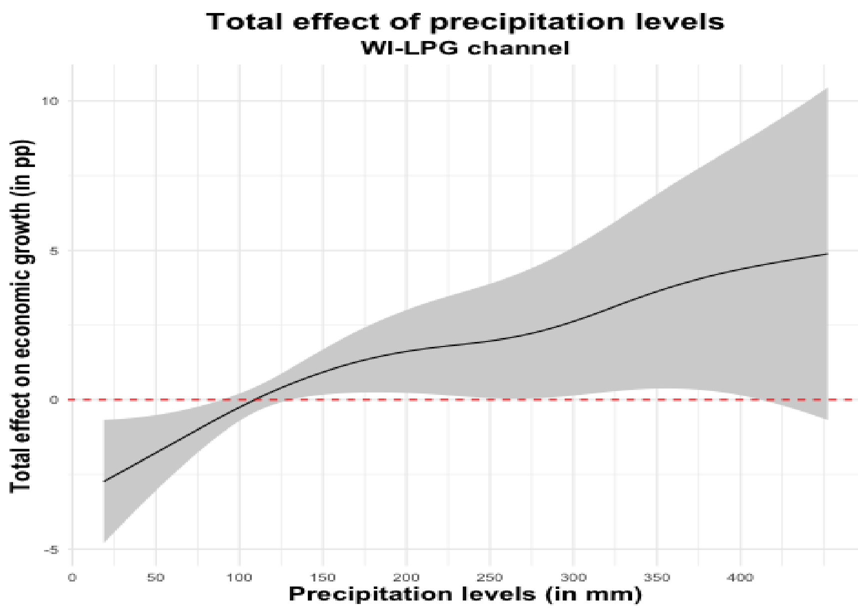

Figure 4: **Plot of the total effect of a rise in precipitation level:** Figure represents plots of a smooth term, $M_2(P)$, for Model 'V-f' in Column (6) of Table 3. The smooth term represents the total effect of a 1 mm rise in contemporaneous precipitation level on the per capita economic growth through *WI-LPG* channel.

6.2.1. Selection of the optimal damage specification

The CV with ridge regression reveals that 55 out of 84 alternative specifications have statistically similar predictive ability by the parameter of RMSE. The remaining 29 specifications have significantly higher RMSE than the specification with the least RMSE. Next, we follow the MCS procedure to decide which of these 55 specifications belong to the superior set based on the prediction error and find all of them to qualify for the superior set of models. Therefore, out-of-sample metrics of RMSE and MCS filter out 29 specifications out of consideration. Most notably, model specifications suggested by Dell et al. (2012) and Burke et al. (2015) also fail these out-of-sample criteria.

Subsequently, we employ a linear regression model for these 55 specifications and use the aGVIF statistic to check for any evidence of possible multicollinearity. Table 4 tabulates results of 12 specifications which have aGVIF less than 4.00 [Column (3)] for all the variables considered in the model[12]. The alternative specification can be read as follows: For example, combination 'A1-B2-C1-D2' refers to the 'A1' form of term $b_1(.)$, 'B2' form of term $b_2(.)$, 'C1' form of $b_3(.)$, and 'D2' form of $b_4(.)$. Notably, the specification suggested by Kalkuhl and Wenz (2020) is rejected due to the presence of high multicollinearity.

Finally, the Bayes factor [Column (4)] reveals the value of $p_{BIC}(H_0|Data)$ indicating the probability

[12]The model specification with lowest RMSE as per CV corresponds to the model with the combination of forms 'A2-B2-C2-D1'. However, aGVIF for these models is greater than 4.00 for precipitation level in the form 'D1', rejecting this model for further assessment.

Table 4: **Selection of optimal damage function**

Alternative specifications	**(1) Rigde-RMSE**	**(2) MCS loss**	**(3) aGVIF** < 4.00	**(4) Bayes factor**
A1-B2-C1-D2	0.3479 (0.042)	-1.07e-16	Yes	1.0000
A1-B2-C1-D3	0.3503 (0.033)	-1.72e-16	Yes	1.0000
A1-B2-C2-D2	0.3510 (0.060)	-9.43e-17	Yes	1.0000
A1-B2-C2-D3	0.3602 (0.024)	-2.98e-16	Yes	1.0000
A2-B2-C1-D2	0.3395 (0.025)	-3.95e-16	Yes	1.0000
A2-B2-C1-D3	0.3460 (0.038)	8.33e-17	Yes	0.9994
A2-B2-C2-D2	0.3469 (0.040)	-1.41e-16	Yes	1.0000
A2-B2-C2-D3	0.3444 (0.024)	-6.61e-17	Yes	0.8396
A3-B2-C1-D2	0.3442 (0.037)	-1.54e-16	Yes	1.0000
A3-B2-C1-D3	0.3424 (0.040)	-9.69e-17	Yes	0.9970
A3-B2-C2-D2	0.3382 (0.059)	-1.42e-16	Yes	1.0000
A3-B2-C2-D3	0.3466 (0.027)	8.07e-18	Yes	NULL

This table presents results of 12 (out of 84) specifications which have aGVIF less than 4.00. Column (1) provides parameter value of RMSE obtained from ridge regression with K-fold cross validation. Column (2) presents the loss value based on MCS procedure. Column (3) indicates whether the aGVIF is less than 4.00 and Column (4) represents the value of $p_{BIC}(H_0|Data)$ (parameter of BF) indicating the probability to favour the null model 'A3-B2-C2-D3' (lowest BIC specification) as compared to other specifications, given the Data. The specifications can be read as follows: For example, combination 'A1-B2-C1-D2' refers to the 'A1' form of term $b_1(.)$, 'B2' form of term $b_2(.)$, 'C1' form of $b_3(.)$, and 'D2' form of $b_4(.)$.

to favour the null model 'A3-B2-C2-D3' (lowest BIC specification) as compared to the specification under consideration, given the Data. We find that the BIC of all the 11 specifications is significantly higher than the null model since their $p_{BIC}(H_0|Data) > 0.75$. Therefore, our selection procedure suggests the 'A3-B2-C2-D3' specification as a better fit than that suggested by Kalkuhl and Wenz (2020), Dell et al. (2012), and Burke et al. (2015). Accordingly, we consider the model specification combination 'A3-B2-C2-D3' as our optimal specification to estimate the parameters for the damage function, which is presented as follows:

$$\begin{aligned} \widehat{\text{WI-EG}}_{it} = \; & \left(b_{11} + b_{12} \times P_{it-1} + b_{13} \times P_{it-1}^2\right) \times \Delta T_{it} \\ & + (b_{21} + b_{22} \times P_{it-1}) \times \Delta P_{it} \\ & + (b_{31} + b_{32} \times T_{it-1} \times P_{it-1}) \times \Delta P_{it-1} \\ & + b_{41} \times P_{it} + b_{42} \times P_{it}^2 + b_{43} \times P_{it}^3 \\ & + \kappa_i + \nu_{it} \end{aligned} \tag{11}$$

6.2.2. Estimates of damage specification

We consider two specifications to present our damage estimates in Table 5. Column (1) presents the estimates of Equation (11). Column (2) represents the parsimonious specification model among the ones listed in Table 4. Understandably, this specification is found to be satisfactory based on the three parameters of RMSE, MCS, and aGVIF but is considered sub-optimal on account of the parameter of BF. We observe that despite the parsimonious specification being rejected due to its remarkably greater BIC than the optimal model, the modified R^2 reveals it can explain 96.7% of the variation in the data. However, this is still lower than the optimal specification of Equation (11), which accounts for 97.5% of the variation.

Focusing on the estimates of Equation (11)—Column (1) of Table 3—we observe $\hat{b}_{11} < 0$, suggesting that the base marginal effect of a positive temperature change on the per capita economic growth, through *WI-TFPG* channel, is -1.36 pp per 1°C temperature change. However, $\hat{b}_{12} > 0$ and $\hat{b}_{13} < 0$ indicate that this base marginal adverse effect decreases at a lower level of lagged precipitation but increases at a higher level of lagged precipitation. Accordingly, for every one standard deviation rise (69.77 mm) from the mean lagged precipitation level (122.81 mm), the adverse effect of 1°C temperature change on the per capita economic growth diminishes by 0.26 pp.

We find that the base marginal effect of a positive contemporaneous precipitation change ($\hat{b}_{21} > 0$) on the economic growth is 0.66 pp per 100 mm. The additional marginal effect ($\hat{b}_{22} < 0$) of a contemporaneous precipitation change decreases the benefit of base marginal effect on the per capita economic growth by 0.0068 pp as lagged precipitation increases by one standard deviation from its mean.

Table 5: **Estimates of damage function**

	(1) A3-B2-C2-D3 Optimal	(2) A1-B2-C1-D2 Parsimonious
Weather induced TFP growth (WI-TFPG)		
ΔT	-1.3593***	-0.8517***
	(0.0685)	(0.0213)
$Lag.P \times \Delta T$	0.0059***	
	(0.0010)	
$Lag.P^2 \times \Delta T$	-0.0000092***	
	(0.0000029)	
ΔP	0.0066***	0.0091***
	(0.0009)	(0.0009)
$Lag.P \times \Delta P$	-0.000068***	-0.000081***
	(0.0000039)	(0.0000035)
$\Delta Lag.P$	-0.0043***	-0.0019***
	(0.0007)	(0.0004)
$Lag.T \times Lag.P \times \Delta Lag.P$	0.00000056***	
	(0.00000013)	
Weather induced LP growth (WI-LPG)		
P	0.0534***	0.0334***
	(0.0019)	(0.0013)
P^2	-0.0002***	-0.000037***
	(0.000009)	(0.0000026)
P^3	0.00000018***	
	(0.000000013)	
Observations	1,210	1,210
State FE	Yes	Yes
Adjusted R^2	0.975	0.967
BIC	171.81	491.21

The results in the table represent the estimates of the parsimonious and optimal damage specification. Column (1) presents the estimates of optimal damage specification presented in Equation (11). The model in Column (2) represents the parsimonious specification model, which satisfies the parameters of RMSE, MCS, and aGVIF but is rejected due to the parameter of BF

The optimal specification is selected after comparing with alternative specifications for out-of-sample performance metrics—K-fold cross-validation with ridge regression and model confidence set—and in-sample performance metrics—adjusted generalized variance inflation factor and Bayes factor tests.

The specifications can be read as follows: For example, combination 'A1-B2-C1-D2' refers to the 'A1' form of term $b_1(.)$, 'B2' form of term $b_2(.)$, 'C1' form of $b_3(.)$, and 'D2' form of $b_4(.)$. Standard errors are in parentheses. Significance level: * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

We also observe that the base marginal effect of a positive lagged precipitation change ($\hat{b}_{31}<0$) on the per capita economic growth is -0.43 pp per 100 mm. The additional marginal effect ($\hat{b}_{32}>0$) of a lagged precipitation change corrects the detrimental base marginal effect for a given mean lagged temperature (23.58°C) and precipitation level (122.81 mm). Hence, a 1°C rise from the mean lagged temperature level for a given mean lagged precipitation level reduces the adverse base effect of a lagged precipitation change by 0.0069 pp per 100 mm. On the other hand, one standard deviation rise (69.77 mm) in mean lagged precipitation level at a given mean lagged temperature level decreases the adverse base effect of a lagged precipitation change on the per capita economic growth by 0.0013 pp per 100 mm.

Finally, we find a cubic association ($\hat{b}_{41} > 0$, $\hat{b}_{42} < 0$, and $\hat{b}_{43} > 0$) between contemporaneous precipitation level and the per capita economic growth through *WI-LPG* channel. It indicates that the marginal effect of contemporaneous precipitation level on the economic growth displays a U-shape curve. We find that a one standard deviation rise (69.68 mm) in mean contemporaneous precipitation level (122.99 mm) results in a positive marginal effect of 1.88 pp on the per capita economic growth.

6.3. Robustness exercises and additional analysis

In this sub-section, we present robustness exercises to boost confidence in the reliability of the VC-GAM estimates. We also conduct the heterogeneity analysis across states and over the years using VC-GAM estimates. Finally, we discuss the medium- and long-run impact of weather variables on the per capita economic growth.

6.3.1. Robustness checks

We perform the robustness tests for the results of *the* optimal VC-GAM tabulated in Column (6) of Table 3. Table 6 presents the different estimates of EDF for smooth terms on account of changes in specifications, data and avoidance of overfitting techniques. Our results demonstrate that either the EDF estimates are robust and consistent in spite of these changes or these changes are within the permissible limits of our main results.

Alternative specifications

Column (1) of Table 6 reiterates the main results from Column (6) of Table 3. Column (2) controls for feedback effect by considering two-year lags (instead of one) of the per capita economic growth in the optimal VC-GAM. We also consider three-year lags of the dependent variable and test if the per capita economic growth Granger-causes weather variables (using Granger non-causality test proposed by Dumitrescu and Hurlin, 2012) as additional checks in Appendix D. We find that the null hypothesis of 'Granger causality for at least one state' is rejected for all the weather variables.

Column (3) of Table 6 incorporates a year lag of population growth along with contemporaneous population growth rate. Following Desbordes and Eberhardt (2024) and Kumar and Maiti (2024a), Column (4) accounts for the unobserved common factors by including three-year lagged values of cross-section averages of dependent variable and weather levels. This approach also controls for spatial dependence, if any. We consider the log transformation of temperature and precipitation levels in Column (5).

Alternative data

Column (6) of Table 6 includes only balanced panel data of 25 states from 1982-83 till 2021-22. We alternatively consider the per capita NSDP growth rate, instead of the per capita GSDP growth rate, which is available from 1960-61 to 2021-22 for 33 states. Furthermore, we use an alternative definition of the per capita GSDP growth as computed by the EPWRF database, which considers the average population of the year for computation of the per capita GSDP. The results for the per capita NSDP and alternative per capita GSDP growth rate are available in Appendix D.

Alternative techniques to avoid overfitting

In VC-GAM, the knots determine the complexity of the basis function used for determining the smooth term. Notably, the higher the knots, the more flexibility is allowed, which can result in overfitting. Accordingly, we reduce the number of knots from ten to five as robustness in Column (7) of Table 6. Alternatively, we consider a thin plate regression spline technique with shrinkage (TPRSS) for basis function instead of double-penalty optimization. Finally, we consider linear state-specific trends instead of quadratic state-specific trends. The results of TPRSS and linear state-specific trends are available in Appendix D.

Table 6: **Robustness checks: Effective degrees of freedom**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Alternative specifications				Alternative data	Overfitting
	Main results	g_y 2-Lags	g_L 1-Lags	Spatial dependence	Log transform	Balanced data	Reduced knots
Weather induced TFP growth (WI-TFPG)							
$g_{\Theta_{T,2}}(Lag.P) \times \Delta T$	1.2075**	1.0940**	1.2106***	1.1650**	1.6192**	1.3775***	1.2529***
$g_{\Theta_{P,2}}(Lag.P) \times \Delta P$	1.2924***	1.2740***	1.4166***	1.5070***	0.9987**	1.2654***	1.3411***
$g_{\Theta_{P,3}}(Lag.T \times Lag.P) \times Lag.\Delta P$	0.9364***	0.9491***	0.9442***	0.9491***	0.8475**	0.8116**	0.8657***
Weather induced LP growth (WI-LPG)							
$M_2(P)$	2.7768***	4.1530***	3.1415***	0.8053**	6.5751***	3.3188***	2.0089***
Observations	1210	1144	1177	1111	1210	1000	1210
State-specific Trend	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Fixed effects	State, year	State, year	State, year	State, year	State, year	State, year	State, year
Adj R^2	0.358	0.352	0.344	0.343	0.373	0.382	0.357

This table includes the Effective Degrees of Freedom (EDF) for each smooth term in the VC-GAMs. The significance of the EDF values for the smooth terms is determined using an F-test. EDF values reflect the complexities of the link between predictor and outcome variables.
Column (1) reiterates the main results from Column (6) of Table 3. Column (2) considers two lags of dependent variable g_y. Results including a year lag of population growth, g_L, are presented in Column (3). Column (4) controls for the presence of spatial dependence by considering three-year lagged cross-section average values of the per capita economic growth, temperature and precipitation level. Column (5) considers the log transformation of temperature and precipitation level. Column (5) employs our optimal specification for balanced data. Finally, in column (7), we consider 5 knots instead of 10 for computing estimates of smooth terms.
All models have state-fixed effects, year-fixed effects and quadratic state-specific trend terms as controls. Error term follows the Scaled-t distribution. Significance levels: * 10%, ** 5%, and *** 1%.

6.3.2. Heterogeneity across state and years

We use *the* optimal VC-GAM estimates of Column (6) of Table 3 to analyze how weather variables affect the per capita economic growth in different states and across time. The VC-GAM framework allows us to calculate the marginal effect of weather changes on the per capita economic growth for each observation by leveraging on the predicted values of each smooth term. In case of the marginal effect of precipitation level on the per capita economic growth, we utilize a simple epsilon difference approach[13] to determine the derivative of smooth term with respect to the precipitation level. To account for state-wise and year-wise effects, we calculate, within each subgroup (created based on state or year), the group-average marginal effect (G-AME), which is equal to the average of the observation-level marginal effects.

State-wise analysis

Figure 5 plots the G-AME across states for a positive contemporaneous temperature change [Panel (a)], contemporaneous precipitation change [Panel (b)], lagged precipitation change [Panel (c)], and rise in contemporaneous precipitation level [Panel (d)]. Referring to Panel (a), we observe that while all states, in general, face the negative consequences of a positive temperature change on the per capita economic growth, only the higher precipitation states of Andaman and Nicobar Islands, Assam, Goa, Kerala, Meghalaya, Mizoram, and Tripura (with average lagged precipitation greater than 190 mm) are not affected by a positive temperature change. However, due to very high precipitation that may result in a flood-like situation, Panel (b) shows that the per capita economic growth of some of these states (Andaman and Nicobar Islands, Goa, Kerala, and Meghalaya) is affected by positive precipitation change. These results highlight the dependence on the lagged precipitation level while understanding the marginal effect of a contemporaneous weather change on the per capita economic growth.

Expectedly, Panel (c) indicates that a positive lagged precipitation change decreases the per capita economic growth for states (Arunachal Pradesh, Nagaland, Manipur, Meghalaya, Mizoram, and Assam) with high lagged precipitation and moderate lagged temperature levels. States (Uttarakhand and Chandigarh) with low lagged precipitation and moderate lagged temperature levels benefit from a positive lagged precipitation change. Moreover, we observe that states (Chhattisgarh, Maharashtra, Gujarat, Tamil Nadu, Telangana, Andhra Pradesh, and Puducherry) with high lagged temperature but low lagged precipitation levels suffer due to a positive lagged precipitation change. On the other hand, states (Andaman and Nicobar Islands, Goa, and Kerala) experiencing high lagged precipitation along with high lagged temperature level benefit from a positive lagged precipitation change. This heterogeneity highlights the interactive effect of lagged temperature and precipitation levels while understanding the marginal effect of a lagged precipitation change on the

[13] $\frac{dy}{dx} = \frac{f(x+\xi/2)-f(x-\xi/2)}{\xi}$ where, here $f(.)$ is the predicted value of smooth term under consideration, and ξ is the step size to use when calculating numerical derivatives.

per capita economic growth.

Finally, we observe, from Panel (d), that all the per capita economic growth of states experience a positive rise due to marginal increase in precipitation level except in case high precipitation states, that is, Andaman and Nicobar Islands, Arunachal Pradesh, Assam, Goa, Kerala, Meghalaya, Mizoram, and Tripura.

Year-wise analysis

Figure 6 presents the year-wise G-AME on the per capita economic growth of India for a positive contemporaneous temperature change [Panel (a)], contemporaneous precipitation change [Panel (b)], lagged precipitation change [Panel (c)], and rise in contemporaneous precipitation level [Panel (d)]. We observe that a positive temperature change [Panel (a)] has a detrimental effect on India's per capita economic growth for all the years. Similarly, a rise in the precipitation level [Panel (d)] benefits India over the years. However, G-AME on the year-wise per capita economic growth of a positive precipitation change [Panel (b)] is insignificant as it affects only some states mentioned above.

We find that a positive lagged precipitation change affects India's per capita economic growth except in the fiscal year 2006-2007 [Panel (c)]. To better understand this anomaly, we look at weather events in the fiscal year 2005-2006, as the marginal effect of a lagged precipitation change depends on the interplay of lagged temperature and precipitation level. According to the India Meteorological Department (Mausam, 2006a, 2006b), certain parts of India saw extreme heatwave conditions followed by untimely rains, with some regions experiencing floods as a result of the heavy precipitation. These conditions may equate to high lagged precipitation and temperature levels in Figure 3. As a result, we observe a positive marginal effect on the per capita economic growth in the fiscal year 2006-2007 due to a positive precipitation change in the fiscal year 2005-2006.

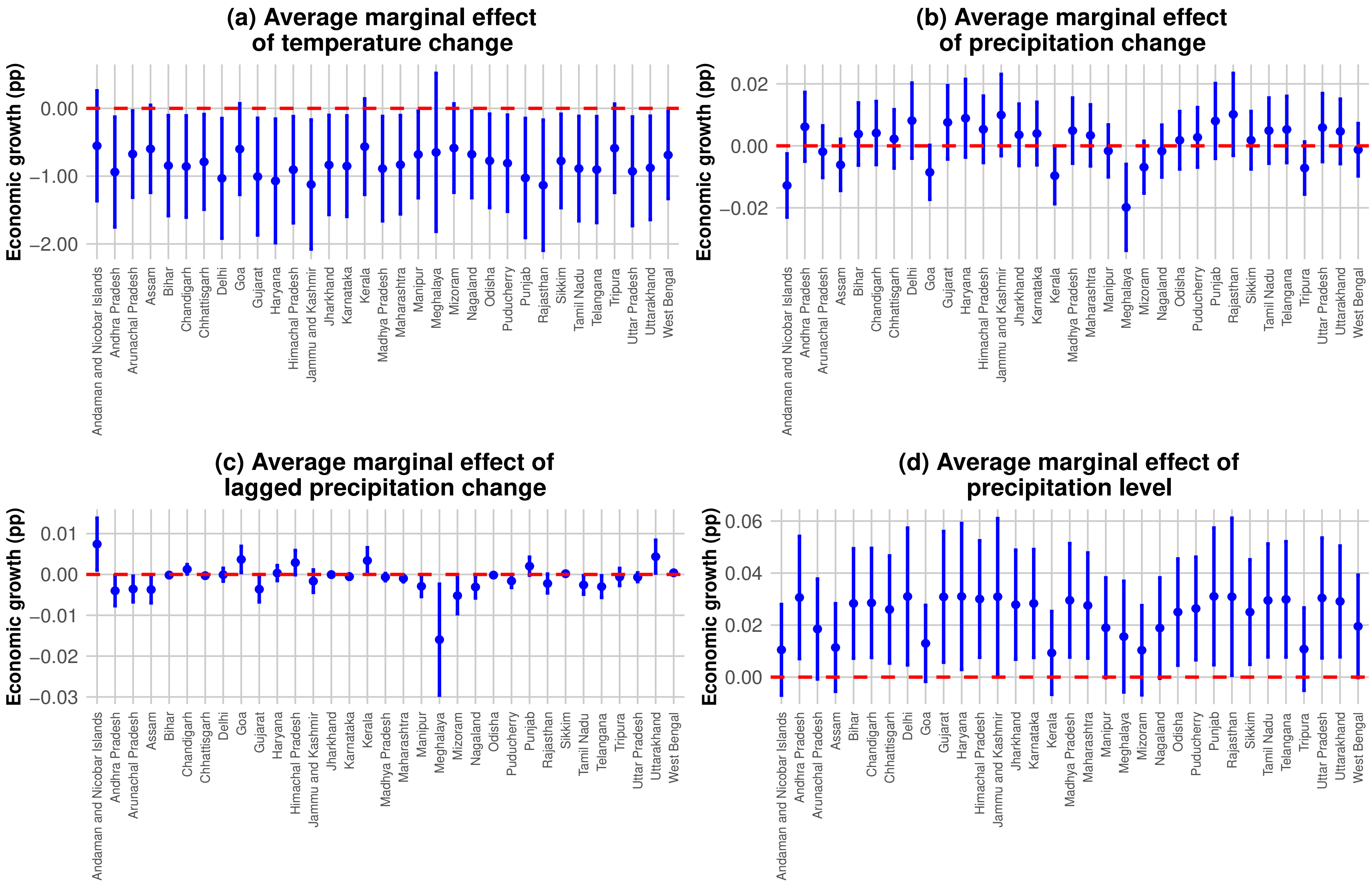

Figure 5: **State-wise heterogeneity:** This figure plots the average marginal effect across states for a positive contemporaneous temperature change [Panel (a)], contemporaneous precipitation change [Panel (b)], lagged precipitation change [Panel (c)], and rise in contemporaneous precipitation level [Panel (d)].

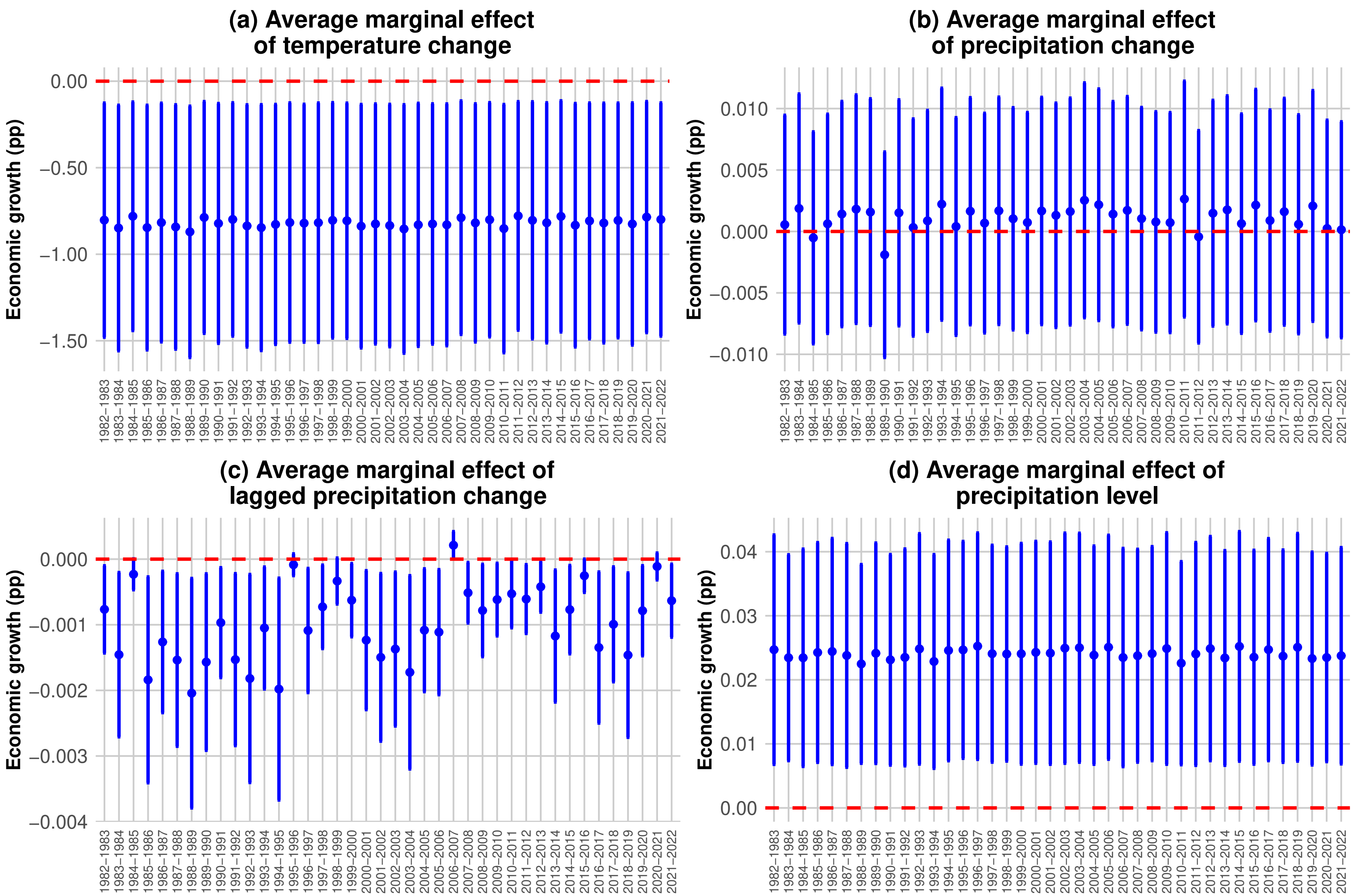

Figure 6: **Year-wise heterogeneity:** This figure plots the average marginal effect over years for a positive contemporaneous temperature change [Panel (a)], contemporaneous precipitation change [Panel (b)], lagged precipitation change [Panel (c)], and rise in contemporaneous precipitation level [Panel (d)].

6.3.3. Medium- and long-run effects

The estimates of optimal damage specification in Column (1) of Table 5 measures the marginal impact of weather variables on the annual per capita economic growth and is interpreted as a short-run impact. In the following analysis, we investigate the medium- and long-run effects of weather variables on per-capita economic growth. We define the period for medium- and long-run impact as five and ten years, respectively and propose the following cumulative growth regression specification:

$$\begin{aligned}\sum_{r=t}^{t+p} \widehat{\text{WI-EG}}_{ir} &= b_{p,1}(P_{it-1}) \times \Delta T_{it} + b_{p,2}(P_{it-1}) \times \Delta P_{it} \\ &\quad + b_{p,3}(T_{it-1} \times P_{it-1}) \times \Delta P_{it-1} + b_{p,4}(P_{it}) + \kappa_{p,i} + \nu_{ir}\end{aligned} \tag{12}$$

$\sum_{r=t}^{t+p} \widehat{\text{WI-EG}}_{ir}$ refers to the cumulative WI-EG of 'p' years ahead where $p = \{5, 10\}$. The coefficients $b_{p,.}(.)$s are a function of weather variables of the initial year 't'. Accordingly, $b_{p,1}(.)$, $b_{p,2}(.)$, and $b_{p,3}(.)$ are interpreted as the marginal effects on the cumulative per capita economic growth of next 'p' years for a change in temperature, precipitation and lagged precipitation in the initial year 't'. Similarly, $b_{p,4}(.)$ is the total effect of the initial year precipitation level on the cumulative growth of the next 'p' years. $\tilde{\kappa}_{p,i}$ are state fixed effects. $\tilde{\nu}_{ir}$s are the error terms for the given cumulative period 'r' and are assumed to be independent and identically distributed.

We utilize balanced data of 25 states for 40 years to estimate Equation (12) and divide it into non-overlapping periods of 5 (10) years for medium (long) term impact assessment. Thus, we have a balanced dataset of 25 states, eight periods for medium-run impact, and four for long-run impact analysis. We define 84 specifications for $b_{p,.}(.)$s corresponding to $b(.)$s in Section 5.3.1. We also follow the optimal model selection procedure as described in Section 5.3.2. Accordingly, we find the optimal specification of 'A2-B2-C1-D1' for a 5-year period (medium-run) and 'A1-B1-C1-D3' for a 10-year period (long-run). The estimates of these specifications are tabulated in Table 7.

Column (1) of Table 7 reiterates the estimates of the optimal damage specification from Column (1) of Table 5. Column (2) tabulates the estimates of the medium-run optimal damage specification. In the case of impact on the per capita economic growth through the *WI-TFPG* channel, we find that the base adverse (favourable) marginal effect of contemporaneous temperature (precipitation) change vanishes in the medium-run. However, the adverse (favourable) marginal effect of contemporaneous temperature (precipitation) change still exists and is conditional on the initial year lagged precipitation level. On the contrary, an adverse marginal effect of lagged precipitation change persists in the medium run, but the interplay of lagged temperature and precipitation level disappears. Moreover, we find no significant impact of variations in contemporaneous precipitation level on the per capita economic growth through the *WI-LPG* channel.

Column (3) of Table 7 presents the estimates of optimal damage specification for the long-run

Table 7: **Estimates of damage function: Medium- and long-run**

	(1) Short-run A3-B2-C2-D3	(2) Medium-run A2-B2-C1-D1	(3) Long-run A1-B1-C1-D3
Weather induced TFP growth (WI-TFPG)			
ΔT	-1.3593***	1.1640	-0.1886*
	(0.0685)	(7.9130)	(0.1113)
$Lag.P \times \Delta T$	0.0059***	-0.1541***	
	(0.0010)	(0.0582)	
$Lag.P^2 \times \Delta T$	-0.0000092***		
	(0.0000029)		
ΔP	0.0066***	-0.1399	0.0005
	(0.0009)	(0.1385)	(0.1260)
$Lag.P \times \Delta P$	-0.000068***	0.0013**	
	(0.0000039)	(0.0006)	
$\Delta Lag.P$	-0.0043***	-0.1079**	-0.1872*
	(0.0007)	(0.0053)	(0.0988)
$Lag.T \times Lag.P \times \Delta Lag.P$	0.00000056***		
	(0.00000013)		
Weather induced LP growth (WI-LPG)			
P	0.0534***	-0.1104	-0.5954
	(0.0019)	(0.0024)	(0.5348)
P^2	-0.0002***		0.0030
	(0.000009)		(0.0033)
P^3	0.00000018***		-0.000006
	(0.000000013)		(0.000006)
Observations	1,210	200	100
State FE	Yes	Yes	Yeas
Adjusted R^2	0.975	0.799	0.821
BIC	171.81	1810.18	951.95

The results in the table represent the estimates of the optimal functional form of damage estimates. Column (1) of Table 7 reiterates the estimates of the optimal damage specification from Column (1) of Table 5. Column (2) tabulates the estimates of the medium-run optimal damage specification. Column (3) presents the estimates of optimal damage specification for the long-run impact.
The optimal form is selected after comparing with alternative specifications for out-of-sample performance metrics—K-fold cross-validation and model confidence set— and in-sample performance metrics—adjusted generalized variance inflation factor and Bayes factor tests. Significance level: * p < 0.10 ** p < 0.05 *** p < 0.01.

impact. We observe that the weather variables do not have any impact on the per capita economic growth, indicating no long-term effect of shocks in weather variables on the next ten years' cumulative economic growth. Hence, we find that while the shocks in weather changes continue to impact the economic growth in the medium-run through the *WI-TFPG* channel, this effect vanishes in the long-run. Our results further indicate that the impact of weather levels through the *WI-LPG* channel does not persist in the medium- and long-run.

7. Discussion and conclusion

Our paper provides a generalized theoretical framework for empirical analysis of the possible impact of temperature and precipitation shocks on the per capita economic growth. Using standard bin regression as our preliminary analysis, we hypothesize the relation of the impact of weather changes on the per capita economic growth of India. We test these hypotheses by utilizing the data-driven semi-parametric econometric approach known as VC-GAM and also quantify the economic damages from variations in weather level and change. We choose the optimal specification that best estimates the economic damages quantified by comparing the out-of-sample and in-sample properties of 84 variants of prominent parametric specification. Finally, the study employs the optimal specification model to estimate the non-linear impact of weather level and weather change on the per capita economic growth through the *WI-TFPG* and *WI-LPG* channels.

We find that given a lower precipitation level in the preceding year, there is an adverse marginal effect of a positive temperature change. On the other hand, an adverse marginal effect of a positive precipitation change is experienced when we have a higher precipitation level in the preceding year. Most importantly, we observe that along with contemporaneous precipitation change, lagged precipitation change also plays a crucial role in determining the impact on the per capita economic growth. We find that a high lagged precipitation level combined with a low to moderate lagged temperature level exacerbates the detrimental impact of a positive lagged precipitation change on the per capita economic growth of India.

We believe that one potential mechanism by which contemporaneous and lagged weather variables have an impact on the per capita economic growth is through their influence on soil moisture quality[14]. A lower precipitation level in the preceding year may deplete the soil moisture quality, whereas a higher precipitation level may replenish or over-replenish it. As a result, the soil moisture content at the end of the previous year can serve as the starting point for the current year's economic activities. For example, with less than optimal soil moisture content in the current year, even a slight increase in temperature change may reduce the soil moisture quality further. This reduction in soil moisture quality may affect the per capita economic growth. On the other hand, an optimally replenished soil moisture quality reduces the marginal benefit of precipitation change.

[14] Refer to Blignaut and Van Heerden (2009), Gilmont et al. (2018), Greve et al. (2014), Li et al. (2022), Mittelbach and Seneviratne (2012), Moeck et al. (2020), and Pérez-Blanco and Sapino (2022) for details.

In some circumstances, a positive precipitation change may even have negative consequences such as waterlogging or floods, disrupting agricultural production, damaging infrastructure, and lowering industrial output.

In the case of a positive lagged precipitation change, our findings show that a high lagged precipitation level, when complemented with a low to moderate lagged temperature level, harms the per capita economic growth. This combination of lagged weather levels aids in soil moisture retention based on the concept of Clausius-Clapeyron relation and evapotranspiration[15]. Under these conditions, a positive lagged precipitation change may cause floods. This flooding not only disrupts the economic activity in the immediate year but can also have a lasting negative effect on the per capita economic growth for the following year.

Our empirical approach of considering the interplay of weather variables provides us with a specification [Refer to Equations (11)] that differs from those considered in the existing literature for India (Jain et al., 2020; Kumar and Maiti, 2024a; Sandhani et al., 2023). We find that our specification gives a better match for Indian data, in terms of out-of-sample and in-sample performance metrics, than the specifications taken into account by Burke et al. (2015), Jain et al. (2020), Dell et al. (2012), Sandhani et al. (2023), and Kalkuhl and Wenz (2020).

Certain important implications emerge from these differences in specification. Ricke et al. (2018) use specifications proposed by Dell et al. (2012) and Burke et al. (2015) for the damage function to calculate the social cost of carbon at the country level. Our analysis indicates that India's damage function differs from those specifications, emphasizing possible country-level differences in damage specification. This suggests that each country may need a customized damage function to quantify weather impacts effectively. Therefore, by taking into consideration unique country subtlety in weather impacts, our technique has the potential to enhance the computation of a realistic social cost of carbon at the country level.

Moreover, Dietz and Venmans (2019) have demonstrated a direct relationship between cumulative global emissions of greenhouse gases (GHG) and changes in the mean temperature globally, albeit this relationship might not hold true at the country level. Nonetheless, the damage function is frequently modelled as a function of GHG emissions in Environmental Dynamic Stochastic General Equilibrium models[16] even for country-level analysis. Our empirical approach can be used to measure the economic damage of weather shocks from the per capita economic growth and compute the damage parameters which connect country-level economic damages and global GHG emissions.

[15] The Clausius-Clapeyron equation illustrates how the water-holding capacity of the atmosphere increases. Evapotranspiration is the physical process of transferring water from the land (by evaporation and transpiration) to the atmosphere. Higher temperatures, as stated by Clausius-Clapeyron, can increase evapotranspiration rates, reducing soil moisture quality (Kleidon and Schymanski, 2008; Wang and Bras, 2011; Zhang et al., 2016)

[16] Refer to Annicchiarico and Di Dio (2015) and Fischer and Springborn (2011) for examples of damage function considered.

With this approach, climate policy for various economies might be examined in greater detail. By accounting for the effects of country weather patterns, this improved damage function may advance our understanding of the effectiveness of climate policy and its implications for economic outcomes.

The objective of this paper is to examine the influence of weather variables on the overall economic growth rate. Although we estimate the impact of weather variables on the per capita economic growth of India, we have not exclusively considered adaptation to these effects in our model. Further, we have restricted ourselves to analysis using state-level data based on the availability of data. However, future research can consider night-light data as a proxy for economic activity, which may enable a detailed analysis of the impact of weather at a granular level.

Moreover, future studies can examine the impact of weather on overall economic growth while accounting for variables like income levels and the level of sectoral development. This would make it possible to find any differential relationship between weather variables and the economic growth, which might offer more detailed explanations of how some aspects of the economy are more susceptible to weather fluctuations. Furthermore, additional research could concentrate on specific sectors like services, industry, or agriculture. With a more focused approach, it would be possible to gain a better understanding of how various economic sectors react to weather variations, which might result in a more efficient and customized climate change adaptation policy.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics*, *65*, 103207. https://doi.org/10.1016/j.jmacro.2020.103207

Annicchiarico, B., & Di Dio, F. (2015). Environmental policy and macroeconomic dynamics in a new Keynesian model. *Journal of Environmental Economics and Management*, *69*, 1–21. https://doi.org/10.1016/j.jeem.2014.10.002

Auffhammer, M., Ramanathan, V., & Vincent, J. R. (2006). Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proceedings of the National Academy of Sciences*, *103*(52), 19668–19672. https://doi.org/10.1073/pnas.0609584104

Auffhammer, M., & Steinhauser, R. (2012). Forecasting the path of US CO2 emissions using state-level information. *Review of Economics and Statistics*, *94*(1), 172–185. https://doi.org/10.1162/REST_a_00152

Bardhan, P. K. (1973). Size, productivity, and returns to scale: An analysis of farm-level data in Indian agriculture. *Journal of political Economy*, *81*(6), 1370–1386. https://doi.org/10.1086/260132

Bernardi, M., & Catania, L. (2018). The model confidence set package for R. *International Journal of Computational Economics and Econometrics*, *8*(2), 144–158. https://doi.org/10.1504/IJCEE.2018.091037

Birthal, P. S., Hazrana, J., & Negi, D. S. (2021). Impacts of climatic hazards on agricultural growth in India. *Climate and Development*, *13*(10), 895–908. https://doi.org/10.1080/17565529.2020.1867045

Blignaut, J., & Van Heerden, J. (2009). The impact of water scarcity on economic development initiatives. *Water Sa*, *35*(4). https://doi.org/10.4314/wsa.v35i4.76800

Buja, A., Hastie, T., & Tibshirani, R. (1989). Linear smoothers and additive models. *The Annals of Statistics*, 453–510. https://www.jstor.org/stable/2241560

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

Carleton, T. A. (2017). Crop-damaging temperatures increase suicide rates in India. *Proceedings of the National Academy of Sciences*, *114*(33), 8746–8751. https://doi.org/10.1073/pnas.1701354114

Chang, J.-J., Mi, Z., & Wei, Y.-M. (2023). Temperature and GDP: A review of climate econometrics analysis. *Structural Change and Economic Dynamics*, *66*, 383–392. https://doi.org/10.1016/j.strueco.2023.05.009

Chatfield, C. (1996). Model uncertainty and forecast accuracy. *Journal of Forecasting*, *15*(7), 495–508. https://doi.org/10.1002/(SICI)1099-131X(199612)15:7%3C495::AID-FOR640%3E3.0.CO;2-O

Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from India. *American Economic Journal: Applied Economics*, *13*(4), 101–124. https://doi.org/10.1257/app.20190249

Damania, R. (2020). The economics of water scarcity and variability. *Oxford Review of Economic Policy*, *36*(1), 24–44. https://doi.org/10.1093/oxrep/grz027

Damania, R., Desbureaux, S., & Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, *102*, 102335. https://doi.org/10.1016/j.jeem.2020.102335

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95. https://doi.org/10.1257/mac.4.3.66

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740–98. https://doi.org/10.1257/jel.52.3.740

Desbordes, R., & Eberhardt, M. (2024). Climate change and economic prosperity: Evidence from a flexible damage function. *Journal of Environmental Economics and Management*, *125*, 102974. https://doi.org/10.1016/j.jeem.2024.102974

Dietz, S., & Venmans, F. (2019). Cumulative carbon emissions and economic policy: In search of general principles. *Journal of Environmental Economics and Management*, *96*, 108–129. https://doi.org/10.1016/j.jeem.2019.04.003

Duchon, J. (1977). Splines minimizing rotation-invariant semi-norms in sobolev spaces. *Constructive Theory of Functions of Several Variables: Proceedings of a Conference Held at Oberwolfach April 25–May 1, 1976*, 85–100. https://doi.org/10.1007/BFb0086566

Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

EPWRF. (2011). India time series [Retrived from http://www.epwrfits.in/].

Fischer, C., & Springborn, M. (2011). Emissions targets and the real business cycle: Intensity targets versus caps or taxes. *Journal of Environmental Economics and Management*, *62*(3), 352–366. https://doi.org/10.1016/j.jeem.2011.04.005

Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, *87*(417), 178–183. https://doi.org/10.1080/01621459.1992.10475190

Gallup, J. L., Sachs, J. D., & Mellinger, A. D. (1999). Geography and economic development. *International regional science review*, *22*(2), 179–232. https://doi.org/10.1177/016001799761012334

Gawande, K. (1997). Generated regressors in linear and nonlinear models. *Economics Letters*, *54*(2), 119–126. https://doi.org/10.1016/S0165-1765(97)00014-1

Gilmont, M., Hall, J. W., Grey, D., Dadson, S. J., Abele, S., & Simpson, M. (2018). Analysis of the relationship between rainfall and economic growth in Indian states. *Global environmental change*, *49*, 56–72. https://doi.org/10.1016/j.gloenvcha.2018.01.003

Greve, P., Orlowsky, B., Mueller, B., Sheffield, J., Reichstein, M., & Seneviratne, S. I. (2014). Global assessment of trends in wetting and drying over land. *Nature geoscience*, *7*(10), 716–721. https://doi.org/10.1038/ngeo2247

Hainmueller, J., Mummolo, J., & Xu, Y. (2019). How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice. *Political Analysis*, *27*(2), 163–192. https://doi.org/10.1017/pan.2018.46

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, *79*(2), 453–497. https://doi.org/10.3982/ECTA5771

Hastie, T., & Tibshirani, R. (1993). Varying-coefficient models. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *55*(4), 757–779. https://doi.org/10.1111/j.2517-6161.1993.tb01939.x

Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: Biased estimation for Nonorthogonal problems. *Technometrics*, *12*(1), 55–67. https://doi.org/10.1080/00401706.1970.10488634

Jain, A., O'Sullivan, R., & Taraz, V. (2020). Temperature and economic activity: Evidence from India. *Journal of Environmental Economics and Policy*, *9*(4), 430–446. https://doi.org/10.1080/21606544.2020.1727776

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, *104*, 105624. https://doi.org/10.1016/j.eneco.2021.105624

Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, *103*, 102360. https://doi.org/10.1016/j.jeem.2020.102360

Kleidon, A., & Schymanski, S. (2008). Thermodynamics and optimality of the water budget on land: A review. *Geophysical Research Letters*, *35*(20). https://doi.org/10.1029/2008GL035393

Kolstad, C. D., & Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*. https://doi.org/10.1093/reep/rez024

Kotz, M., Levermann, A., & Wenz, L. (2022). The effect of rainfall changes on economic production. *Nature*, *601*(7892), 223–227. https://doi.org/10.1038/s41586-021-04283-8

Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., & Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change*, *11*(4), 319–325. https://doi.org/10.1038/s41558-020-00985-5

Krishnan, R., Sanjay, J., Gnanaseelan, C., Mujumdar, M., Kulkarni, A., & Chakraborty, S. (2020). *Assessment of climate change over the Indian region: A report of the ministry of earth sciences (MOES), government of India*. Springer Nature.

Kumar, N., & Maiti, D. (2024a). *The Dynamic Causal Impact of Climate Change on Economic Activity - A Disaggregated Panel Analysis of India*.

Kumar, N., & Maiti, D. (2024b). Long-run macroeconomic impact of climate change on total factor productivity - Evidence from emerging economies. *Structural Change and Economic Dynamics*, *68*, 204–223. https://doi.org/10.1016/j.strueco.2023.10.006

Letta, M., & Tol, R. S. (2019). Weather, climate and total factor productivity. *Environmental and Resource Economics*, *73*(1), 283–305. https://doi.org/10.1007/s10640-018-0262-8

Li, W., Migliavacca, M., Forkel, M., Denissen, J. M., Reichstein, M., Yang, H., Duveiller, G., Weber, U., & Orth, R. (2022). Widespread increasing vegetation sensitivity to soil moisture. *Nature Communications*, *13*(1), 3959. https://doi.org/10.1038/s41467-022-31667-9

Marra, G., & Wood, S. N. (2011). Practical variable selection for generalized additive models. *Computational Statistics & Data Analysis*, *55*(7), 2372–2387. https://doi.org/10.1016/j.csda.2011.02.004

Masson, M. E. (2011). A tutorial on a practical Bayesian alternative to null-hypothesis significance testing. *Behavior research methods*, *43*, 679–690. https://doi.org/10.3758/s13428-010-0049-5

Mausam, E. (2006a). Hot weather season (March - May 2005). *MAUSAM*, *57*(2), 363–378. https://doi.org/10.54302/mausam.v57i2.481

Mausam, E. (2006b). Monsoon season (June to September 2005). *MAUSAM*, *57*(3), 527–566. https://doi.org/10.54302/mausam.v57i3.495

Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture*, *13*(4), 660–665. https://doi.org/10.1016/S2095-3119(13)60701-7

Mitra, S. K. (2014). Nonlinear impact of rain on foodgrain production in India. *Applied Economics Letters*, *21*(14), 1001–1005. https://doi.org/10.1080/13504851.2014.904483

Mittelbach, H., & Seneviratne, S. I. (2012). A new perspective on the spatio-temporal variability of soil moisture: temporal dynamics versus time-invariant contributions. *Hydrology and Earth System Sciences*, *16*(7), 2169–2179. https://doi.org/10.5194/hess-16-2169-2012

Moeck, C., Grech-Cumbo, N., Podgorski, J., Bretzler, A., Gurdak, J. J., Berg, M., & Schirmer, M. (2020). A global-scale dataset of direct natural groundwater recharge rates: A review of variables, processes and relationships. *Science of the total environment*, *717*, 137042. https://doi.org/10.1016/j.scitotenv.2020.137042

Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2023). Climate change and economic activity: evidence from US states. *Oxford Open Economics*, *2*, odac010. https://doi.org/10.1093/ooec/odac010

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, *108*, 102445. https://doi.org/10.1016/j.jeem.2021.102445

Nordhaus, W. (2018). Evolution of modeling of the economics of global warming: Changes in the DICE model, 1992–2017. *Climatic change*, *148*(4), 623–640. https://doi.org/10.1007/s10584-018-2218-y

Pattanayak, A., Kumar, K. K., & Anneboina, L. R. (2021). Distributional impacts of climate change on agricultural total factor productivity in India. *Journal of the Asia Pacific Economy*, *26*(2), 381–401. https://doi.org/10.1080/13547860.2021.1917094

Pérez-Blanco, C. D., & Sapino, F. (2022). Economic sustainability of irrigation-dependent ecosystem services under growing water scarcity. Insights from the Reno River in Italy. *Water Resources Research*, *58*(2). https://doi.org/10.1029/2021WR030478

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of applied econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature*, *51*(3), 860–872. https://doi.org/10.1257/jel.51.3.860

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological methodology*, 111–163. https://doi.org/10.2307/271063

Ramsay, T. O., Burnett, R. T., & Krewski, D. (2003). The effect of concurvity in generalized additive models linking mortality to ambient particulate matter. *Epidemiology*, *14*(1), 18–23.

Rana, A., Moradkhani, H., & Qin, Y. (2017). Understanding the joint behavior of temperature and precipitation for climate change impact studies. *Theoretical and Applied Climatology*, *129*, 321–339. https://doi.org/10.1007/s00704-016-1774-1

Reiss, P. T., & Ogden, R. T. (2009). Smoothing parameter selection for a class of semiparametric linear models. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *71*(2), 505–523. https://doi.org/10.1111/j.1467-9868.2008.00695.x

Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, *8*(10), 895–900. https://doi.org/10.1038/s41558-018-0282-y

Sandhani, M., Pattanayak, A., & Kavi Kumar, K. (2023). Weather shocks and economic growth in India. *Journal of Environmental Economics and Policy*, *12*(2), 97–123. https://doi.org/10.1080/21606544.2022.2087745

Sankar, U. (1970). Elasticities of substitution and returns to scale in Indian manufacturing industries. *International Economic Review*, 399–411. https://doi.org/10.2307/2525320

Shao, J. (1997). An asymptotic theory for linear model selection. *Statistica sinica*, 221–242. https://www.jstor.org/stable/24306073

Simonsohn, U. (2023). Don't bin, GAM instead: Hainmueller et al.'s Binning & Kernel estimators are only valid for experimental data. *Available at SSRN 4638476*. http://dx.doi.org/10.2139/ssrn.4638476

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827. https://doi.org/10.1086/713733

Taraz, V. (2018). Can farmers adapt to higher temperatures? Evidence from India. *World Development*, *112*, 205–219. https://doi.org/10.1016/j.worlddev.2018.08.006

Tol, R. S. (2024). A meta-analysis of the total economic impact of climate change. *Energy Policy*, *185*, 113922. https://doi.org/10.1016/j.enpol.2023.113922

Wang, J., & Bras, R. (2011). A model of evapotranspiration based on the theory of maximum entropy production. *Water Resources Research*, *47*(3). https://doi.org/10.1029/2010WR009392

WMO. (2022). State of the Climate in Asia 2021.

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *73*(1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x

Wood, S. N. (2017). *Generalized additive models: An introduction with R*.

World Bank Group. (2024). Climate change knowledge portal, https://climateknowledgeportal.worldbank.org/ [Date Accessed: Monthly average temperature and precipitation data for India subnational units].

Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley interdisciplinary reviews: Water*, *3*(6), 834–853. https://doi.org/10.1002/wat2.1168

Zhao, X. (2018). *The economic impact of temperature shocks on China and India using subnational data*.

Appendix

A. Theoretical framework for weather effect on Labour productivity level

We assume that the temperature and precipitation level impact the labour productivity level instead of labour productivity growth. Accordingly, economic output is now $Y_t = \Theta(T_t, P_t, t) \cdot F_t[K_t, A_t(T_t, P_t)L_t]$.

Taking log and differentiating Y_t with respect to t, we obtain:

$$\frac{dln(Y_t)}{dt} = \frac{dln\Theta(.)}{dt} + \frac{dlnF_t(.)}{dt}$$

$$\frac{dln(Y_t)}{dt} = \frac{\partial ln\Theta(.)}{\partial T_t}\frac{dT_t}{dt} + \frac{\partial ln\Theta(.)}{\partial P_t}\frac{dP_t}{dt} + \frac{\partial ln\Theta(.)}{\partial t} + \frac{1}{F_t(.)}\left[\frac{\partial F_t(.)}{\partial K_t}\frac{dK_t}{dt} + \frac{\partial F_t(.)}{\partial A_t(.)L_t}\frac{dA_t(.)L_t}{dt}\right]$$

$$\begin{aligned}\frac{dln(Y_t)}{dt} &= g_{\Theta_T}(T_t, P_t) \times \frac{dT_t}{dt} + g_{\Theta_P}(T_t, P_t) \times \frac{dP_t}{dt} + g_{\Theta_O}(t) + \eta_{K_t} \times g_{K_t} \\ &+ (\tau_t - \eta_{K_t}) \times \left[g_{A_T}(T_t, P_t) \times \frac{dT_t}{dt} + g_{A_P}(T_t, P_t) \times \frac{dP_t}{dt} + g_{L_t}\right]\end{aligned}$$

Rearranging the above equation, we obtain:

$$\begin{aligned}\frac{dln(Y_t)}{dt} = &\overbrace{[g_{\Theta_T}(T_t, P_t) + (\tau_t - \eta_{K_t}) \times g_{A_T}(T_t, P_t)] \times \frac{dT_t}{dt}}^{\text{Temperature change induced TFP + LP growth}} \\ &+ \underbrace{[g_{\Theta_P}(T_t, P_t) + (\tau_t - \eta_{K_t}) \times g_{A_P}(T_t, P_t)] \times \frac{dP_t}{dt}}_{\text{Precipitation change induced TFP + LP growth}} \\ &+ g_{\Theta_O}(t) + \eta_{K_t} \times g_{K_t} + (\tau_t - \eta_{K_t}) \times g_{L_t}\end{aligned}$$

B. Summary statistics

Table B1 provides mean and standard deviation values of variables across different states. Data for the states of Chandigarh, Chattisgarh, Jammu and Kashmir, Jharkhand, Nagaland, Sikkim and Uttarakhand are available from the fiscal year 1993-94 and that for Mizoram from the fiscal year 1999-2000. Data for other states are available from fiscal year 1980-81 to 2021-22.

Table B1: **Summary across states**

States	**GSDP per-capita (in Rs)**	**Economic growth (in %)**	**Temperature (in °C)**	**Temperature change (in °C)**	**Precipitation (in mm)**	**Precipitation change (in mm)**
Andaman and Nicobar Islands	70,832 (49,824)	4.48 (7.87)	27.14 (0.36)	0.02 (0.36)	255.01 (29.86)	1.10 (40.14)
Andhra Pradesh	56,134 (34,675)	4.68 (4.40)	28.03 (0.28)	0.01 (0.28)	76.45 (11.04)	0.55 (15.35)
Arunachal Pradesh	60,434 (31,228)	4.42 (5.22)	19.16 (0.42)	0.02 (0.41)	150.96 (16.57)	-0.48 (24.54)
Assam	39,502 (14,239)	2.67 (3.04)	23.40 (0.38)	0.01 (0.39)	190.46 (24.13)	-0.94 (34.86)
Bihar	16,899 (7,949)	3.53 (8.51)	25.54 (0.35)	0.01 (0.34)	97.86 (13.03)	-0.03 (16.74)
Chandigarh	1,53,226 (66,372)	5.13 (6.83)	23.68 (0.44)	0.03 (0.45)	95.89 (15.10)	1.02 (22.05)
Chhattisgarh	55,036 (19,810)	3.94 (5.05)	26.22 (0.25)	0.02 (0.35)	112.22 (12.07)	-0.37 (14.18)
Delhi	1,44,426 (78,351)	3.91 (5.23)	25.33 (0.52)	0.02 (0.50)	58.00 (12.06)	0.77 (16.82)
Goa	1,57,489 (1,04,944)	5.28 (9.21)	26.61 (0.30)	0.01 (0.32)	214.83 (56.36)	0.69 (68.66)
Gujarat	74,802 (52,956)	5.31 (7.91)	27.25 (0.40)	0.02 (0.42)	62.05 (16.84)	-0.45 (23.95)
Haryana	84,438 (52,183)	4.61 (4.75)	25.16 (0.50)	0.02 (0.48)	50.45 (9.15)	0.52 (13.31)
Himachal Pradesh	74,893 (46,164)	4.55 (3.77)	8.61 (0.53)	0.03 (0.43)	83.97 (12.22)	0.43 (19.61)
Jammu and Kashmir	59,370 (16,317)	3.30 (3.67)	3.30 (0.40)	0.04 (0.37)	40.26 (6.76)	0.00 (10.95)
Jharkhand	41,366 (12,438)	3.18 (8.24)	25.30 (0.35)	0.00 (0.34)	101.40 (11.55)	1.08 (15.08)
Karnataka	75,671 (47,215)	4.91 (3.93)	26.00 (0.28)	0.01 (0.29)	97.05 (15.96)	0.59 (17.87)
Kerala	74,068 (45,515)	4.59 (3.82)	26.40 (0.25)	0.02 (0.24)	225.27 (32.63)	0.77 (41.96)
Madhya Pradesh	32,584 (17,806)	4.34 (7.45)	25.86 (0.37)	0.01 (0.46)	87.53 (15.97)	0.01 (23.84)
Maharashtra	78,267 (45,908)	4.54 (4.35)	26.82 (0.32)	0.01 (0.39)	101.93 (18.80)	-0.07 (23.61)
Manipur	36,048 (11,244)	2.50 (4.41)	20.48 (0.34)	0.01 (0.37)	148.57 (17.44)	-0.50 (24.28)
Meghalaya	44,238 (17,040)	2.94 (3.56)	22.19 (0.36)	0.01 (0.37)	319.15 (50.74)	-1.17 (68.78)
Mizoram	80,542 (39,996)	6.83 (6.22)	22.77 (0.30)	0.00 (0.31)	196.74 (20.87)	-1.69 (33.15)
Nagaland	51,862 (21,146)	4.21 (6.86)	20.09 (0.30)	0.02 (0.41)	149.08 (16.33)	-0.57 (26.79)
Odisha	41,607 (22,953)	3.99 (6.89)	26.16 (0.27)	0.01 (0.26)	117.36 (12.28)	0.55 (16.33)
Puducherry	89,094 (47,231)	3.98 (8.55)	28.81 (0.28)	0.02 (0.25)	109.11 (20.39)	1.12 (30.36)
Punjab	71,479 (31,873)	3.46 (2.33)	24.23 (0.49)	0.02 (0.44)	58.71 (10.84)	0.48 (16.28)
Rajasthan	45,339 (22,781)	4.03 (8.44)	26.17 (0.44)	0.02 (0.46)	38.44 (7.82)	0.12 (10.45)
Sikkim	1,41,501 (94,446)	7.40 (9.84)	6.04 (0.36)	0.00 (0.45)	117.33 (14.48)	0.60 (18.54)
Tamil Nadu	72,492 (47,316)	5.09 (4.05)	27.66 (0.27)	0.02 (0.25)	88.26 (14.32)	0.78 (20.69)
Telangana	67,882 (48,525)	5.24 (5.16)	27.76 (0.30)	0.01 (0.32)	84.36 (13.59)	0.33 (19.30)
Tripura	38,049 (27,329)	5.38 (4.52)	25.08 (0.34)	0.01 (0.37)	199.95 (31.68)	-1.13 (43.50)
Uttar Pradesh	28,405 (11,077)	3.05 (3.09)	25.77 (0.44)	0.01 (0.44)	78.53 (12.10)	0.24 (16.02)
Uttarakhand	93,152 (50,919)	5.77 (5.24)	14.14 (0.42)	0.03 (0.45)	90.89 (15.97)	0.98 (20.94)
West Bengal	40,851 (19,947)	3.96 (2.81)	25.88 (0.35)	0.01 (0.34)	145.69 (14.54)	0.11 (22.13)

Standard deviation in parentheses

C. Post-diagnostics test for error distribution

We compare the Overall decompose with backward elimination model with weather combination 'f' [Model 'V-f' from Column (6) of Table 3] with the same model assuming Gaussian distribution instead of the Scaled-t distribution. Figure C1 and C2 provide the Q-Q plot, histogram of residuals, residuals vs linear predictor plot, and response vs fitted value plots for post-diagnostic analysis. The Q-Q and histogram of residual plots indicate that the model with scaled-t distribution is a better fit as it efficiently captures the effect of outliers and ensures the normality of residuals for hypothesis testing.

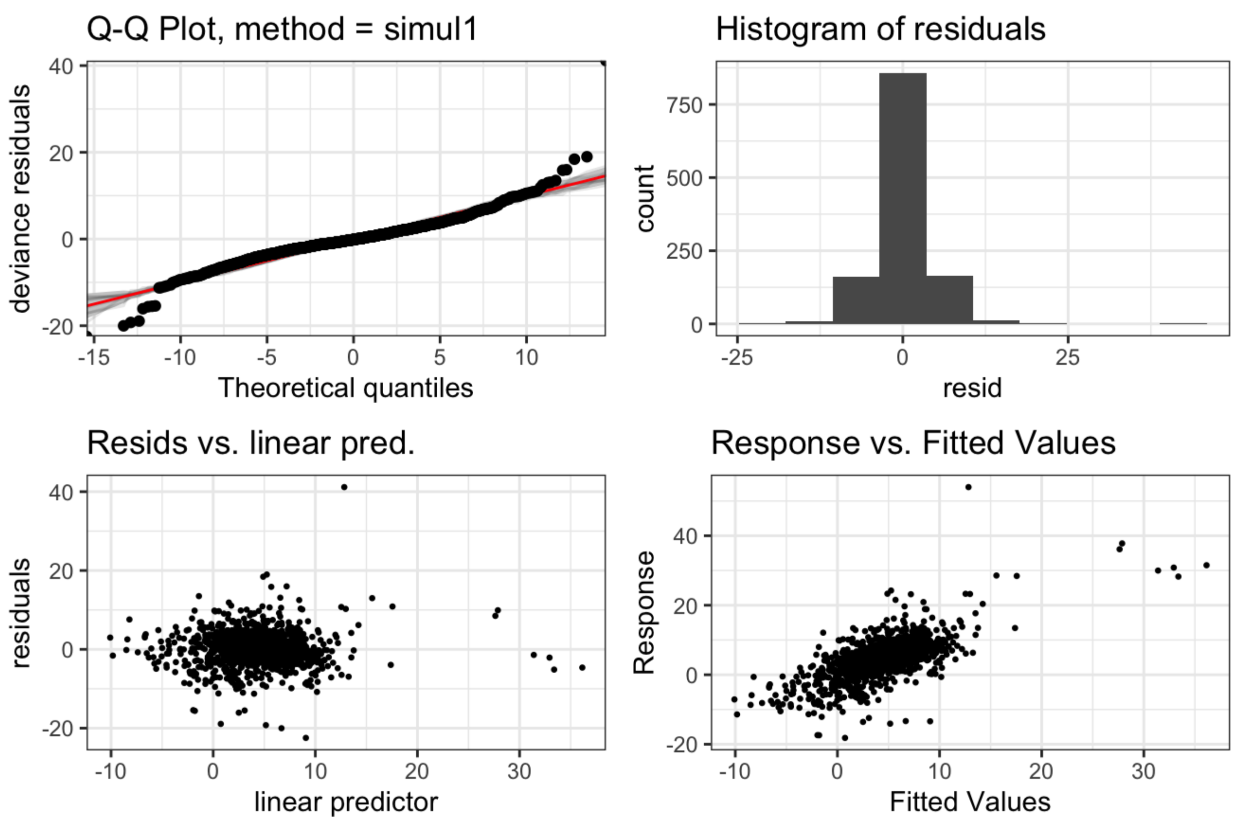

Figure C1: **Post-diagnostic plots for the Normal distribution:** The plots are post-diagnostic plots for the Overall decomposed with BE model with weather combination 'f' ('V-f'), and errors are normally distributed.

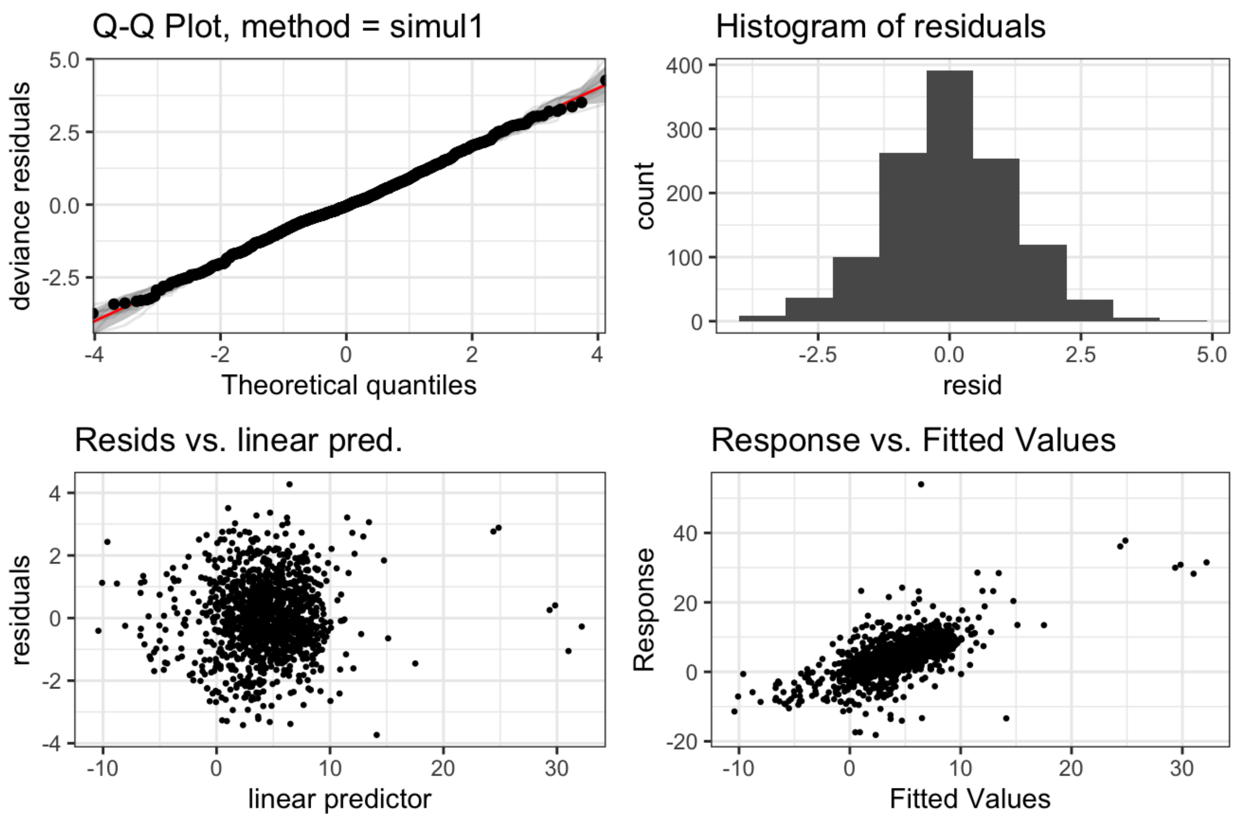

Figure C2: **Post-diagnostic plots for the Scaled-t distribution:** The plots are post-diagnostic plots for the Overall decomposed with BE model with weather combination 'f' ('V-f'), and errors are scaled-t distributed.

D. Robustness checks

This section presents the additional robustness checks as mentioned in the main paper. Column (1) of Table D1 restates the main results from Column (6) of Table 3. Column (2) presents estimates after considering the three-year lags of the dependent variable instead of one in the main paper. Column (3) considers the per capita NSDP growth rate instead of the per capita GSDP growth rate, as NSDP is available for an extended period. Column (4) utilizes an alternative definition of per capita GSDP growth as computed by the EPWRF database. Column (5) employs a thin plate regression spline technique with shrinkage (TPRSS) for basis function instead of double-penalty optimization. Column (6) restricts the state-specific trend term to be linear instead of quadratic term in the main paper. We observe that the adjusted R^2 decreases in all these alternative specifications. Nevertheless, our results demonstrate that either the EDF estimates are robust and consistent in spite of these changes or these changes are within the permissible limits of our main results.

Table D1: **Robustness checks: Effective degrees of freedom**

	(1)	(2)	(3)	(4)	(5)	(6)
		Alternative specification	Alternative data		Overfitting	
	Main results	g_y 3-Lags	NSDP data	EPWRF SDPgr	TPRSS	Linear trend
Weather induced TFP growth (WI-TFPG)						
$g_{\Theta_{T,2}}(Lag.P) \times \Delta T$	1.2075**	0.8697*	0.1785	1.3038**	1.5314**	1.2590**
$g_{\Theta_{P,2}}(Lag.P) \times \Delta P$	1.2924***	1.1540***	0.9458**	1.2238***	1.5299***	1.0550**
$g_{\Theta_{P,3}}(Lag.T \times Lag.P) \times Lag.\Delta P$	0.9364***	1.3277**	1.7094***	0.8652***	1.1236***	1.3290**
Weather induced LP growth (WI-LPG)						
$M_2(P)$	2.7768***	3.9894***	5.3631***	2.8253***	0.8799***	3.173***
Observations	1210	1111	1663	1177	1210	1210
State-specific Trend	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Linear
Fixed effects	State, year	State, year	State, year	State, year	State, year	State, year
Adj R^2	0.358	0.345	0.231	0.303	0.302	0.356

This table includes the Effective Degrees of Freedom (EDF) for each smooth term in the VC-GAMs. The significance of the EDF values for the smooth terms is determined using an F-test. EDF values reflect the complexities of the link between predictor and outcome variables.

Column (1) reiterates the main results from Column (6) of Table 3. Column (2) considers three lags of dependent variable g_y. Columns (3) and (4) consider alternative datasets of NSDP and per capita GSDP, respectively, as per the EPWRF database. Columns (5) and (6) represent results with alternative overfitting techniques of thin plate regression spline with shrinkage (TPRSS) and linear state-specific trend terms, respectively.

All models have state and year fixed effects and control for state-specific quadratic trends except Column (6). Error term follows a skewed t-distribution. Significance levels: * 10%, ** 5%, and *** 1%.

We also test for possible reverse causality by employing the Granger non-causality test proposed by Dumitrescu and Hurlin (2012). Table D2 presents the p-values, which test if the per capita economic growth Granger-causes weather variables in the presence of lags 1, 2, and 3 for per capita economic growth. The null hypothesis states that Granger causality exists for at least one state.

We find that the null hypothesis is rejected for all weather variables.

Table D2: **Granger non-causality test (p-value)**

	Dependent variable			
	Temperature level	**Precipitation level**	**Temperature change**	**Precipitation change**
Lag order of per capita economic growth				
Lag 1	0.9985	0.5556	0.9425	0.4955
Lag 2	0.1139	0.3048	0.7858	0.3897
Lag 3	0.8856	0.6158	0.7233	0.4478

The table presents the p-values of the Granger non-causality test (Dumitrescu and Hurlin, 2012). We employ specifications of different lag orders of per capita economic growth as independent variables and weather variables as dependent variables. The null hypothesis states that per capita economic growth Granger-causes weather variables for at least one state.