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Long-run macroeconomic impact of climate change on total factor productivity - Evidence from Emerging Economies

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Long-run macroeconomic impact of climate change on total factor productivity - Evidence from Emerging Economies *

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Abstract

Emerging economies (EMEs) often ignore effective mitigation strategies for climate risks to prioritise growth acceleration. This paper shows that EMEs cannot sustain their economic growth trajectory due to the adverse impact of climate change on total factor productivity (TFP). Using a standard growth model, it demonstrates how temperature rise and variation from growing industrial emissions reduce capital productivity along with the damage to ecosystem services and labour productivity, adversely impacting total factor productivity (TFP). A cross-sectional augmented auto-regressive distributed lag model (CS-ARDL), which addresses the issues of endogeneity and cross-sectional dependence with stochastic trends, has been applied to 21 EMEs over the period from 1990 to 2018 and reveals a strong negative impact of temperature rise on total factor productivity. Although EMEs have heterogeneous impacts across the countries depending upon their climatic zones and income levels, a one-degree increase in temperature, on average, decreases the TFP by approximately 3 per cent. It is much higher in the extreme climatic zones and less developed EMEs.

JEL Code: O47, Q50, O44

Keywords: TFP, Temperature Shocks, Panel CS-ARDL, Emerging markets

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1 Introduction

Emerging market economies (EMEs)[1] often prioritise the policy measures for growth acceleration to overcome their various development challenges, overlooking the strong mitigation strategies for dealing with the climate change risks, which adversely affect total factor productivity (TFP). Growing industrial pollution and fossil fuel consumption have resulted in a rapid rise in global temperature and emissions, damaging ecosystems and factor productivity and raising concerns about the sustainability of long-term growth in EMEs. The existing literature revealed that high temperatures are associated with reduced economic output [Dell et al., 2014, Burke et al., 2015b, Hsiang et al., 2013, Tol, 2022, Chang et al., 2023]. Recently, Integrated Assessment Models (IAMs) theoretically argue that climate change may alter the total factor productivity, which significantly and negatively impacts growth and prosperity in the future [Moore and Diaz, 2015a, Dietz and Stern, 2015, Moore and Diaz, 2015b]. Further, Letta and Tol [2019] has empirically established a negative and linear relationship between temperature and TFP growth in developed and developing economies. While estimating the impact in the literature, some components of factor productivity (e.g., capital productivity) and the ecosystems that add to the aggregate total factor productivity are ignored analytically and empirically. This paper considers them to study the impact of temperature on TFP and its components. We have included the impact of temperature on capital productivity, including labour productivity and ecological services. This crucial factor has been overlooked in the existing literature. Moreover, the existing methods [Kumar and Khanna, 2019, Letta and Tol, 2019] suffer from an estimation bias arising from cross-sectional dependence, stochastic temperature trends, and heterogeneity for variations in geo-climatic zones across countries and development. The CS-ARDL model has been applied to eliminate such estimation biases. Since TFP is vital for long-run economic growth, any negative impact of the temperature rise on TFP would require a significant reassessment of future growth projections [Tol and Yohe, 2006, Letta and Tol, 2019]. EMEs play a dominant role in global growth, and a better understanding of the temperature-productivity nexus is very important to foresee their long-term sustainability and world economic progress. Therefore, this paper investigates the long-term[2] impact of temperature rise on total factor productivity that includes labour and capital productivity and ecosystem services at the aggregate level. This is extremely important when emerging economies try to return to the growth track after the COVID-19-led crisis.

The COVID-led crisis has severely exposed a threat to human activities due to the growing vulnerability to climate risks. In the recent past, the climate risks displayed significant losses that account for the damages to factor productivity and ecological services. The rising greenhouse gas (GHG) stocks significantly contribute to global warming [IPCC, 2018]. Weather anomalies brought on by climate change have further wreaked devastation around the globe. Extreme weather events caused 11,778 reported disasters between 1970 and 2021, with just over 2 million deaths and US 4.3 trillion dollars in economic losses[WMO, 2023]. Extreme weather events, e.g., droughts, heat waves, cold waves, storms, flooding, hurricanes, and wildfires, are significantly

[1] Emerging markets have no formal definition but are categorised in terms of market access and sustained economic progress in GDP. IMF classifies countries into advanced economies and EMEs based on per capita income, export diversification and financial integration. EMEs have grown faster than most developing economies.

[2] This research defines the long-run relationship that exists in the steady-state from a macro perspective. The long-run relation can be estimated using the error correction term of the cross-sectional augmented autoregressive distributed lag model (CS-ARDL) approaches [Ditzen, 2021]. This study investigates such a long-term impact of annual temperature and its fluctuations at the time (t) on $\log(TFP)$ at the time ($t+n$) at the aggregate level, where n represents the average time required for the complete effect to be realised.

intensified by climate changes [Goyal et al., 2022]. Emerging markets are especially vulnerable to the economic and social consequences of these climate transformations due to geographical factors and levels of development, which restrict their adaptive capacity[3]. Therefore, such weather deterioration is more harmful to the emerging markets facing social and economic challenges in fostering productivity growth that determines economic growth. This urges the EMEs to undertake mitigation strategies to reduce the burden of climate change. Whatever may be the adoption strategies, it is important to understand the mechanism and magnitude of temperature rise on the productivity impact. The mechanism by which temperature affects TFP through its components has not been empirically established at the aggregate level in the existing studies [Somanathan et al., 2021, Letta and Tol, 2019, Kumar and Khanna, 2019]. Identifying the potential channels through which temperature impacts TFP will help policymakers allocate resources efficiently to sectors that are most vulnerable to the adverse consequences of climate change.

The existing studies, which quantified the impact of temperature on macroeconomic indicators, have mainly used reduced-form econometrics methods and hence suffered from potential biases in panel data analysis [Kahn et al., 2021, Chang et al., 2023]. Climate change variables have been mostly treated as exogenous indicators, ignoring the possibility of reverse causality. When estimating whether climate change will impact economic growth, the temperature may not be strictly exogenous but rather weakly exogenous. In other words, economic growth in the past could have feedback effects on future temperature [Kahn et al., 2021]. Moreover, Schultz and Mankin [2019] emphasised national governments run the weather stations from which meteorological data is collected, and this impacts the level of coverage and the continuity of such coverage depending on their political capabilities. The state's capacity to govern and run its bureaucracy may impact its ability to create and maintain meteorological stations. Severe instability could cause damage to infrastructure and be forced to divert government resources away from gathering weather data, resulting in gaps in the record that are directly related to the outcome of interest. This apart, the existing studies have overlooked the potential presence of unit roots in the form of stochastic trends in panel data. If the temperature rises in almost all countries in a sample, it may contain stochastic trends and the presence of cross-sectional dependence [Kahn et al., 2021]. This study aims to avoid these issues and is methodologically substantially different from these studies. This study relies on the cross-sectional augmented autoregressive distributed lag model (CS-ARDL) [Chudik and Pesaran, 2015, Ditzen, 2021] to avoid the cross-sectional dependence and heterogeneous effect of temperature on TFP across countries that allows us to test for weak exogeneity and find consistent parameter in the presence of feedback effect from TFP to temperature.

This paper contributes to the literature on climate productivity in several ways. We empirically establish three potential channels (i.e. labour productivity, capital productivity and damage in ecosystem services) through which temperature change affects total factor productivity in the long-run. To the best of our knowledge, this paper is the first to establish the effect of temperature rise on capital productivity as the performance of machines deteriorates in extreme temperatures. Understanding temperature's impact on TFP guides targeted policies for adaptation and mitigation, addressing specific sectors or broader strategies to minimise productivity decline. Micro-level studies in the literature provide empirical justification and analytical support in these regards [Somanathan et al., 2021, Stevens, 2019].

Second, this paper offers an improved econometrics model (i.e., CS-ARDL) to establish long-term relations that utilise diverse data in time and space and control for unobservable omitted

[3]The Global climate finance falls short of the estimated 3-6 trillion dollars per year needed to achieve Paris Agreement goals [Prasad et al., 2022]. Less developed countries lack the ability to mobilise the requisite funds and hence rely on external finance.

variables. It allows different specifications to distinguish short- and long-term climate impacts and identify potential adaptation effects using appropriate specifications. More specifically, this paper explicitly focuses on the long-term effect of a persistent increase in temperature using a panel cointegration technique. Kaufmann et al. [2010] modelled surface temperature as a time variable that exhibits a stochastic trend together with radiative force and provides the potential for a better understanding of the probable drivers of climate change and strategies to mitigate its effects. Similarly, Pretis [2020] applied the energy-balance climate models [4] to establish a cointegrated system econometrically in discrete time. It gives cointegration methods for estimating climate responses and evaluating their feedback. Additionally, it is possible to assess uncertainty in integrated assessment models of the economic implications of climate change using the estimated parameters. This study applies the CS-ARDL error correction term tests for a long-term relationship, which addresses the issue of heterogeneity by presenting estimates for certain groups of countries with similar characteristics of climate exposure and level of development. The estimation methods applied here sufficiently address potential cross-sectional dependence resulting from simultaneous common shocks or spillovers among economies. In comparing the magnitude of results, it is identified that the conventional panel fixed effect (FE) estimation models substantially underestimate the impact magnitude. In those models, a one-degree Celsius temperature increase was associated with a 1.7% point decrease in total factor productivity (TFP), Whereas the CS-ARDL model suggests a drop of 3% points, showing a greater impact.

Third, unlike the existing studies, this paper empirically tests for reverse causality between temperature and TFP. Kahn et al. [2021] argued for potential feedback effects of TFP growth on temperature. Even Schultz and Mankin [2019] argued that economic and political factors arising from declined production could alter meteorological measurement. Hence, this study used PVECM-based (panel vector error correction model) Granger causality and Xiao et al. [2022], Juodis et al. [2021] Granger causality to find the direction of causality. The study found evidence for short-run bi-directional causality between temperature and TFP using Xiao et al. [2022], Juodis et al. [2021] Granger causality. In contrast, the PVECM-based short-run Granger causality test does not find such evidence. However, the findings of this paper suggest that the relationship between temperature and TFP is complex and depends on the time horizon considered.

Fourth, the study investigated the heterogeneous effects of temperature rise across countries due to their variation in geo-climatic locations. It found negative impacts in all countries included in our data sample but revealed a greater effect in the two extreme climatic zones than in the moderate temporal countries. This study finds evidence of a non-linear impact of temperature on TFP. Previously, Letta and Tol [2019] did not find evidence of non-linearity in its sample with a combination of negative and positive impacts of temperature rise, leading to a smaller effect in the aggregate.

Finally, a greater impact of temperature rise found in this study suggests that the EMEs are required to improve climate prediction accuracy, promote energy conservation, support green technologies in high-energy-consuming industries more seriously, and invest more in technologies to deal with extreme climatic events. This study also offers the channels of dampening effects by which temperature impacts TFP. Moreover, we project the impact of climate change on TFP in emerging markets, assuming no additional adaptation measures that could reduce the sensitivity of output to high temperatures, consistent with the prior empirical literature on climate impacts [Kumar and Khanna, 2019, Letta and Tol, 2019, Zhang et al., 2015]. This paper predicted how

[4] Energy balance models (EBMs) of the climate system are highly simplified models that provide effective conceptual tools for understanding climatic changes. The radiation budget that accounts for the energy flowing in from the Sun and leaving the Earth is used to determine the global temperature.

climate change would be expected to affect TFP in the future and found that it would drop by 14.2 percentage points under the "business as usual GHG emission scenario from 2023 to 2099 and by 1.37 percentage points under the "strict GHG emission scenario." The future impact of climate change is much worse in less developed emerging markets.

The remainder of the paper is organised as follows. Section 2 provides a brief literature review of the temperature-TFP nexus. Section 3 presents the conceptual background and mechanism through which temperature could impact the level of total factor productivity. Section 4 presents the econometric methodology and describes the data. Estimation results are presented in section 5, and section 6 concludes the paper.

2 Literature Review

Extreme weather events and rising global temperatures are pressing global issues with serious implications for human and economic well-being. The projections of the Intergovernmental Panel on Climate Change [IPCC, 2014] revealed that mean global temperatures could increase upto 2°C to 4.8°C by 2100 compared to pre-industrial levels. Extensive research has consistently established the detrimental effects of climate change on economic activities (see [Tol, 2022, Chang et al., 2023]). Several scholars [Dell et al., 2012, Acevedo et al., 2020] have established a robust and linear relationship between temperature fluctuations and economic growth. Burke et al. [2015b] found country-level economic production concave in temperature. Various micro-econometric studies have documented the adverse impact of climate change on the agriculture sector [Schlenker and Roberts, 2009], labour productivity [Somanathan et al., 2021, Letta and Tol, 2019], labour supply [Graff Zivin and Neidell, 2014, Somanathan et al., 2021], human conflict [5] [Burke et al., 2015a], industry and trade [Dallmann, 2019], exports [Jones and Olken, 2010] and real exchange rate [Cha et al., 2021].

A relatively overlooked issue is the long-term impact of climate change on total factor productivity (TFP). Given the preeminent importance of TFP for long-run economic growth [Solow, 1956, Mankiw et al., 1992], if climate change harms TFP growth rates, this would entail a radical revision of future projected growth estimates [Letta and Tol, 2019]. The social cost of carbon (SCC) estimated by Integrated assessment models (IAMs) assumes that the TFP is exogenously determined. Recently, several scholars have modified the assumption and allowed climate change to impact TFP. For example, Dietz and Stern [2015] assumed climate change as an endogenous damage driver, particularly for TFP, and found a rapid increase in the social cost of carbon if the global mean temperature is above the pre-industrial level [6]. Moore and Diaz [2015b] found that climate change directly affects economic growth via the impact on TFP and investment, which, in turn, increases the social cost of carbon. Moreover, an extensive body of research has consistently revealed that developing nations experience a disproportionately severe negative impact of temperature variations on macroeconomic activities compared to their advanced economies [Burke et al., 2015b, Dell et al., 2012, Kumar and Khanna, 2019]. The impact of higher temperatures is expected to be more severe in emerging market economies due to their greater reliance on agriculture and limited adaptive capacity. Additionally, many low- and middle-income countries among emerging market economies are situated in regions characterised by low latitudes, where intense heat extremes are projected to occur with greater frequency and intensity [Diffenbaugh and Burke, 2019, Harrington et al., 2016].

[5] Burke et al. [2015a] showed the impact of climate change on human conflicts, including interpersonal and inter-group conflict, riots and civil wars

[6] This is in the era before the industrial revolution. Some studies have suggested that the pre-industrial level baseline might be 1700-1800

Empirical evidence on the nexus between temperature rise and total factor productivity at the aggregate level is limited. While employing the ratio of total agricultural production to total agricultural input as an indicator for total factor productivity (TFP), Ortiz-Bobea et al. [2018] revealed that the impact of climate change on TFP is detrimental. They observed that weather shocks positively influenced productivity growth in most USA states but hurt productivity in four northern states. Moreover, when weather effects were omitted from the model, it resulted in biased estimations of factors contributing to TFP growth across various regions. Similar results were estimated for Australian farm sectors by Chancellor et al. [2021]. Using the panel fixed effect model, Letta and Tol [2019] found that temperature negatively impacts the TFP growth rate. Kumar and Khanna [2019] used stochastic frontier analysis to show a negative impact of temperature on production efficiency and found that climate change has adversely affected poor and developing countries.

In summary, numerous empirical studies have found the negative impact of temperature on labour productivity [Adhvaryu et al., 2018, Letta and Tol, 2019], labour supply [Somanathan et al., 2021], and cognitive abilities [Hancock et al., 2007]. The temperature can also impact capital productivity [Mortier et al., 2010, Collins, 1963]. The specific mechanism through which ecosystem services impact TFP hinges on reallocating resources away from research and development towards climate change mitigation and adopting eco-friendly technologies. This may also reduce the productivity of agricultural land and labour. However, the literature did not estimate the combined impact of temperature increase on the TFP. Building on the recent works [Letta and Tol, 2019, Kumar and Khanna, 2019], this paper employs the cross-sectional augmented autoregressive Distributed Lag (CS-ARDL) approach, as opposed to the panel data fixed effect (FE) method utilised in the prior studies to find better estimates.

3 Conceptual framework: Temperature and total factor productivity (TFP)

It is evident in the existing literature that the temperature rise does not only affect the favourable ecosystem services and labour productivity but also damages the productivity of capital goods used in production. This section builds a framework to show that the global temperature affects the TFP via three channels, i.e., reduction in ecosystem services, capital productivity and labour productivity. According to a recent report by European Commission[7], burning fossil fuels, cutting down forests, and farming livestock are increasingly influencing the climate and the earth's temperature. But, the climatic response exhibits intricacies whereby temperature ascends by a notable margin, say 5 degrees, within one locale, yet concurrently witnesses a descent of 2 degrees within another. Every country is not contributing at the same speed, but the aggregate damage to the atmosphere is responsible for global warming [Hansen et al., 2010]. The warming may differ substantially within specific land masses and ocean basins. We attempted to model this.

Let us assume a global production function of final goods that costlessly assimilates intermediate outputs produced at the country level. There are many countries in the world, each producing a single variety using their capital and labour. At the country level, each pollutes the environment as a negative externality and consumes fossil fuels [Cole et al., 2005, Cole and Elliott, 2005]. The aggregate emission level is assumed to monotonically raise the global temperature, which essentially damages the ecosystem, labour and capital productivity and, thereby, the total factor productivity. Let us build the model formally.

[7] $https://climate.ec.europa.eu/climate-change/causes-climate-change\_en$

Assume that N identical countries produce one variety of intermediate goods each. Each economy has two types of agents: households and firms. Households provide labour (L), receive wages and interest incomes used to buy goods and services and save to accumulate capital assets (K). The model assumes that all households have identical preferences, wage rates, and assets per person. On the other hand, the firms employ workers and take the assets from households to produce intermediate goods. While producing the goods, the firms pollute more by using higher capital-intensive machines requiring fossil fuel consumption and emitting carbon that raises the surface pollution level.

3.1 Household

Each household wants to maximise lifetime utility as given by

$$U = \int_0^\infty u[c_t]e^{-\rho t}dt; \quad u'(c) > 0, u''(c) < 0 \tag{1}$$

where ρ is the discount factor and $c(t)$ represents per capita consumption. For simplicity, assume the form of instantaneous utility function as follows:

$$u(c_t) = \frac{c_t^{1-\theta} - 1}{1-\theta} \tag{2}$$

where, $\theta > 0$, so the elasticity of marginal utility equals to the constant $-\theta$. Households use the income that they do not consume to accumulate as assets. The capital depreciates at δ rate. Capital owners and workers are paid according to their marginal productivity, denoted as r (rent) and w (wage). If the amount of capital (K) is assumed as assets and C is the consumption, the motion of capital can be expressed as (by ignoring t subscript):

$$\dot{K} = (r - \delta).K + w.L - C \tag{3}$$

Labour (L) is fixed in an economy. Dividing both sides by L, this expression can be represented in terms of per capita as follows:

$$\dot{k} = (r - \delta).k + w - c \tag{4}$$

Where, $k = K/L$ and $c = C/L$. This would serve as the budget constraint for the household. So, the household would maximise lifetime utility (U) subject to this constraint.

3.2 Firms

Assume that there are N identical countries worldwide, and each possesses one firm only producing Y_{it} intermediate output in i-th period. One single world output is produced for consumption by bundling each country's varieties costlessly. Assuming that the intermediate goods produced by the respective countries are substitutable by σ, the world output can be expressed as

$$X_t = \left[\sum_{i=1}^{N} Y_{it}^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} \tag{5}$$

Where, Y_{it} is the quantity of input variety $i = 1, .., N$. We assume that $\sigma > 1$, so it is meaningful to consider changes in the number of inputs. If inputs are all equally priced in identical countries, then their quantities are also equal, $Y_{it} = Y_t$, and the above expression can be presented as follows: $X_t = N^{\sigma/(\sigma-1)}Y_t$. Note that $N^{\sigma/(\sigma-1)} > 1$, capturing the productivity gain in the final goods production or world production arising from a rise in the number of intermediate varieties. This means that the higher the variety of intermediate production at the country level, the greater the productivity gain in the final goods production. It may also apply to the emission level.

3.3 Emission and temperature

While producing intermediate goods at the country level, it emits pollution. The production needs to consume fossil fuels that further release carbon emissions. The temperature, T_t, may rise depending on the global emission level, E_t, which is essentially influenced by global production. Let us assume that the global emission level is $E_t = X_t^{\phi}; \phi > 0$, where ϕ is the emission elasticity of global production. This suggests that the emission level rises with global production at a diminishing rate for $0 < \phi < 1$. Since the emission level cannot grow fast once it reaches a higher level, it is expected that ϕ lies between zero and one. The global temperature rises with the emission level and can be represented in logarithmic form, i.e., $T_t = \ln E_t$. Combining the emission and temperature functions, the global temperature can be expressed as:

$$T_t = \phi \ln X_t \tag{6}$$

This suggests that temperature rises with global production. If global production is assumed to affect the temperature at the country level, the rising temperature due to growing global emissions damages ecological services and capital and labour productivity. Similar to Cole and Elliott [2005], we consider a Cobb-Douglas production function with the productivity components attached to the factors and ecological content in efficiency terms. Assume that A_K and A_L represent the efficiencies of capital and labour, respectively, and $A(T_{it})$ shows the level of ecosystem services capturing the quality state of the environment. If labour L_{it} and capital K_{it} are used to produce output (Y_{it}) at $t-$th period in the i-th economy, the production function country can be specified as follows:

$$Y_{it} = A(T_{it}) \left[A_K(T_{it}) K_{it} \right)^{\alpha} \left(A_L(T_{it}) L_{it} \right]^{1-\alpha} = B_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \tag{7}$$

Where, $B_{it} = A(T_{it}) A_K(T_{it})^{\alpha} A_L(T_{it})^{1-\alpha}$, which denotes the aggregate productivity term. Note that the production function exhibits constant return to scale. The TFP depends on the level of ecosystem services and the productivity of capital and labour, which are further influenced by the global temperature and are identical for similar countries. Here, T_t representing the global temperature at t affects Y_{it} at the country-level production. A_k and A_L are capital and labour productivity, respectively, and both depend on T_t; α and $1 - \alpha$ are capital and labour elasticities, respectively.

Suppose that the damage function of ecological services due to global warming is represented as $A(T_t) = A(1 - \mu_A T_t)$, where μ_A is positive and captures the rate of ecological damages. This could also be expressed as $Ae^{-\mu_A T_t}$. By substituting T_t, we get $A(T_t) = Ae^{-\mu_A \phi \ln E_t} = AX_t^{-\mu_A \phi} = A\left(N^{\sigma/(\sigma-1)} Y_t\right)^{-\mu_A \phi}$. Similarly, capital and labour productivity are assumed to be damaged at μ_K and μ_L due to global temperature rise. Then, we can define the damage functions of capital and labour productivity as $A_K(T_t) = A_K(1 - \mu_K T_t)$ and $A_L(T_t) = A_L(1 - \mu_L T_t); \mu_K, \mu_L > 0$. In the similar way, they can be presented as $A_K(T_t) = AX_t^{-\mu_K \phi} = A_K\left(N^{\sigma/(\sigma-1)} Y_t\right)^{-\mu_K \phi}$ and $A_L(T_t) = AX_t^{-\mu_L \phi} = A_L\left(N^{\sigma/(\sigma-1)} Y_t\right)^{-\mu_L \phi}$. Substituting these damage functions in (eq 7), the production function can be simplified as follows:

$$Y_t = BDY_t^{-\Omega} K_t^{\alpha} L_t^{1-\alpha} \tag{8}$$

Where, $B = AA_K^{\alpha} A_L^{1-\alpha}; \Omega = [\mu_A + \alpha\mu_K + (1-\alpha)\mu_L]\phi; D = N^{-\Omega\sigma/(\sigma-1)}$. B denotes the TFP without damage. Ω represents the rate of damage due to temperature rise. It would be zero iff $\phi = 0$ or $\mu_A = \mu_K = \mu_L = 0$. D represents the aggregate productivity loss or distortions arising from the damages. Again, $D = 0$ when $\Omega = 0$. Now, rearranging the Y_t term, we find the modified production function as follows:

$$Y_t = (BD)^{\frac{1}{1+\Omega}} K_t^{\frac{\alpha}{1+\Omega}} L_t^{\frac{1-\alpha}{1+\Omega}} \tag{9}$$

Note that this function no longer exhibits constant return to scale. The return to scale is $\frac{1}{1+\Omega}$. If $0 < \phi < 0$, we get that $\Omega > 0$ and $\frac{1}{1+\Omega} < 1$. Hence, it exhibits a decreasing return to scale. If $L_t = L$, the production function can be represented in per capita terms (in the lower letters) as follows:

$$y_t = (BD)^{\frac{1}{1+\Omega}} k_t^{\frac{\alpha}{1+\Omega}} L^{\frac{-\Omega}{1+\Omega}} \tag{10}$$

Note that the output per capita, y_t, contains the term of productivity loss, D, due to the damage.

3.4 Steady State and TFP terms

If the marginal productivity of capital is defined as the rental rate, we get the rental rate (r_t) as follows:

$$r_t = \left(\frac{\alpha}{1+\Omega}\right) (BD)^{\frac{1}{1+\Omega}} k_t^{-1+\frac{\alpha}{1+\Omega}} L^{-\frac{\Omega}{1+\Omega}} - \delta \tag{11}$$

Since $\frac{\alpha}{1+\Omega}$ is fraction, r_t will be falling with the rise of k_t. Applying the Hamiltonian optimisation method, we find the growth rate of the economy as follows:

$$\frac{\dot{c}}{c} = \frac{1}{\theta}\left[\frac{\alpha}{1+\Omega}(BD)^{\frac{1}{1+\Omega}} k_t^{\frac{\alpha-\Omega-1}{1+\Omega}} L^{\frac{-\Omega}{1+\Omega}} - (\delta+\rho)\right] \tag{12}$$

The first of the third bracket declines with capital accumulation. It will converge to $\delta + \rho$. At steady state, $k_t = k^*$. Therefore, we find:

$$k^* = \left[\left(\frac{(\delta+\rho)(1+\Omega)}{\alpha}\right)^{1+\Omega} \frac{L^{\Omega}}{BD}\right]^{-\frac{1}{1+\Omega-\alpha}} \tag{13}$$

If we substitute k^* in the production function (10), we find the steady state output per capita as follows:

$$y^* = (BD)^{\frac{1}{1+\Omega}} L^{\frac{-\Omega}{1+\Omega}} k^{*\frac{\alpha}{1+\Omega}} \tag{14}$$

The average productivity of capital and total factor productivity are defined in terms of y_t/k_t and y_t/k_t^{α} and found as follows (for $\Omega > 0$):

$$\frac{y_t}{k_t} = (BD)^{\frac{1}{1+\Omega}} L^{\frac{-\Omega}{1+\Omega}} k_t^{\frac{\alpha-\Omega-1}{1+\Omega}} \tag{15}$$

$$TFP_t = (BD)^{\frac{1}{1+\Omega}} L^{\frac{-\Omega}{1+\Omega}} k_t^{\frac{-\alpha\Omega}{1+\Omega}} \tag{16}$$

It shows that TFP is falling with capital accumulation during the transition period. Note that when $\Omega = 0$, we find that $TFP_t|_{\Omega=0} = B$. Moreover, the higher the value of D, the lower the TFP. Because the higher the Ω lower would be TFP_t. This productivity loss can be decomposed by taking the deviation of TFP_t (in logarithm form) for $\Omega > 0$ and $\Omega = 0$, i.e., $\Delta \log TFP_t = \log TFP_t|_{\Omega>0} - \log TFP_t|_{\Omega=0}$

$$\Delta \log TFP_t = -\frac{1}{1+\Omega}[\Omega \log B + \log D] - \frac{\Omega}{1+\Omega}\log L - \frac{\alpha\Omega}{1+\Omega}\log k_t \tag{17}$$

Equation 17 decomposes the loss of TFP into three sources. All three components on the right-hand side are negative, representing the loss on each account. The first term of the right-hand side captures the loss of productivity due to ecological damage, and the second and third terms contain the loss of productivity with respective to the damage in labour and capital efficiencies, respectively.

At $k_t = k^*$, TFP would be fixed at TFP^*, much smaller than B for $\Omega > 0$. Moreover, for a positive value of either μ_A, μ_K, μ_L or ϕ, we find that $\Omega > 0$ and the TFP will be lower. In other words, productivity would decline if the temperature rise damages any of the three sources. Therefore, the production technology adversely affecting the temperature may widen the negative impact on physical capital, ecology and labour, and hence, it becomes an empirical question.

4 Data and Empirical Strategy

4.1 Data sources, sample composition and descriptive statistics

This study gathers climate indicators from the World Bank Climate Change Knowledge portal.[8]. The total precipitation is measured in millimetres per year, while the temperature is reported in degrees Celsius. The Climatic Research Unit (CRU) of the University of East Anglia provides data on temperature and precipitation for geographical areas. The World Bank Climate Change knowledge portal uses them to create an area-weighted average of climatic variables. Most economic variables used in this study were sourced from the Penn World Table 10.0 [Feenstra et al., 2015] and the World Development Indicators [WDI]. The total factor productivity at constant national prices, normalised for each country to one in 2017, was obtained from the Penn World Table 10.0[9]. We use the Penn World Table employment statistics for the number of people engaged in production activity. We also obtained Foreign direct investment (FDI), trade openness [10], institutional quality, labour force participation, GDP and human capital available at World Development Indicators (see Table 1).

Together with climate indicators and economic variables, this study gathers a complete balanced panel data of 21 Emerging markets economies (EMEs)[11] over the period from 1990 to 2018. Table 1 provides descriptions of the variables. To deal with the heterogeneity in the analysis, the data sample has been divided by sub-sample average temperature[12] and income

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

[9] The Törnqvist index values are calculated for consecutive periods in the chain together, eliminating the need for a single base year. This index is derived by taking the weighted geometric mean of the price relatives, with the arithmetic averages of the value shares in the two periods serving as weights.

[10] We calculated trade openness as the ratio of the sum of export and import to GDP

[11] Argentina, Brazil, Bulgaria, Chile, China, Colombia, Egypt, India, Indonesia, Iran, Malaysia, Mexico, Morocco, Nigeria, Peru, Philippines, Russia, South Africa, Thailand, Turkey and Ukraine.

[12] We created three sub-samples having average temperature range 0-10, 10-20 and 20-30 into cold, moderate and hot regions. The categorisation of temperature into distinct bins, based on the

groups[13]. The study used the Climate Change Knowledge Portal (CCKP) temperature data to project future impact. It presents four distinct RCP[14] Scenarios outlined representative concentration pathways incorporating various greenhouse gas emissions, air pollutant emissions, and land use. The RCP scenarios assessed the costs associated with reducing emissions while considering various concentration pathways, including stringent mitigation scenarios (RCP 2.6), two intermediate scenarios (RCP 4.5 and RCP 6.0), and one scenario involving high emissions (RCP 8.5), which is also referred to as the business-as-usual scenario. To improve the accuracy of the findings, the CCKP (World Bank) employed a multi-model ensemble approach that combined monthly data from 16 different models. The description of data details, including their source and the reasoning behind their selection, is provided in Table 1.

This study examines the patterns of total factor productivity (TFP) in emerging market economies (EMEs), as shown in Figure A2 in the Online Appendix. South Africa and Brazil exhibit the highest TFP levels, while Thailand has the lowest between 1990 and 2018. Our dataset shows the highest annual mean temperatures in Brazil, India, Egypt, and Nigeria, whereas Russia and Ukraine have the lowest temperatures[15].

frequencies of weather events falling into each bin, is employed as a method to discern the heterogeneous impacts of temperature on economic indicators. This approach enables us to explore the nuanced relationship between temperature and total factor productivity, considering the varying effects of different temperature ranges. [Zhang et al., 2018a, Deschênes and Greenstone, 2011, Barreca, 2012, Behrer and Park, 2017]

[13]In the sub-sample, countries with a per capita income below 4,000 dollars are classified as "less-developed emerging market," while those with an income above 4,000 dollars per capita are considered "developed emerging markets."

[14]Representative concentration pathways (RCPs) are comprehensive and encompass four distinct pathways of greenhouse gas (GHG) emission, air pollutant emission, and land use. RCP scenarios are designed to evaluate the costs associated with emission reductions for various concentration pathways. The RCP framework comprises four different pathways, including stringent mitigation scenarios (RCP 2.6), two intermediate scenarios (RCP 4.5 and RCP 6.0), and one scenario characterised by very high emissions (RCP 8.5). RCP 8.5 is also called the business-as-usual scenario.

[15]For Summary Statistics (see Supplementary material Table A3 Online Appendix)

Table (1) Compendium of Variable Definitions and Data Sources: Rationale and Previous Literature

Variables	Definitions	Source of Data	Indicator Justification: Rationale and Existing Literature
Economic Variables			
Total factor productivity	TFP at constant national price (2017=1)	Penn World Table Productivity Data Sheet	[Letta and Tol, 2019, Kumar and Khanna, 2019]
Human Capital	secondary schl. enrollment rate, secondary (% gross)	World Development Indicators (WDI, 2016)	[Islam et al., 2010, Wei and Hao, 2011]
EXGDP	Exports of goods and services (current US$)	World Development Indicators (WDI, 2016)	construction of Trade openness variable [Miller and Upadhyay, 2000]
IMGDP	Imports of goods and services (current US$)	World Development Indicators (WDI, 2016)	construction of Trade openness variable [Miller and Upadhyay, 2000]
Institutional quality	General government final consumption expenditure (% of GDP)	World Development Indicators (WDI, 2016)	[Rodrik et al., 2004, North, 1990, Venard, 2013]
Foreign direct investment	Foreign direct investment, net inflows (% of GDP)	World Development Indicators (WDI, 2016)	[Findlay, 1978, Blalock and Gertler, 2009, Azman-Saini et al., 2010]
Total Labour force	Labor force, total	World Development Indicators (WDI, 2016)	[Yildirim et al., 2009, Henseler and Schumacher, 2019]
Output	GDP (current US$)	World Development Indicators (WDI, 2016)	[Kahn et al., 2021, Dell et al., 2014]
Employment	Number Of Persons engaged (in millions)	Penn World Table Productivity Data Sheet	[Yildirim et al., 2009, Henseler and Schumacher, 2019]
Capital stock	Capital Stock at Constant 2017 national Prices (in mil. 2017 US)	Penn World Table Productivity Data Sheet	[Henseler and Schumacher, 2019, Hallegatte, 2005, Mortier et al., 2010]
Capital Productivity	(GDP per unit of capital)	Author Construction	[Hallegatte, 2005, Mortier et al., 2010]
Labour Productivity	(GDP per unit labour)	Author construction	[Henseler and Schumacher, 2019, Letta and Tol, 2019]
Forest area (sq. km)	Proxy for ecosystem services	World Development Indicators (WDI, 2016)	[Riley and Gardiner, 2020]
Cereal yield	Cereal Yield (kg per hectare)	World Development Indicators (WDI, 2016)	[Kahn et al., 2021]
Manufacturing	Manufacturing value-added s % of GDP	World Development Indicators (WDI, 2016)	[Acevedo et al., 2020]
Agriculture	Agricultural value-added as % of GDP	World Development Indicators (WDI, 2016)	[Acevedo et al., 2020]
Natural resources rent	Total natural resources rents (% of GDP)	World Development Indicators (WDI, 2016)	[Akadiri et al., 2023]
Weather Indicators			
Rainfall	Rainfall Precipitation	Climate Change Knowledge Portal (World Bank)	[Kahn et al., 2021, Letta and Tol, 2019, Kumar and Khanna, 2019]
Weather	Max Temperature	Climate Change Knowledge Portal (World Bank)	[Giovanis and Ozdamar, 2022]
Weather	Average Temperature	Climate Change Knowledge Portal (World Bank)	[Kumar and Khanna, 2019, Letta and Tol, 2019]
Weather	Long term temperature anomalies	Author Construction	[Barrios et al., 2010, Portmann et al., 2009]
Weather	temperature volatility	Author Construction	Diebold and Rudebusch [2022]
Weather	Negative temperature shocks	Author Construction	[Kahn et al., 2021]
Weather	Positive temperature shocks	Author Construction	[Kahn et al., 2021]
Projected Weather Data			
Weather	Projected Temperature RCP 2.6 Scenario	Climate Change Knowledge Portal (World Bank)	[Kumar and Khanna, 2019, Letta and Tol, 2019]
Weather	Projected Temperature RCP 4.5 Scenario	Climate Change Knowledge Portal (World Bank)	[Kumar and Khanna, 2019, Letta and Tol, 2019]
Weather	Projected Temperature RCP 6.0 Scenario	Climate Change Knowledge Portal (World Bank)	[Kumar and Khanna, 2019, Letta and Tol, 2019]
Weather	Projected Temperature RCP 8.5 Scenario	Climate Change Knowledge Portal (World Bank)	[Kumar and Khanna, 2019, Letta and Tol, 2019]

4.2 Empirical Strategy

4.2.1 Non-stationarity

Since most economic variables in time series likely exhibit stochastic trends, performing unit root tests on the series is reasonable. Two main types of panel unit root tests have been employed in the literature. The first-generation unit root test is the most commonly used, based on the assumption that cross-sections are independent. However, the first-generation unit root test is subject to size distortion in the presence of common shock among countries simultaneously. Hence, the second-generation unit root test is preferred. The Pesaran unit root test [Pesaran, 2007a, 2003] uses cross-sectional dependence with serially correlated terms. This test filters out cross-sectional dependence by augmenting individual ADF regressions with the cross-sectional average of lagged and first differences of the individual series as proxies for unobserved common factors. Both the first-generation unit root test [Im et al., 2003, Levin et al., 2002] and the second-generation unit root test [Pesaran, 2007b] are utilised in this study.

4.2.2 Long run estimate and cointegration

The existing literature, which quantified the impact of temperature on macroeconomic variables, has mainly used a set of reduced-form econometric methods [Dell et al., 2012, Letta and Tol, 2019, Hsiang et al., 2013]. However, if one or more independent variables are not strictly exogenous, the standard FE estimator used in the model specification will result in biased estimations. Moreover, Kahn et al. [2021] has questioned these methodologies for three reasons. First, the temperature is assumed as an exogenous indicator, which rules out reverse causality[16]. Second, these methods ignore the potential presence of unit root in the form of stochastic trend [17]. Third, they have ignored the potential presence of cross-sectional dependence. This study aims to address these issues with improved methodologies using the cross-sectionally augmented ARDL(CS-ARDL) framework, which considers slope heterogeneity and cross-sectional dependence to establish the long-term relationship between temperature levels and TFP. One of the main advantages of this estimation method is its ability to estimate the long-run effects in large dynamic heterogeneous panel data models with cross-sectionally dependent errors. While estimating the long-run effects using panel data, the existing studies (e.g., panel data fixed effect [Letta and Tol, 2019], Stochastic Frontier Analysis [Kumar and Khanna, 2019], Fully modified ordinary least squares (FMOLS) technique [Pedroni, 2001], panel dynamic ordinary least square (DOLS) approach [Mark et al., 2005]) did not take into account cross-sectionally dependent errors. The cross-sectional dependence may lead to a biased estimate due to serial or cross-correlation between common factors and idiosyncratic errors. Such cross-sectional dependence can be eliminated by using the cross-sectional average of the dependent and independent variables in the model. Chudik and Pesaran [2015] included dynamic panels with heterogeneous coefficients and weakly exogenous regressors in the cross-sectionally augmented ARDL method.

[16] When estimating whether climate change will impact economic growth, the temperature may not be strictly exogenous but rather weakly exogenous to income growth. So, economic growth in the past could have feedback effects on future temperatures. Kahn et al. [2021] and Schultz and Mankin [2019] emphasised that a government runs the weather stations from which meteorological data is collected and that this impacts the level of coverage and the continuity of such coverage depending on their political capabilities. The ability of the state to control and run its bureaucracy may affect its capacity to create and maintain meteorological stations. Moreover, violence and instability could cause damage to infrastructure or divert government resources away from gathering weather data, resulting in gaps in the record that are directly related to the outcome of interest.

[17] Kahn et al. [2021] found temperature has been rising for almost all the countries in their sample, indicating that temperature may contain stochastic trend

Based on ARDL specification estimation, this method is augmented with cross-sectional averages to eliminate the impacts of unobserved common components from the long-term estimates. The CS-ARDL approach appropriately incorporates cross-sectional averages into individual regression to filter out the effects of common factors, similar to the Common Correlated Effects (CCE) estimators. The significant advantage of this method (CS-ARDL) is its consideration of all three critical panel characteristics: dynamics, heterogeneity, and cross-sectional dependency. The main benefit of this method is its ability to accurately estimate the long-term effects while accounting for cross-sectional dependence, which is critical for making correct policy recommendations.

Long run estimate

Given a greater degree of financial and trade integration among emerging markets, the estimation can suffer from cross-sectional dependence among countries. The CS-ARDL model takes care of slope heterogeneity and cross-sectional dependence. It first estimates the short-run coefficient and then derives the long-run coefficient. This method employs a dynamic panel data approach incorporating lagged dependent variables as regressors to examine the long-term relationship between temperature and total factor productivity for the i-th country at the t-th period. If the $log(TFP)$ measures total factor productivity and T denotes the annual temperature, this model can be presented as follows:

$$log(TFP)_{i,t} = \alpha_i + \sum_{l=1}^{p_{TFP}} \lambda_{l,i} log(TFP)_{i,t-l} + \sum_{l=0}^{p_T} \beta_{l,i}(T)_{i,t-l} + \sum_{l=0}^{p_K} \gamma'_{i,l} \overline{\mathbf{z}}_{t-l} + e_{i,t}. \tag{18}$$

with $\overline{\mathbf{z}}_{t-l} = \left(\overline{log(TFP}_{i,t-l}, \overline{(T)}_{i,t-l}\right)$. Further, $\overline{log(TFP)_t} = N^{-1}\sum_{i=1}^{N} \ln TFP_{it}$ and $\overline{T}_t = N^{-1}\sum_{i=1}^{N} T_{it}$ are the averages of the lagged log(TFP) and the annual mean temperature. We focus on the long-run average effect of temperature on $log(TFP)$, which can be calculated from the mean values of the individual country coefficients [Pesaran et al., 1995]. The subscript i refers to their coefficients and shows they can vary across cross-section observations. α_i represents individual country specific factors. The parameters, p_{TFP} and p_T, denote the lags of $log(TFP)$ and annual mean temperature.

We are interested in the long-run average impact of temperature at time t on the total factor productivity on time at $t + n$, where n is the time taken (on average) for the full effect to be realised. The long run coefficient offers this effect, and the mean group coefficient is:

$$\begin{aligned} \hat{\theta}_{CS-ARDL,i} &= \frac{\sum_{l=0}^{p_T} \hat{\beta}_{l,i}}{1 - \sum_{l=1}^{p_{TFP}} \hat{\lambda}_{l,i}} \\ \hat{\bar{\theta}}_{MG} &= \sum_{i=1}^{N} \hat{\theta}_i \end{aligned} \tag{19}$$

We have also tested the sign and significance of the annual mean temperature, including other covariates such as trade openness, foreign direct investment, human capital, institutional quality, and precipitation as controls in our estimation.

Cointegration

The long-run estimates obtained from the CS-ARDL model are consistent. The asymptotic normality of these estimates holds true for both stationary and non-stationary underlying variables under the condition that the residuals are stationary. When the residuals are stationary, it implies the presence of co-integration between integrated economic time series. Numerous studies have shown that the common correlated effects (CCE) estimator yields accurate size tests irrespective of the stationary or non-stationary nature of the variables, as long as the residuals are stationary, indicating the existence of co-integration. The use of CS-ARDL helps estimate the long-run coefficients and test the cointegration. The error correction model of CS-ARDL can be written as follows:

$$\begin{aligned}\Delta log(TFP)_{i,t} =& \phi_i \left[log(TFP)_{i,t-1} - \theta_i (T)_{i,t}\right] \\ &- \sum_{l=1}^{p_{TFP-1}} \lambda_{l,i} \Delta_l log(TFP)_{i,t-1} - \sum_{l=1}^{p_T} \beta_{l,i} \Delta_l (T)_{i,t} + \sum_{l=0}^{p_K} \gamma_{i,I} \bar{z}_{i,t} + \mu_{i,t}\end{aligned} \tag{20}$$

ϕ_i is the error correction coefficient. If ϕ_i is negative and statistically significant, the cointegration exists between $log(TFP)$ and annual temperature as a long-run forcing variable. The test of significance of the above estimate is used as a test for cointegration [18].

This implies that no relevant integrated variables are omitted if a set of variables is cointegrated. Any non-stationary variable not included in the cointegrating relationship would be part of the error term and cause non-stationary residuals, making it difficult to identify cointegration. If cointegration between variables exists, this relationship would still exist even if other relevant variables are added. The cointegration property remains invariant even when the model is extended.

4.2.3 Cross-sectional dependence, causality, sub-sample estimates, endogeneity and non-linearity

Another issue in large panel data estimation is cross-sectional dependence. It is a common problem in literature while using many observations across cross-sections and time. The unobserved common factors can be strong if they affect all countries in the sample or weak if they affect the subset of the countries. Strong factors are induced in the cases of climate change, global shocks, etc., and weak factors may be due to greater financial and trade integration or pollution spillover. Both annual temperature and $log(TFP)$ share common factors without accounting for this in estimation (Equation 18), which may produce an inconsistent and biased coefficient.

The standard method for addressing unobserved common factors involves time dummies and de-meaning the data. However, this technique is only effective if cross-sectional dependence assumptions originate from a common source and remain the same across countries. In cases where the pair-wise cross-section covariance of error components varies across individual series, cross-section de-meaning is not generally applicable and cannot eliminate cross-sectional dependence. However, the CS-ARDL includes a cross-sectional average as a proxy for the unobserved common factors. This approach is known as common correlated effects (CCE). It allows for the heterogeneous effects by correlating the observed regressor with common factors. Chudik, Pesaran, and Tosetti [2011] provided proof of consistency and asymptotic normality of the CCE estimator subject to the finite number of observed common factors than the alternative principal component-based approach. In addition, we explicitly test for cross-sectional dependence (CD) in the residuals of

[18] Following the existing literature, we also use this confirmatory cointegration test. Results of Kao and Pedroni panel cointegration are provided in supplementary material Table A4 Online Appendix

estimated models using the CD test of Pesaran [2021]. The CD test statistic is defined as

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \tag{21}$$

where

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{it} \hat{\varepsilon}_{jt}}{\left(\sum_{t=1}^{T} \hat{\varepsilon}_{it}^2\right)^{\frac{1}{2}} \left(\sum_{t=1}^{T} \hat{\varepsilon}_{jt}^2\right)^{\frac{1}{2}}}$$

This is the sample estimate of the pairwise correlation of the residuals of the estimated models, $\hat{\varepsilon}_{it}$. The CD test statistic is normally distributed under the null hypothesis of no cross-sectional dependence.

Another advantage arising from the presence of cointegration is that the estimates of the long-run parameters are, in general, robust and consistent (e.g. [Pesaran et al., 1995]). The implication is that endogeneity should not lead to inconsistent long-term parameter estimates [Engle and Granger, 1987]. The CS-ARDL estimator remains unaffected by heteroscedasticity, as its variance/covariance estimator relies solely on the difference between individual and mean group estimates [Ditzen, 2021]. After establishing the long-run relationship, we also estimate the causal relationship between TFP and annual temperature. The causality can be unidirectional or bi-directional simultaneously. Following the literature, we use the panel causality test based on the PVECM and Granger non-causality test [Xiao et al., 2022]. To distinguish between cause and effect, the "arrow of time" can be used, which is based on the idea that the cause occurs before the effect. This assumption, of course, eliminates the idea that projections about future temperatures influence current levels of TFP. Since the current total factor productivity primarily depends on the past and the present rather than the predicted temperature scenario, we do not believe this option will likely occur [Herzer, 2019, 2020].

Moreover, the existing studies have suggested that the impact of climate change is not the same across all countries [Dell et al., 2012]. Nonetheless, the conventional dynamic panel estimators, e.g., ordinary least square (OLS), instrumental variables estimation IV, and generalised method of moments (GMM), impose slope homogeneity restrictions across countries, which may produce invalid and misleading estimates of the average slope coefficients in the presence of heterogeneous coefficients [Pesaran et al., 1995]. Therefore, we use a heterogeneous CS-ARDL mean estimator. In addition, we address the issue of parameter heterogeneity by including sub-sample estimates based on the level of development and climate exposure.

In parallel, a nonlinear relationship between temperature and $log(TFP)$ can be verified in two ways. First, a cross-sectionally augmented non-linear ARDL (CS-NLARDL) framework uses two indicators, temperature positive and negative temperature shocks, taking partial sum decomposition from mean temperature and testing for long and short-run asymmetry using the Wald test. Second, a squared temperature term is introduced to adopt the nonlinearity in the model. The squared temperature establishes non-linear relationships in climate-growth nexus literature [Letta and Tol, 2019, Acevedo et al., 2020, Hsiang et al., 2013].

5 Empirical results

5.1 Panel unit root test

The order of integration for the panel data series has been presented first using three-panel unit root tests proposed by Im et al. [2003], Levin et al. [2002] and Pesaran [2007a]. We report the null hypothesis results in the presence of a unit root in Levin et al. [2002] and Im et al. [2003] with intercept and trend, where the intercept varies across countries. Similar to Pesaran [2007a], we compute unit root statistics using lag orders of 0, 1, and 2, respectively. Results of panel unit roots are reported in the Online Appendix (See supplementary material Table A2 Online Appendix). In the set of economic variables, $log(TFP)$ exhibits difference stationarity and is integrated into order 1. As additional control co-variates, trade openness and human capital are integrated into order 1, while foreign direct investment, institutional quality, including all climate indicators, are stationary at this level. Annual mean temperature, maximum temperature, and precipitation exhibit the level of stationarity. Therefore, we observe a combination of both stationary and integrated series.

5.2 Long run estimate and cointegration

We report the result of the baseline specification of equation 18, which provides an estimated coefficient of the relationship between annual mean temperature and $log(TFP)$ in Table 2. Chudik and Pesaran [2015] suggested that a rule of thumb number for lags inclusion in the CS-ARDL model should be an integer part of $T^{\frac{1}{3}}$, where T denotes data span. Dynamic common correlated effects provide inconsistent estimates if the cross-section's lags are too large [Chudik and Pesaran, 2015, Herzer, 2019]. Following these works, we took the number of lags to be one.

The long-run estimate suggests a significant negative relationship between the annual mean temperature and the $log(TFP)$. Regarding the magnitude of impact, an increase in one-degree temperature decreases approximately 3% of TFP in the long run, on average (see column 1 in Table 2). Letta and Tol [2019] concluded that an increase in one degree Celsius decreases total factor productivity growth by 0.49%, and Kumar and Khanna [2019] provide results where one degree Celsius increase is associated with 0.1% change in production efficiency. Comparing our findings to standard panel fixed effect estimation, we find an underestimation of the impact magnitude (see Table A.1). A one-degree Celsius temperature increase resulted in a 1.7% point drop in total factor productivity (TFP) according to FE estimation, whereas CS-ARDL analysis suggested a 3% point decrease. Underestimating the magnitude of temperature's impact on total factor productivity can lead to inadequate resource allocation and ineffective policies for adaptation and mitigation.

The CD test rejects the presence of cross-sectional dependence Pesaran [2021] as reported in Table 2, Column 1. We compute Pesaran [2007a] CIPS panel unit root test for the residual as a test for cointegration [Holly et al., 2010, Baltagi and Griffin, 1997]. We find the presence of cointegration between $log(TFP)$ and annual temperature, suggesting the long-run relationship between temperature shocks and $log(TFP)$. These results confirm that the estimated coefficients are non-spurious.

Table (2) Estimates of the long-run relationship between temperature and TFP

Variables	(1) CS-ARDL	(2) CS-ARDL	(3) PMG-ARDL	(4) PMG- ARDL	(5) NSYC-IV	(6) NSYC-IV
Mean Temperature	-0.0322*		-0.0458**		-0.0079**	
	(0.0146)		(0.0116)		(0.0047)	
Maximum Temperature		-0.0222*		-0.0387*		-0.0084**
		(0.0099)		(0.0105)		(0.0049)
CIPS Statistics	-7.236***	-7.377***	-3.835***	-3.481***	NA	NA
Cointegration	Yes	Yes	Yes	Yes	NA	NA
CD Statistics	-0.19	-0.45	10.674***	10.366***	NA	NA
R-Squared(Mean group)	0.64	0.63	0.48	0.53	NA	NA
Number of observation	609	609	609	609	609	609
Number of Countries	21	21	21	21	21	21

Notes: The dependent variable is log (Total factor productivity) in CS-ARDL model [Chudik and Pesaran, 2015, Ditzen, 2021]. PMG: Pooled mean Group; NSYC-IV: Defactored instrument variable estimation Norkutė et al. [2021]. CD: Cross-sectional dependence test [Pesaran, 2021] - The CD statistics have a null hypothesis of no cross-sectional independence in the residual of the estimated model. CIPS is cross-sectionally augmented IPS of the residuals of long-run relationships. () contains a standard error. **(***)(**) (*) indicate the level of significance at the (1%) (5%) and (10%).**

5.3 Robustness

We check the robustness of the estimated results using three distinct approaches: first, by employing two alternative estimation techniques; second, by employing three alternative indicators as proxies for temperature shock; and finally, by incorporating additional control variables.

We examine the relationship between $log(TFP)$ and annual mean temperature using two alternative techniques: de-factored instrumental variable estimation [Norkutė et al., 2021] and pooled mean group ARDL [Pesaran and Smith, 1995]. The de-factored instrument variable estimation [Norkutė et al., 2021] is a two-stage instrument variable approach that employs the principal component analysis (PCA) and has been utilised to extract common factors from exogenous covariates. This can then be utilised as valid instruments. In the subsequent stage, the PCA is employed again to extract factors from second-stage residual and de-factored covariates as valid instruments. Compared to alternative methods that rely on iterative principal component analysis, this approach has a distinct advantage as it can avoid potential drawbacks, e.g., size distortion, computational complexity, and limited flexibility. We also used pooled mean group ARDL [Pesaran and Smith, 1995] to estimate the long-run relationship between $log(TFP)$ and annual variation in mean temperature. PMG-ARDL relies on both pooling and averaging techniques. PMG-ARDL allows for both homogeneous long-run and heterogeneous short-run coefficients. Estimates of long-run relationship from both pooled mean group ARDL and de-factored error correction approach produce quantitatively similar results (see Columns 3 and 5 in Table2). Nonetheless, when it comes to the PMG-ARDL model, it is important to note that CD statistics reveal the existence of cross-sectional dependence. As a result, the outcomes of the PMG-ARDL approach must be interpreted carefully and with caution. The findings using PMG-ARDL and de-factored instrument variable estimation suggest mean temperature suggests a significant negative impact on $log(TFP)$.

In addition, we also examine the relationship between annual maximum temperature and $log(TFP)$. An increase in maximum temperature renders the country less inhabitable, potentially reducing both labour and capital productivity. Giovanis and Ozdamar [2022] used maximum temperature as a proxy for climate change to study its relationship with fiscal balance. Annual maximum temperature exhibits a negative and statistically significant coefficient (see columns 2, 4 and 6 of Table 2). Both the PMG-ARDL and de-factored instrument variable estimation produce consistent findings. As additional robustness exercises, we included temperature anomalies and temperature volatility as independent regressors instead of temperature levels. The procedure for calculating temperature anomalies is straightforward: a pre-defined multi-year mean temperature is subtracted from a particular temperature observation, and the difference is divided by the temperature's standard deviation. The standard deviation accounts for natural differences in climate variability between nations and corrects for historical variances. This transformation minimises the impact of missing observations, altitude variation, and urban heat impacts while balancing temperature changes across geographic units [Barrios et al., 2010, Portmann et al., 2009].

Temperature volatility is measured as the difference between maximum and minimum temperature. Temperature extremes like heat waves highly depend on how the entire temperature distribution changes, including both central tendency and variability. Such temperature extremes can have detrimental impacts on society and the economy. Temperature volatility can affect output directly but can also raise the stress level of workers and reduce labour productivity [Diebold and Rudebusch, 2022]. This study's findings confirm that temperature anomalies and temperature volatility have a detrimental impact on the $log(TFP)$ (see columns 2 and 3 Table A.1). This result is consistent across all estimated models, providing robust evidence for the negative relationship between temperature and productivity. The negative effect of temperature anomalies and volatility on $log(TFP)$ is further supported by the statistical significance of their respective coefficients, suggesting that even small changes in temperature can have substantial economic consequences.

Table (3) Estimates of the long-run relationship between temperature and TFP with additional variables

Variables	(1) CS-ARDL Log(TFP)	(2) CS-ARDL Log(TFP)	(3) CS-ARDL Log(TFP)	(4) CS-ARDL Log(TFP)	(5) CS-ARDL Log(TFP)
Mean Temperature	-0.0361*	-0.0379***	-0.0364*	-0.0554*	-0.0398*
	(0.0162)	(0.0122)	(0.0143)	(0.0278)	(0.0156)
Precipitation	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Human Capital		0.0014*	0.0012	0.0017	0.0018
		(0.0006)	(0.0012)	(0.0016)	(0.0014)
Trade openness			0.0998*	0.0082	0.1032*
			(0.0443)	(0.0547)	(0.0499)
Institutional quality				-0.0055*	
				(0.0025)	
Foreign direct investment					-0.0020
					(0.0019)
Error correction term	-0.9866***	-1.0825***	-1.2899***	-1.2123***	-1.4116***
CIPS Statistics	-7.140 ***	-7.698 ***	-10.952***	-9.429***	-10.009
Cointegration	Yes	- Yes	Yes	Yes	Yes
CD Statistics	-0.72	0.11	-0.11	-0.54	-0.73
R-Squared(Mean group)	0.35	0.42	0.62	0.71	0.58
Number of observation	609	474	426	389	426
Number of Countries	21	21	18	16	18

Notes: The dependent variable is log (Total factor productivity) in CS-ARDL model: Cross-sectional autoregressive distributed lag of CD [Chudik and Pesaran, 2015, Ditzen, 2021]: The CD statistics has the null hypothesis of no cross-sectional independence in the residual of the estimated model. CIPS is cross-sectionally augmented IPS of the residuals of long-run relationship.() contains standard errors. **(***)(**) (*) indicate the level of significance at the (1%) (5%) level (10%) level**

Although discussed in the previous section, the omitted variables are not a problem if co-integration exists among variables. We perform additional robustness tests to examine long-run estimates of annual mean temperature, including precipitation, human capital, trade openness, institutional quality and foreign direct investment, which shows the negative impact. The long-run estimate of annual mean temperature is statistically significant and negative (reported in Table 3). Overall, we find consistent evidence of annual temperature's negative and significant impact on $log(TFP)$ across all models. We find the presence of co-integration in all the models as the coefficient of error correction term is negative and significant. Moreover, the CIPS panel unit root test results reject the null hypothesis of the presence of unit root in the residual. We also applied the CD test proposed by Pesaran [2021] to investigate the cross-sectional dependence in all our models, and the results suggest the absence of cross-sectional dependence.

5.4 Mechanisms and Adaptation

Annual mean temperature rise can affect total factor productivity through input productivity and reduction in ecosystem services[19]. We use the ratio of output to labour as a proxy of labour productivity and output to capital as a proxy of capital productivity. Forest cover area has been taken as a proxy for ecological services. Regression results of annual mean temperature separately on three variables are presented in 4.

Annual mean temperature negatively and significantly impacts capital and labour productivity (see column 3, Table 4). The production can be adversely affected by the uncertainty arising from extreme weather events caused by climate change [IPCC, 2014]. Extreme weather events can trigger resource reallocation, impacting total factor productivity (TFP) by disrupting resource allocation efficiency. Farmers and investors may choose the incorrect mix of agricultural inputs due to the increased uncertainties surrounding climate change. Investors cut their investments, which leads to less capital and labour and maybe lowers TFP. In estimated models of input productivity (refer to columns 1,2,3 and 4 of Table 4), the results indicate significant negative error correction terms, suggesting the presence of cointegration. Furthermore, the CD statistics indicate no evidence of cross-sectional dependence in the model. These findings provide evidence that the models are well-specified.

The annual mean temperature exhibits a negative and statistically significant relationship with labour and capital productivity in Models 2 and 4 of Table 4, implying that climate change dampens them. One can argue that developing countries face greater challenges in capital accumulation during high temperatures primarily due to their reliance on agriculture, which is particularly vulnerable to temperature fluctuations. This is because higher temperatures can diminish the productivity of agriculture, resulting in lower financial and physical output. As a result, savings may decrease, which in turn can limit the accumulation of capital. Also, elevated temperature-induced extreme weather events can damage physical capital. Higher temperatures can also have negative effects on capital productivity. The elevated temperatures can limit the effectiveness of lubricants in reducing surface friction between mechanical components [Mortier et al., 2010], increase failure rates by increasing the volume of input materials required [Collins, 1963], and slow down hardware processing speed. Furthermore, natural disasters caused by climate change can increase physical risk to capital. Temperature dampens capital efficiency and capital productivity' magnifying its impact on TFP. The decreased capital accumulation and disruptions in agriculture-dependent sectors further diminish TFP by distorting resource allocation and production efficiency.

The existing literature on micro-level studies indicates that temperature can have a detrimental impact on various aspects of economic productivity, including labour productivity [Adhvaryu et al., 2018], labour supply [Somanathan et al., 2021], and cognitive abilities [Hancock et al., 2007]. Our macro-level results support them (refer Table 4). Micro-level studies consistently demonstrate the negative impact of extreme temperatures on labour productivity in labour-intensive manufacturing industries [Stevens, 2019, Cai et al., 2018]. In a study of Chinese industrial firms, Zhang et al. [2018b] found higher temperatures have detrimental effects on both total factor productivity (TFP) and output. Chen and Yang [2019] found that rising temperatures decrease labour productivity, reduce investment, and increase inventory levels. Somanathan et al. [2021] conducted a comprehensive study in India, highlighting the link between high temperatures, decreased worker outputs, and the impact on firm-level production. These findings emphasised the importance of understanding and addressing the economic implications of temperature changes. Labour supply can be reduced with extreme heat through health channels. Warmer temperatures affect working hours in weather-exposed industries and leisure

[19] For detail, see Section 3

time allocation, leading to short-term reallocation or unemployment and changes in labour supply, thus affecting TFP [Graff Zivin and Neidell, 2014]. Extreme heat and cold have reduced work time in China [Garg et al., 2020]. Somanathan et al. [2021] discovered an increased absenteeism in response to high temperatures in an Indian industrial factory. Negative impacts of temperature on both labour supply and labour productivity can have a compounding effect on total factor productivity (TFP) by reducing available labour resources and decreasing the efficiency of the production process. The estimated results in columns 1 and 3 of table 4 are consistent with the literature.

The third mechanism by which extreme events may impact TFP is driven by reducing ecosystem services and shifting resources away from research and development towards climate mitigation efforts. We use forest cover as a proxy for ecosystem services. The findings obtained through the CS-ARDL specification reveal that rising temperatures have a dual effect: a decrease in ecosystem services and a simultaneous increase in natural resource rent. Furthermore, the decline in forest cover resulting from deforestation or unsustainable logging practices leads to resource depletion, ecological degradation, and a reduced capacity to generate natural resource rent over the long term. This relationship is further observed in the estimated coefficients of forest cover and natural resource rent presented in columns 5 and 3 of Table 4 and Table A.2, respectively. The decrease in ecosystem services, particularly in the form of forest cover, can impact total factor productivity (TFP) through various channels[20]. The declined ecology may raise the greater possibility of bacterial and viral infections, known as zoonotic disease transmission, due to the increased human-wildlife interactions, potentially resulting in the deterioration of human health, increased healthcare costs, and productivity losses, ultimately affecting TFP.

[20] Decreased forest cover reduces natural resource availability, contributes to soil erosion and land degradation, disrupts ecosystem services, and diminishes tourism revenue, all of which negatively impact total factor productivity (TFP).

Table (4) Temperature shocks and mechanism

Regressor	(1) Labour CS-ARDL Production function Component	(2) Capital CS-ARDL	(3) Labour productivity CS-ARDL Productivity measure	(4) Capital productivity CS-ARDL	(5) Forest cover CS-ARDL Ecosystem service
Mean Temperature	-0.8059**	-0.1375**	-449.2864**	-0.0050**	-0.0084
	(0.4327)	(0.0823)	(265.4978)	(0.0029)	(0.0085)
Error correction term	-0.9057***	-0.9952***	-0.8948***	-0.9550***	-0.2795***
CIPS Statistics	-8.954 ***	-9.741***	-7.457***	-8.778***	-8.338
Cointegration	Yes	Yes	Yes	Yes	Yes
CD Statistics	1.41	-0.03	-0.97	-2.27*	0.99
R-squared (Mean Group)	0.60	0.32	0.50	0.34	0.90
Number of observation	609	609	609	609	609
Number of Countries	21	21	21	21	21

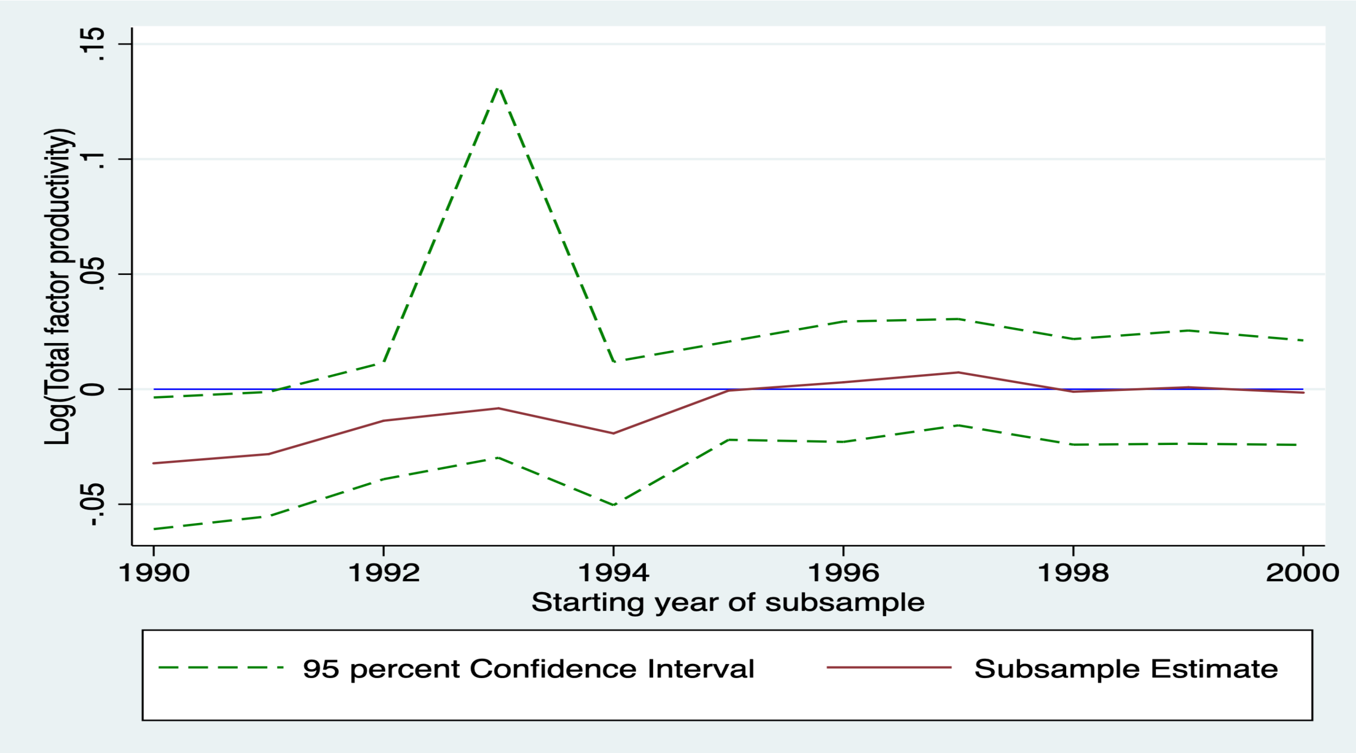
Notes: CS-ARDL: Cross-sectional autoregressive distributed lag of Chudik and Pesaran [2015]Ditzen [2021] CD: Cross-sectional dependence test of Pesaran [2021] CIPS is cross-sectionally augmented IPS of the residuals of long run relationship. () contains a standard error. **(***)(**) (*) indicates the level of significance at the (1%) (5%) (10%)**

Labour -Number Of Persons engaged (in millions), Capital-Capital Stock at Constant 2017 national Prices (in mil. 2017 US $), Labour productivity - GDP per unit of labour, Capital productivity- GDP per unit of capital. Forest cover - Forest Area (sq. km)

Adaptation and mitigation of climate change require factor reallocation in the short run and investment in research and development in the long run. As some sectors are more vulnerable to heat than others, a sectoral-level analysis was conducted to identify the necessary adaptation policies for climate change mitigation. The negative impact of climate change on sectors, with a similar magnitude in emerging economies (see Table A.2), suggests that climate change has significant and widespread economic effects. This study finds similar to Dell et al. [2012], where they observe significant and comparable effects of temperature on agricultural and industrial sectors. Understanding these effects can help policymakers and stakeholders develop effective mitigation and adaptation strategies, including investments in resilient infrastructure, improving crop management practices, and promoting sustainable manufacturing practices. Further, the presence of cointegration is confirmed with stationary residual. However, the estimated CD statistics show the presence of cross-sectional dependence. As temperature increases, crops undergo heat stress, leading to decreased yields. This decline in agricultural output directly affects the country's overall productivity since the agricultural sector holds significant importance, particularly in emerging markets economies. The estimated impact of temperature rise on cereal yield is negative and significant (see Column 4 A.2). The disruption in cereal yield can impact food prices and supplies, potentially impacting food security. It is well established that climate change impacts agricultural productivity and output.

If countries are adapting appropriate measures to climate change, we expect the estimate of the long-run relationship between climate change and $log(TFP)$ to shrink over time. Using the CS-ARDL methodology with a full sample and dropping one year to create a sub-sample. Figure 1 shows that the estimated coefficients do not shrink over time. One possible explanation is that rising temperatures may undermine the effectiveness of both mitigation and adaptation measures intended to address climate change. Additionally, firms may be reluctant to adopt available technologies designed to address climate change due to concerns about the associated costs or a lack of awareness about the potential impact of future extreme climate events. Another factor to consider is that emerging markets may experience structural changes in their growth patterns, resulting in a sectoral reallocation of growth from heat-exposed sectors to those less affected by heat.

Figure (1) Long-Run Effects of Climate Change on Log(TFP) with different sub-sample based on Starting year



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

5.5 Causality

The results in table 5 reveal a long-run causal relationship runs from annual mean temperature to $log(TFP)$. To test for causality, we use two tests for Granger causality - panel vector error correction model (PVECM)-based Granger causality and Xiao-Juodis method of Granger causality [Xiao et al., 2022, Juodis et al., 2021].

The Granger causality establishes whether an indicator changes the other variable or gets affected by that variable, and it also establishes the direction of causality between two variables. We employed the PVECM based on the Granger causality test to identify the direction of causality.

$$(\Delta lnTFP_{it}) = c_{1i} + \alpha_1 ec_{i,t-1} + \sum_{j=1}^{k} \phi_{11} ln(TFP)_{i,t-j} + \sum_{j=1}^{k} \phi_{12} ln(T)_{i,t-j} + \epsilon_{it}^{TFP} \tag{22}$$

$$(\Delta T_{it}) = c_{2i} + \alpha_2 ec_{i,t-1} + \sum_{j=1}^{k} \phi_{21} ln(TFP)_{i,t-j} + \sum_{j=1}^{k} \phi_{22} ln(TFP)_{i,t-j} + \epsilon_{it}^{T} \tag{23}$$

where lagged differences show short-run dynamics, while the error correction term gives a long-run relationship, the optimal lag length was chosen to be 2 using the information criteria. Here, ec refers to the error correction term, and k is the number of optimal lags.

Specifically, the error correction term represents the deviation from the long-run relationship. At the same time, the adjustment coefficients, α_1 and α_2, capture how $lnTFP_{it}$ and T_{it} respond to the deviation from long-run relationship. In PVECM-based Granger causality, there are two sources of causality, i.e. error correction and lagged dynamic terms. The lagged dynamic term captures the short-run Granger causality test. We can perform three types of causality - weak, short-run Granger causality and strong exogeneity tests.

To test for weak exogeneity, we set the coefficient of the error correction term to zero. The short-run Granger causality test is performed on the lagged value of the explanatory variable. In strict exogeneity, we test the joint significance of the error correction term and the lagged value of the explanatory variable. Weak exogeneity is akin to long-run causality. Hence, if we fail to reject the null hypothesis of weak exogeneity of temperature shock, total factor productivity has no causal impact. The results from Table 5 (panel 2.1) show that the null hypothesis of weak exogeneity is rejected at the 1% level for annual temperature. Similarly, short-run Granger causality is rejected at a 10% level. Finally, strong exogeneity, which does not differentiate between the short and long runs, is rejected, implying that annual temperature Granger causes total factor productivity. In contrast, we find no evidence of reverse causality of $log(TFP)$ to temperature (see Table 5 panel 2.2). Long-run and short-run Granger causality are rejected, implying no evidence of reverse causality from $log(TFP)$ to annual temperature.

The model developed by Xiao et al. [2022], Juodis et al. [2021] for no Granger causality is valid for homogeneous or heterogeneous coefficients. Under the null hypothesis, the causality parameter will be zero. Hence, it is homogeneous Juodis et al. [2021] used a split panel jackknife and construct estimators that are free from nickel bias. This approach has several advantages over the model offered by Dumitrescu and Hurlin [2012]. Although Dumitrescu and Hurlin [2012] test accounts for heterogenous slope under the null and alternative hypothesis, it is only justified for the sequence when $\frac{N}{T^2}$ tends to zero. This implies that the method can suffer substantial size distortion if T is sufficiently smaller. This method involves running N individual regressions to obtain N individual-specific Wald statistics, which are subsequently averaged over the cross-section. The results obtained from Juodis et al. [2021], Xiao et al. [2022] for Granger non-causality indicate bidirectional causality between temperature and TFP in the short-run, indicating the presence of reverse causality in contrast to the findings of PVECM-based Granger causality. The null hypothesis of "average temperature does not Granger cause log(TFP)" is rejected, suggesting causality runs from annual temperature to $log(TFP)$ based on the significant Wald coefficients. Additionally, we observe causality running from $log(TFP)$ to temperature (see panel 15).

Therefore, this study shows that the relationship between temperature and TFP is complex and depends on the time horizon considered. Specifically, we find mixed evidence for short-run bi-directional causality between them, with the improved method by Xiao et al. [2022] suggesting bi-directional causality. In contrast, the PVECM-based short-run Granger causality test does not find such evidence. However, the PVECM-based approach finds evidence for unidirectional long-run causality from temperature to TFP, as indicated by the significant coefficient of the error correction term and the rejection of the null hypothesis for weak exogeneity.

Table (5) Causality tests between log(TFP) and Temperature shock

1. Juodis, Karavias and Sarafidis (2021) Granger non-causality test				
		HPJ Wald Statistics	Number of Lags	
H0- average temperature does not Granger cause Log (TFP)		5.0259**	1	
H0- Log(TFP) does not Granger cause average temperature		4.8071**	1	
2. Granger causality test based on PVECM				
	Chi-square statistics	Coefficient on lagged TEMP	coefficient of lagged TEMP	Number of Lags
2.1 H0- average temperature do not Granger cause Log (TFP)				
Weak exogeneity test	66.8811			2
$a_1 = 0$	[0.0000]			2
Short-run Granger non-causality test	4.7973	0.0011	0.0060	2
$\phi_{12j} = 0$	[0.0908]	(0.0029)	(0.0027)	2
Strong exogenity test	71.6148			2
$\phi_{12j} = a_1 = 0$	[0.0000]			2
Number of observations	609			
Number of countries	21			
	Chi-square statistics	Coefficient on lagged LTFP	coefficient of lagged LTFP	Number of Lags
2.2 H0- Log (TFP)do not granger average temperature				
Weak exogeneity test	0.0374			2
$a_1 = 0$	[0.8460]			2
Short-run Granger non-causality test	0.3790	-0.0944	0.3339	2
$\phi_{12j} = 0$	[0.8272]	(0.5363)	(0.5441)	2
Strong exogenity test	0.4180			2
$\phi_{12j} = a_1 = 0$	[0.9635]			2
Number of observations	609			
Number of countries	21			

Notes: [] contains p values of Wald statistics and () contains standard error of the individual coefficient.
(*)(**) (*) indicate the level of significance at the (1%) (5%) level (10%) level**

5.6 Heterogeneity

The existing literature indicates that the effect of annual temperature varies significantly across different geographical regions. The impact of temperature shocks on macroeconomic outcomes is also highly heterogeneous among countries, with differential effects observed between developed and developing nations [Dell et al., 2012, Hsiang et al., 2013, Acevedo et al., 2020, Letta and Tol, 2019]. The standard dynamic panel approach imposes conditions of slope homogeneity across cross-sections that produce inconsistent results and are potentially misleading in the presence of a heterogeneous coefficient. The CS-ARDL employs a heterogeneous mean estimator and takes care of slope heterogeneity.

We address the issue of parameter heterogeneity by re-estimating the impact of long-term annual temperature on $\log(TFP)$ by stratifying our sample into sub-samples based on climate exposure and level of development. Subsequently, we created three sub-sample categories in terms of average temperature: the cold region (0-10 degrees Celsius), the moderate region (10-20 degrees Celsius), and the hot region (20-30 degrees Celsius). In the second sub-sample, we employed the level of development as the criterion and created two sub-samples: less-developed EMEs (with per capita income less than 4000 US dollars) and developed EMEs (with per capita income more than 4000 US dollars).

In all three climate exposure sub-samples, we find a negative impact of annual mean temperature on $log(TFP)$. This study shows that the negative impact of annual mean temperature on $log(TFP)$ remains significant in cold and moderate regions, with adverse effects observed in very hot and cold temperatures. It suggests that as the temperature rises, the productivity drop slowed down a bit from -2.73% in the cold regions to -1.44% in moderately hot regions, and it increased up to -2.69% in the very hot region (see columns 1-3, Table 6). The productivity loss tends to be greater in the extreme climatic regions than the moderately hot regions. These results suggest the potential for non-linearity in the relationship between temperature and TFP[21], labour and physical capital effects [22], energy demand, cost, and supply chain disruption. We have also examined the non-linear relation between temperature and TFP in Section 5.7.

The level of development directly influences a country's ability to cope with weather shocks and reduce associated damages. Higher-income countries typically have well-equipped housing and better government policies that enhance resilience to severe weather events. However, there is a lack of robust evidence on how the development level protects countries against climate change impacts. In the second panel, we find a negative and significant impact of temperature on $log(TFP)$, with the magnitude of the impact being higher in less developed countries than in developed as a one-degree Celcius change in average temperature decreases 5.86% of TFP in the long run whereas, it is 0.6% of TFP in high-income countries(see columns 4-5, Table 6). Property rights in many less developed countries are not well-established, and access to credit is limited, which can lead to further adverse consequences in the face of climate change. Hisali et al. [2011] found richer countries have better property rights and access to credit than poorer countries. Additionally, Di Falco et al. [2011] found that easy access to credit can limit the adverse effect of temperature rise. Poorer countries spend less on productivity-enhancing technologies due to their limited access to credit, which can exacerbate the negative impacts of climate change in these economies. This study finds consistent results similar to Letta and Tol

[21]Different economic activities and sectors have an optimal temperature range in which they operate most efficiently. Rising temperatures negatively affect productivity, benefiting activities sensitive to colder temperatures, like agriculture in colder regions. However, excessive heat reduces productivity beyond the optimal range, particularly for labour-intensive sectors and temperature-sensitive processes.

[22]Heat stress, exhaustion, and heatstroke impair workers' abilities, increasing accident risks and reducing efficiency. Similarly, high temperatures affect machinery and equipment performance, decreasing productivity.

[2019]. Based on country-level data from emerging market economies, the study reveals that developed economies exhibit a smaller marginal effect of heat on productivity.

For the sake of completeness, the error correction term is negative and significant, thus indicating the existence of cointegration. Even CIPS statistics confirm the estimated result is non-spurious. Cross-sectional dependence emphasises that even though fewer countries exist in models 1 and 4, the cross-sectional and time-series data ensure more than enough observations to produce reasonably reliable estimates. However, statistical power is sensitive due to the relatively small sample size.

Table (6) Estimates of the long-run relationship between temperature and TFP

	(1) Cold CS-ARDL	(2) Moderate Hot CS-ARDL	(3) Very Hot CS-ARDL	(4) less-developed EMEs CS- ARDL	(5) Developed EMEs CS-ARDL
Mean Temperature	-0.0273*	-0.0144*	-0.0269	-0.0586*	-0.0056
	(0.0087)	(0.0067)	(0.0197)	(0.0307)	(0.0080)
CIPS Statistics	-3.639***	-2.561**	-5.743***	-3.132***	-6.288***
Cointegration	Yes	Yes	Yes	Yes	Yes
R-squared (Mean Group)	0.43	0.35	0.42	0.29	0.38
Number of observation	112	189	270	189	370
Number of Countries	4	7	10	7	14

Notes: The dependent variable is log (Total factor productivity) CS-ARDL: Cross-sectional autoregressive distributed lag of Chudik and Pesaran [2015]Ditzen [2021] CD: Cross-sectional dependence test of Pesaran [2021] - The CD statistics have the null hypothesis of no cross-sectional independence in the residual of the estimated model. CIPS is cross-sectionally augmented IPS of the residuals of long-run relationships. () contains standard error. Cold - Temperature Bin(0-10 C) , Moderate Hot - Temperature Bin(10-20 C) and Very Hot - Temperature Bin(20-30 C) **(***)(*) (**)Indicate rejection of the null hypothesis at the(1%) (5%) level (10%) level**

5.7 Non-Linearity

The existing literature has investigated the non-linear effects of climate change on economic growth [Burke et al., 2015b, Dell et al., 2012]. In this study, we employed two distinct approaches to explore non-linearity, including the quadratic term [Letta and Tol, 2019, Acevedo et al., 2020]. Again, we utilised a Cross-Sectionally Augmented Non-Linear ARDL model (CS-NARDL) to study the relationship between climate change and total factor productivity.

This study revealed a statistically significant and negative impact of quadratic temperature on TFP, consistent with Letta and Tol [2019]. The negative and significant value of the error correction term suggests the presence of cointegration. Even CIPS Statistics for residual is stationary, supporting cointegration and non-spurious result (Table 7). The CS-NLARDL methodology provides a novel approach for modelling the impact of temperature shocks on $log(TFP)$ that accounts for asymmetry in the response. This implies that positive and negative temperature shocks are not expected to affect TFP similarly. To capture this asymmetry, we have created two variables, one for positive temperature shocks and another for negative temperature shocks. These variables are computed through the use of partial sum decomposition of temperature changes, as defined below:

$$y_t = \beta^+ PosTemp_t + \beta^- NegTemp_t + u_t$$

where $\beta^+$and β^- are the associated long-run parameters and $Temp_t$ is a k$\times$1 vector of regressors decomposed as:

$$Temp_t = Temp_0 + PosTemp_t + NegTemp_t,$$

where $PosTemp_t$ and $NegTemp_t$ sum processes of positive and negative changes in $Temp_t$:

$$PosTemp_t = \sum_{l=1}^{t} \Delta PosTemp_l = \sum_{l=1}^{t} \max\left(\Delta PosTemp_l, 0\right)$$

$$\text{and } NegTemp_t = \sum_{l=1}^{t} \Delta NegTemp_l = \sum_{l=1}^{t} \min\left(\Delta NegTemp_l, 0\right)$$

$$\begin{aligned} \Delta log(TFP)_{i,t} =& \phi_i \left[log(TFP)_{i,t-1} - \theta_{1i}(PosTemp)_{i,t} - \theta_{2i}(NegTemp)_{i,t}\right] \\ & - \sum_{l=1}^{p_y-1} \lambda_{l,i} \Delta_l log(TFP)_{i,t-1} \\ & - \sum_{l=1}^{p_x} \beta_{1l,i} \Delta_l (PosTemp)_{i,t} \\ & - \sum_{l=1}^{p_x} \beta_{2l,i} \Delta_l (NegTemp)_{i,t} + \sum_{l=0}^{p_T} \gamma_{i,I} \bar{z}_{i,t} + \mu_{i,t} \end{aligned} \tag{24}$$

with $\bar{\mathbf{z}}_{t-l} = \left(\overline{log(TFP}_{i,t-l}, \overline{(PosTemp)}_{i,t-l}, \overline{(NegTemp)}_{i,t-l}\right)$.

The results of the CS-NLARDL model indicate a non-linear relationship between temperature shocks and total factor productivity (TFP). Specifically, the impact of positive temperature shocks on TFP is negative, while the impact of negative temperature shocks is positive, confirming the presence of asymmetry. Moreover, the error correction term is negative and significant, suggesting deviations from the long-run equilibrium are corrected over time. To assess the presence of asymmetry between positive and negative temperature shocks, we utilised the Wald test [Bahmani-Oskooee and Arize, 2019, Khatoon et al., 2022]. The results of this test, presented in Table 7, indicate that we can reject the null hypothesis of symmetry in both the short and long run, providing evidence for the absence of asymmetry between positive and negative temperature shocks. Furthermore, the stationary residuals support the non-spuriousness of the estimates and the presence of cointegration.

This study concludes that temperature does have a negative effect and tends to show an inverse U-shaped impact on TFP across the entire sample. Letta and Tol [2019] do not observe a significant non-linear relationship between temperature and TFP growth, in contrast to us. Interestingly, Zhang et al. [2018b] found an inverted u-shaped relationship between temperature and TFP in a micro-econometric study using data from 500,000 Chinese manufacturing firms between 1998 and 2007.

Table (7) Estimates of the Asymmetric Panel CS-ARDL

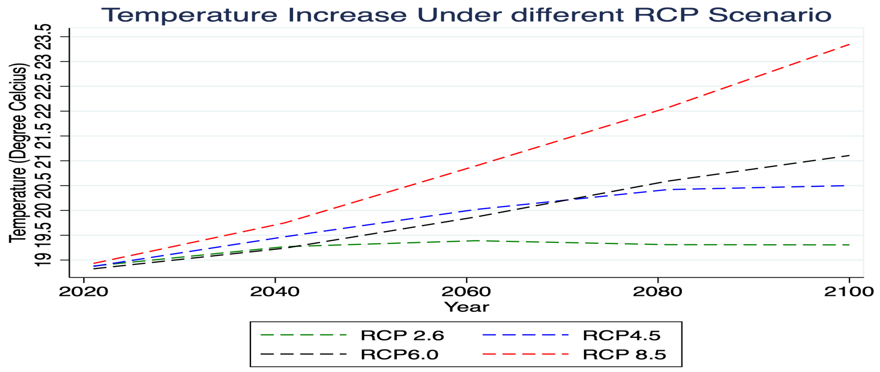
	(1) Asymmetric CS-ARDL Log(TFP)	(2) CS-ARDL with non linear term Log(TFP)
Error correction term	-0.8049***	-1.1618***
Long run coefficient		
Temperature(-ve)	0.0001	
	(0.0068)	
Temperature(+ve)	-0.0013	
	(0.0059)	
Temperature		0.6837
		(0.2870)
Temperature2		-0.0168**
		(0.0086)
Short run coefficient		
Temperature(-ve)	-0.0034	
	(0.0047)	
Temperature(+ve)	-0.0040	
	(0.0044)	
Temperature		0.7379**
		(0.2855)
Temperature2		-0.0190**
		(0.0074)
Long run assymetry		
Temperature(-ve)/ Temperature(+ve)	0.71	
Short run assymetry		
Temperature(-ve)/ Temperature(+ve)	0.52	
CIPS Statistics	-8.129**	-6.789 ***
Cointegration	Yes	Yes
CD Statistics	-0.22	-0.43
R-squared (Mean Group)	0.31	0.40
Number of observation	474	609
Number of Countries	21	21

Notes: The dependent variable is log (Total factor productivity) CS-ARDL: Cross-sectional autoregressive distributed lag of Chudik and Pesaran [2015]Ditzen [2021] CD: Cross-sectional dependence test of Pesaran [2021]. CIPS is cross-sectionally augmented IPS of the residuals of long-run relationships. () contains a standard error. **(***)(**) (*) indicate the level of significance at (1%) (5%) and (10%) level**

5.8 Projected impact of temperature on TFP 2021-2100

We projected the future impact of climate change on the TFP by combining the estimated coefficients (see model 1, Table 2) with the projection of climate change under different RCP scenarios for the period 2021-2100. We assumed that the future impact of climate change on TFP would respond similarly to our observed sample. The projected temperature level data was obtained from the World Bank Climate Change Knowledge Portal, and we employed a multi-model ensemble approach, which combines monthly data from 16 different models for more accurate results. We observe 0.426 Degrees Celsius, 1.627 Degrees Celsius, 2.283 Degrees Celsius and 4.4137 Degrees Celsius rise in temperature levels for RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 scenarios, respectively (see Figure 2).

Figure (2) Temperature under RCP Scenarios over 2021-2100



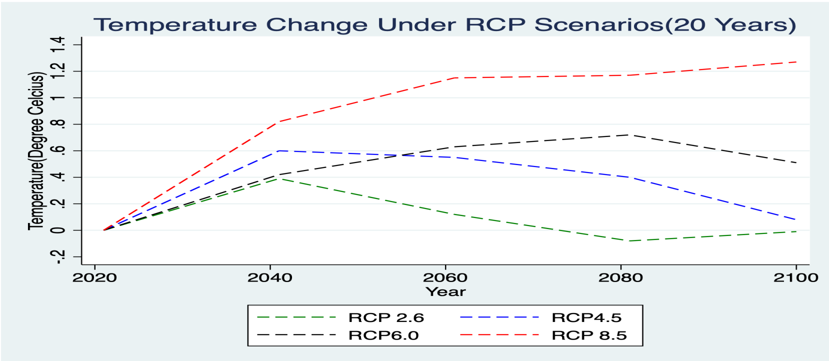


Table (8) TFP projections (%) over the period 2020–2099

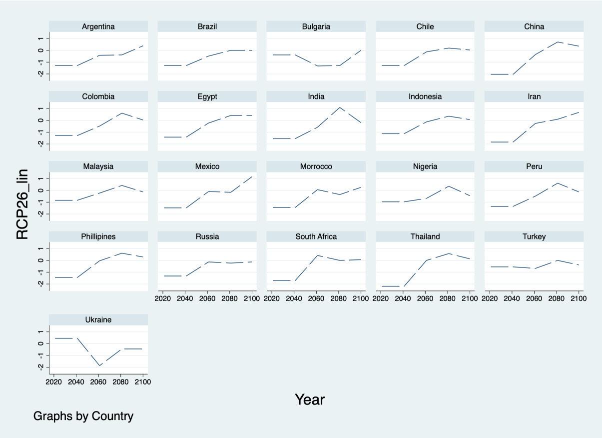
Scenario Level of log(TFP)	2021-2041	2041-2061	2061-2081	2081-2100
RCP 2.6	-1.255	-0.386	+0.2576	+0.032
RCP 4.5	-1.932	-1.771	-1.288	-0.2576
RCP 6.0	-1.3524	-2.02	- 2.32	-1.642
RCP 8.5	-2.6404	- 3.70	-3.77	-4.089

Source: Authors' calculation based on data drawn from the World Bank Climate Change Knowledge Portal

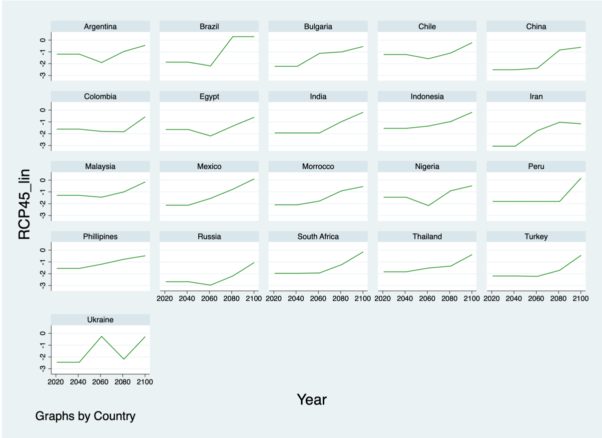
Notes: Positive (+) and Negative(-) sign indicates the magnitude of increase or decrease of the level of TFP in 2021-2100. RCP 2.6 - Low Emission Scenario, RCP 4.5 RCP 6.0- Intermediate emission scenario, RCP 8.5- Business as usual scenario

Using the estimated parameters, we find that the level of TFP decline under the RCP 8.5 (Business as usual) Scenario is the highest, registering at 14.2% points. The declines in TFP levels under RCP 2.6, RCP 4.5, and RCP 6.0 account for 1.37% points, 5.15% points, and 7.34% points, respectively. In the low-emission scenario, the countries would experience a decline in TFP of 1.25% points and 0.38% points, respectively, during the periods 2021-2041 and 2041-2061 and an increase in TFP of 0.25% points and 0.03% points, respectively, in the years 2061-2081 and 2081-2100. Similar trends are shown by the intermediate emission scenarios RCP 4.5 and RCP 6.0. According to the RCP 6.0 Scenario, the TFP declines by 1.352% points between 2021 and 2041, 2.02% points between 2041 and 2061, 2.32% points between 2061 and 2081, and 1.642% points between 2081 and 2010. In the "business as usual" scenario, we observe a sharp reduction in TFP, with declines in TFP of 2.64% points in the period 2021-2041, 3.70% points in the period 2041-2061, 3.77% points in the period 2061-2081, and 4.084% points in the period 2081-2100.

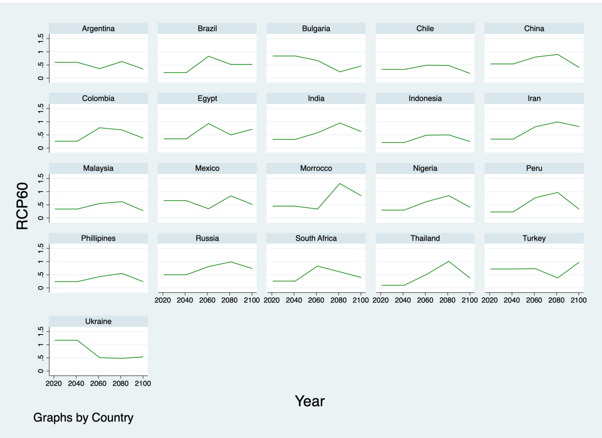
Figure (3) TFP projections (in percentage) over the period 2020–2099 (Linear Projection Estimate)



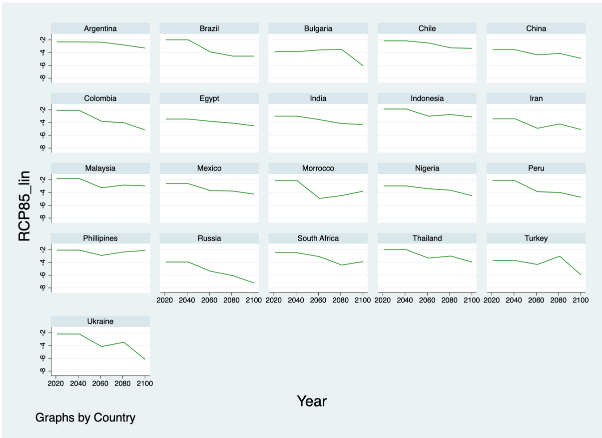
(a) RCP 2.6 Low Emission Scenario



(b) RCP 4.5 Intermediate emission scenario



(c) RCP 6.0 Intermediate emission scenario



(d) RCP 8.5 Business as usual scenario

Source: Authors' calculation based on data drawn from the World Bank Climate Change Knowledge Portal; Note: Figures are percentage changes of the TFP in 2021-2100. RCP 2.6 Low Emission Scenario, RCP 4.5 RCP 6.0 Intermediate emission scenario, RCP 8.5 Business as usual scenario

The future projection of TFP losses due to temperature shocks reveals that the impact of temperature is not uniform across countries under different RCP Scenarios. Specifically, under the RCP 2.6 Scenario, we observe a decline in TFP losses from 2080 to 2100 for developed emerging economies. In contrast, under the business-as-usual scenario, we find adverse effects of temperature shocks in TFP losses, predominantly affecting countries in hot climatic zones. Additionally, we also used projection in conjunction with the estimate of the squared term (see Table 7) in the non-linear estimates. We found similar results (See Online Appendix Table A5 and Figure A3). Similarly, Moyer et al. [2014] and Dietz and Stern [2015] demonstrated that small TFP damages significantly alter consumption growth paths, the social cost of carbon and future growth impacts.

6 Conclusion

This study offered a simple conceptual framework that explained the rise of global temperature from growing carbon emissions and fossil fuel consumption, dampening the total factor productivity by damaging in three channels - losses in ecology, labour and capital productivity. Further, it explored the impact of climate change on TFP using the CS-ARDL model, which is much better than the existing models and offers results closer to the scientific climate model. This model addresses endogeneity, cross-sectional dependence and heterogeneity, producing better estimates. The findings suggest a significant negative effect of temperature rise on the TFP. In the long term, a degree Celcius increase in the mean temperature reduces of TFP by 3.22% points. The robustness of the results has been verified with a set of alternatives. This study overcomes the limitations of current damage functions used in IAM projections. These functions, which calculate the economic impacts of climate change, are often static and fail to consider the dynamic effects of temperature changes on macroeconomic growth. Additionally, integrating long-run estimates into IAMs can improve understanding of the long-term impacts of climate change on welfare [Chang et al., 2023, Moyer et al., 2014, Dietz and Stern, 2015, Tol, 2022]. This further highlights that the TFP (Total Factor Productivity) losses caused by temperature changes can be mitigated but requires greater investments in the research and development sector and encouragement to enhance better energy efficiency and green technologies.

We also find labour productivity, capital productivity, and reduction in ecosystem services as the potential channels through which climate change influences the TFP. Such transmission dynamics of temperature change impacting TFP are vital for effective adaptation policies, enabling policymakers to allocate resources efficiently to vulnerable sectors. This paper conveys that an emerging country cannot sustain growth by ignoring mitigation strategies to control the damage done by the temperature rise.

This apart, climate change has a heterogeneous impact, with greater adverse effects in less developed than relatively developing emerging countries. So, temperature hurts TFP across the entire sample, with poorer countries being more severely affected than richer ones and the extreme climatic zones being more affected than the moderately hot ones. Letta and Tol [2019] do not observe a significant non-linear relationship between temperature and TFP growth, in contrast to us.

This study highlights important policy recommendations and insights on the future implications of climate change in emerging markets. We project the potential future impact of climate change on the TFP using temperature projection data drawn from the climate change knowledge portal combined with our estimated parameter estimate. Under the high emission scenario, TFP declines from 2.6 to 4.0% points. Our findings indicate climate change will greatly harm less developed emerging markets, necessitating substantial climate funds to support effective adaptation and mitigation policies. Policymakers should prioritise raising funds for these purposes, seeking commitments from major international banks such as the European Central Bank, International Monetary Fund and World Bank. Countries can take several actions to address climate change, including enhancing climate prediction accuracy, promoting energy conservation, supporting green technologies in high-energy-consuming industries, investing in technologies for extreme climate events, and providing subsidies to the research and development sector.

However, it is essential to acknowledge the limitations and caveats of this study. TFP calculations are based on the Solow residual method, which may be subject to measurement errors. Unfortunately, no other comprehensive TFP datasets available at the country level cover a similar time frame for the derivation [Letta and Tol, 2019]. Additionally, it is worth noting that potential future climate change, especially under extreme climate scenarios, could lead to a significant rise in sea level, which would be an unprecedented historical event. Future climate impact projections must be suitably discounted to properly account for adaptation and mitigation strategies. Future projection in this study is premised on the assumption that the historical relationship will stay the same. Future research should focus on identifying the potential empirical nexus between climate change and ecosystem services.

To address the asymmetric impacts of climate change through a combination of adaptation and mitigation measures, the strategies for climate finance, green technology, and adherence to the Paris Climate Action Plan require proper planning in terms of priorities for promoting sustainable total factor productivity (TFP) and ensuring a thriving economy for future generations. Failing to take decisive action would further add to the risks of irreversible environmental damage and economic instability and make it imperative for countries to work together to combat the challenges posed by climate change. The benefits of proactive climate action far outweigh the costs, as it leads to a healthier planet, enhanced resilience, and sustainable economic development.

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Appendices

Table (A.1) Addition robustness result with fixed effect, temperature volatility and temperature anomalies

	Log(TFP) Panel Fixed effect	Log(TFP) CS-ARDL	Log(TFP) CS-ARDL
Mean Temperature	-0.0162		
	(0.0123)		
Temperature Volatility		-0.03171	
		(0.0234)	
Temperature Anomalies			-0.4146*
			(0.0085)
Error correction term		-1.4242***	-1.1989***
Economic Indicator	✓	✓	✓
Precipitation	✓	✓	✓
Time fixed effect	✓		
CD Test statistics	-2.955**	0.73	-2.09*
Number of observation	609	609	609
Number of Countries	21	21	21

Notes: CS-ARDL: Cross sectional autoregressive distributed lag of Chudik and Pesaran [2015]Ditzen [2021] CD: Cross sectional dependance test of Pesaran [2021] - The CD statistics has null hypothesis of no cross sectional independance in the residual of estimated model. () contains a standard error. **(***)(*) (**)Indicate rejection of the null hypothesis at the(1%) (5%) level (10%) level** Temperature volatility - the maximum temperature in year t - the minimum temperature in year t-1 , Temperature Anomalies - (Temperature- long run average temperature)/ Standard deviation of temperature

Table (A.2) Temperature shocks and Sectoral impact

Regressor	(1) Manufacturing CS-ARDL Sectoral impact	(2) Agriculture CS-ARDL	(3) Natural Resource rent CS-ARDL Prices	(4) Cereal yield CS-ARDL
Mean Temperature	-0.2011	-0.2056	0.3257	-128.31***
	(0.3961)	(0.2743)	(0.3138)	(39.7184))
Error correction term	-0.9226***	-1.1557***	-0.9899***	-1.3061***
CIPS Statistics	-5.466	-7.182	-9.849***	-9.877***
Cointegration	Yes	Yes	Yes	Yes
CD Statistics	-2.08*	-2.12**	4.12***	-2.27**
R-squared (Mean Group)	0.19	0.35	0.60	0.42
Number of observation	609	609	609	609
Number of Countries	21	21	21	21

Notes: CS-ARDL: Cross sectional autoregressive distributed lag of Chudik and Pesaran [2015]Ditzen [2021] CD: Cross-sectional dependence test of Pesaran [2021]CIPS is cross-sectionally augmented IPS of the residuals of long run relationship .() contains a standard error. **(***)(**) (*) indicates the level of significance at the (1%) (5%) (10%)**

Cereal yield-Cereal Yield (kg per hectare) Manufacturing -Manufacturing value-added s % of GDP Agriculture -Agricultural value-added as % of GDP Natural resources rent-Total natural resources rents (% of GDP)

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8 Declaration of competing interests

The authors do not have any conflict of interest in this research. We declare that we have no competing interests related to this manuscript.

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10 CRediT authorship contribution statement

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

11 Data Availability

Data are available from the corresponding author on reasonable request

Long-run macroeconomic impact of climate change on total factor productivity - Evidence from Emerging Economies

Naveen Kumar*   Dibyendu Maiti†

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A.1 Summary of Studies on the impact of temperature on Total factor productivity

Table (A.1) Summary of Studies on the impact of temperature on Total factor productivity

Study	Study Type	Climate Change measure	Outcome Variable	Period	Estimation Method	Conclusion
Dell et al. [2014]	Empirical(Cross-Country)	Mean Temperature	Growth and level	1950-2003	Panel Fixed effect,Linear	temperature is affecting growth rates, not just income levels
Hsiang et al. [2013]	Empirical(Cross-Country)	Annual Mean Temperture	GDP	1970-2006	Panel Fixed effect,Linear	National output falls 2.5 percent per 1°C warming
Burke et al. [2015]	Empirical(Cross-Country)	Annual Mean Temperture	GDP per capita	1960-2010	Country Fixed effect	Non-linaer relationship
Kahn et al. [2021]	Empirical(Cross-Country),	Long term temperture anamolies	real per capita GDP	1960-2014	Fixed effect , HPJ-Fixed effect, ARDL model	persistent increase in average global temperature by 0.04°C per year, in the absence of mitigation policies, reduces world real GDP per capita by 7.22 percent by 2100
Acevedo et al. [2020]	Empirical(Cross-Country)	fluctuations in temperature	real per capita GDP	1950–2015	Local linear Projection, Linear	a rise in temperature lowers per capita output in countries with high average temperatures, in both the short and medium term,
Dietz and Stern [2015]	Theoretical Model	Allows temperature affect TFP				assumed climate change as an endogenous damage driver, particularly for TFP, and found a rapid increase in the social cost of carbon if the global mean temperature is above the industrial leve
Moore and Diaz [2015]	Theoretical Model	DICE Model(Integrated Assesment Model)				found allowing climate change to directly affect economic growth via the impact on TFP and investment, which, in turn, increases the social cost of carbon
Ortiz-Bobea et al. [2018]	Empirical(USA)-Micro	Avg Temp and Avg Rain	Estimation of Production Function	1960-2004	Bayesian Method	weather shocks accelerated productivity growth in 12 out of 16 states by the equivalent of 11.4% of their group-average TFP growth, but slowed down productivity by the equivalent of 6.5% of the group-average TFP growth in the other four states
Letta and Tol [2019]	Empirical(Cross-Country)	fluctuations in temperature	TFP Growth rate	1960-2006	Fixed effect, Linear	results show a negative relationship only exists in poor countries, where a 1 °C annual increase in temperature decreases TFP growth rates by about 1.1–1.8 percentage points, whereas the impact is indistinguishable from zero in rich countries.it basically confirms the results of Dell et al. (2012) and rejects the conclusions of Burke et al. (2015). We also show that the assumptions of Dietz and Stern (2015), Moore and Diaz (2015) and Moyer et al. (2014) have no empirical grounding.
Kumar and Khanna [2019]	Empirical(Cross-Country)	Annual Mean Temperture	TFP Growth rate	1950-2014	Stochastic Frontier Analysis	an increase in temperature by 1 degree Celcius reduces average efficiency growth while increasing its uncertainty, Heterogenous impact

A.2 Panel unit root test

A.2.1 Panel unit root test

In the first generation panel data unit root test , we estimate following uni-variate model

$$Y_{it} = \mu_i + \phi_i Y_{it-1} + \epsilon_{it} \tag{1}$$

or

$$\Delta Y_{it} = \mu_i + \rho_i Y_{it-1} + \epsilon_{it} \tag{2}$$

where i= 1,2,.... N represents cross-sectional units.

t = 1,2,.....,T represent time series observations and μ_i is fixed effects. Null Hypothesis is

$$H_0 : \rho_i = 0$$

The main difference between different models is the level of heterogeneity. In our paper, we have used IPS and LLC tests.

A.2.2 Levin- Li - Chu test

Levin, Lin, and James Chu [2002] test assumes that all panels have a common auto-regressive parameter. In order to augment the model to take serial correlation into consideration, Levin, Lin, and James Chu [2002]uses lags of the dependent variable. We use the mean corrected form of equation 1.

$$\hat{Y}_{it} = \phi_i \hat{Y}_{it-1} + \epsilon_{it} \tag{3}$$

$$\hat{Y}_{it} = Y_{it} - \bar{Y}_i$$

Given the initial values and assumption that errors are independently and identically distributed.

$$E(\epsilon_{it}) = 0$$

$$E(\epsilon_{it}\epsilon_{js}) = \sigma_i^2 ......\forall i = j, t = s.$$

$$E(\epsilon_{it}\epsilon_{js}) = 0......\forall i \neq j, t \neq s.$$

In Levin, Lin, and James Chu [2002], the null hypothesis that each individual time series contains a unit root is to be tested against the alternative hypothesis that each time series is stationary.

$$H_0 : \rho_i = \rho = 0$$

$$H_A : \rho_i = \rho < 0$$

for all i = 1, . . . N, with auxiliary assumptions about the individual effects $\mu_i = 0$ for all i = 1, . . . N under H_0.

We follow three steps. In Step one augmented dickey fuller regression is run on each cross-section to obtain residuals and then these residuals are adjusted to correct individual specific variances. Once the optimal lag order is determined two auxiliary regression is run to get residuals and these residuals are standardised to control for different variances across 'i'. In step two, We transform the residual and these residuals using orthogonalized transformation[Arellano and Bover, 1995]

$$e_{it}^* = \sqrt{\frac{T-t}{T-t+1}}.(\tilde{e_{it}} - \frac{\tilde{e_{it+1}} + ... + \tilde{e_{it+1}}}{T-1})$$

and with intercept and trend

$$v_{it-1}^* = (\tilde{v_{it-1}} - \tilde{v_{i1}} - \frac{T-1}{T}\tilde{v_{iT}})$$

with intercept and no trend

$$v_{it-1}^* = (\tilde{v_{it-1}} - \tilde{v_{i1}})$$

with no intercept and no trend

$$v_{it-1}^* = (\tilde{v_{it-1}})$$

Finally in step 3 , the pooled regression with NT^* observations

$$e_{it}^* = \rho v_{it-1}^* + \epsilon_{it} \tag{4}$$

where T^* is the average number of observations per individual panel. $T^* = T - \bar{P} - 1$ $\bar{P}$ is the average lag order of the individual ADF regression. Pooled regression is run to obtain t statistics for $H_0 = 0$ which follows a standard normal distribution and we don't require any kernel computation. An alternative hypothesis for Levin, Lin, and James Chu [2002] is the autoregressive process for all cross sections is stationary. It requires pooling of the observations before forming the pooled statistics.

A.2.3 Im–Pesaran–Shin test

Im, Pesaran, and Shin [2003] is more flexible and computationally simple. Im, Pesaran, and Shin [2003] relax the assumptions of common autoregressive parameters. Starting point of the IPS test is the set of Dickey fuller regressions. Im, Pesaran, and Shin [2003] test allows for heterogeneous coefficient of y_{it-1}. ADF regression in IPS

$$Z\Delta Y_{it} = Ze\mu_i + \rho_i ZY_{it-1} + \sum_{j=1}^{p} \beta_{ij} Z\Delta Y_{i,-j} + Z\epsilon_{it}$$

It is a set of ADF test. Null is the presence of unit root in series for all cross sections, the alternative allows for N_1 out of N individual series to have a unit root.

This procedure is conducted in two steps. First, the ADF regression is run for each cross-section and t statistics are obtained for every cross-section. We obtain the IPS t-bar statistics as the average of the individual ADF Statistics as

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i}$$

When t_{ρ_i} is the individual t statistics and $H_0 : \rho_i = 0$ is for all i. Im, Pesaran, and Shin [2003] calculated statistics critical value for $\bar{t}$ for different N and T dickey fuller regression containing intercept only or intercept and linear trend. However, if ρ_i is not zero for some 'i' in general case thenIm, Pesaran, and Shin [2003] shows that the following standardised t bar has an asymptotic distribution.

The values of $E(t_{iT}/\rho_i)$ and $Var(t_{iT}/\rho_i)$ have been computed using Im, Pesaran, and Shin [2003] via simulations for different values of T and ρ_i's

A.2.4 CADF unit root test

We also conducted Pesaran [2003] cross-sectionally augmented Dickey fuller test (CADF) in our analysis. Pesaran suggests the other way than assuming homogeneity of cross-sectional and without requiring balanced panel data. According to Pesaran [2003] Pesaran [2007], one way of accounting for cross-sectional sectional dependence is to augment the ADF regression with lagged cross-sectional mean and its first difference to capture the cross-sectional dependence that is due to the single factor loading model. The simple CADF regression is

$$\Delta Y_{it} = \alpha_i + \rho_i^* Y_{it-1} + d_0 \bar{Y}_{it-1} + \sum_{j=1}^{p} j + 1\Delta Y_{t-j} + \sum_{k=1}^{p} c_k \Delta Y_{i,t-k} + \epsilon_{it}$$

where we choose a number of lags depending on the information criteria. Once we run the CADF regression for each panel, we obtained CADF statistics for the ith cross-section unit and we take an average of all these t statistics to obtain the CIPS statistics.

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF$$

Due to the presence of cross-sectional averages, it makes limiting distribution of these tests different from dickey fuller distribution. Hence Pesaran used a truncated version of Im et al. [2003] test to avoid the problem of moment calculated.

Table (A.2) Panel unit root test result

Variables	First generation unit root test IPS (c) p-value	IPS (c,t) p-value	LLC (c) -p-value	LLC (c,t)	Second generation unit root test CADF lag(0)	CADF lag(1)	CADF lag(2)
Total factor productivity	2.1151	-1.9127**	-0.9173	-0.6272	1.9810	1.6570	0.7780
	(0.9828)	(0.0279)	0.1795	0.2653	0.9760	0.9510	0.7820
Δ Total factor productivity	10.8564***	-11.3223***	-7.6069***	-7.0219***	-11.9290***	-6.1050***	-4.0920***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mean Temperature	-7.1131***	-12.6674***	-6.9556***	-12.1421***	-13.5000***	-7.3510 ***	-7.5660***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Maximum Temperature	-7.9070***	-11.7831***	-5.3834***	-12.1421***	-11.870**	-5.841 ***	-5.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Heat Degree Days	-9.4135***	-12.6674***	-6.6075***	-8.0920***	-14.151**	-8.535 ***	-6.068***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-11.6903***	-12.6324***	-6.7655***	-5.8694***	-15.680**	-5.628 ***	-2.927***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Trade openness	-1.1591	-3.8235***	-2.4651*	-2.1807*	-0.887	-1.009	-1.148
	(0.1232)	(0.001)	(0.006)	(0.014)	(0.188)	(0.156)	(0.875)
Δ Trade openness	-12.4207***	-12.7212***			-10.857***	-2.766***	-2.134
	(0.000)	(0.000)			(0.000)	(0.003)	(0.984)
Human Capital	-3.6227	-2.1873*	-1.3937**	-1.9033*	0.328	-1.009	1.148
	(0.9999)	(0.0144)	(0.0068)	(0.0146)	(0.188)	(0.156)	(0.875)
Δ Human Capital	-8.5126***	-8.6833***			-10.857***	-2.766***	2.134***
	(0.000)	(0.000)			(0.000)	(0.000)	(0.001)
Institutional quality	-1.7083*	-3.3161***	-2.8265*	-0.9507	-0.919	-2.196	-2.382***
	(0.0438)	(0.000)	(0.002)	(0.170)	(0.179)	(0.014)	(0.000)
Foreign Direct Investment	-5.7878***	-6.6931 ***	-3.9650***	-2.7652*	-7.236**	-4.658***	-1.829*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.034)

Notes: c indicates unit root test without intercept and c(t) indicates that we allow for different intercepts (and time trends) for each country. Large negative values lead to the rejection of a unit root in favour of (trend) stationarity. We tested for both first generation unit root test which assumes cross-sectional Independence and second generation unit root test which assumes cross-sectional dependence. **(***)(*) (**)Indicate rejection of the null hypothesis of a unit root at the(1%) (5%) level (10%) level**

Table (A.3) Summary Statistics- Countrywise

Country	TFPGSFA	TFPPenn	GDP	Employment	Temperature volatility	Precip	HC	Tradepen	Inf	GCN	FDI
Argentina	0.44	1.00	3.35	15.58	13.02	596	93.59	0.28	10.36	13.14	2.22
Brazil	0.40	1.11	1.24	75.92	10.660	1758	100.38	0.23	295	19.08	2.62
Bulgaria	.40	1.05	3.25	3.24	10.02	628	93.8	.997	67.81	17.37	6.27
Chile	.29	1.04	1.43	6.15	10.4	537.1	91.05	.625	6.14	11.52	6.07
China	0.12	0.88	4.26	748.1	11.9	610	59.92	0.426	4.11	15.08	3.43
Colombia	0.38	1.00	1.81	16.24	9.26	2629	82.2	0.361	10.96	15.12	3.15
Egypt	0.45	1.06	1.45	19.31	14.63	33	77.6	0.487	10.21	11.25	2.34
India	0.32	0.79	1.06	432.4	11.85	1049	57.31	0.35	7.44	10.85	1.19
Indonesia	0.49	0.90	4.46	97.54	9.46	2581	64.15	0.54	9.46	8.40	1.19
Iran	0.34	1.03	2.70	18.61	14.13	208.4	75.84	0.44	18.99	11.69	0.64
Malaysia	0.44	0.91	1.72	10.44	8.20	3125	76.12	1.72	2.73	12.28	4.13
Mexico	0.40	1.04	8.17	40.96	15.33	765	78.38	0.54	10.07	10.39	2.49
Morocco	0.56	0.88	6.68	9.92	12.48	301	49.05	0.65	2.57	17.83	2.30
Nigeria	-0.20	0.83	2.14	45.22	11.90	1154	37.44	0.37	18.5	4.24	1.74
Peru	0.41	0.96	1.02	12.29	12.25	1540	83.66	0.41	280.3	10.78	3.63
Philippines	0.24	0.83	1.52	31.63	8.4	2469	79.59	0.74	5.7	10.58	1.65
Russia	0.37	0.84	9.61	69.45	9.7	465	92.73	0.54	67.65	17.96	1.78
South Africa	0.54	1.06	2.35	14.79	14.97	455.9	90.44	0.53	6.9	19.40	1.23
Thailand	0.43	0.78	2.41	34.17	10.28	1559.6	73.21	1.13	3.07	13.71	2.37
Turkey	0.43	1.006	4.90	21.65	11.63	574.5	81.56	0.464	37.35	13.00	1.208
Ukraine	0.48	0.82	9.17	20.70	8.67	560.9	96.64	0.93	245.45	19.08	2.87

A.2.5 Trends in Productivity and temperature

Figure (A.2) Trends in Total factor productivity

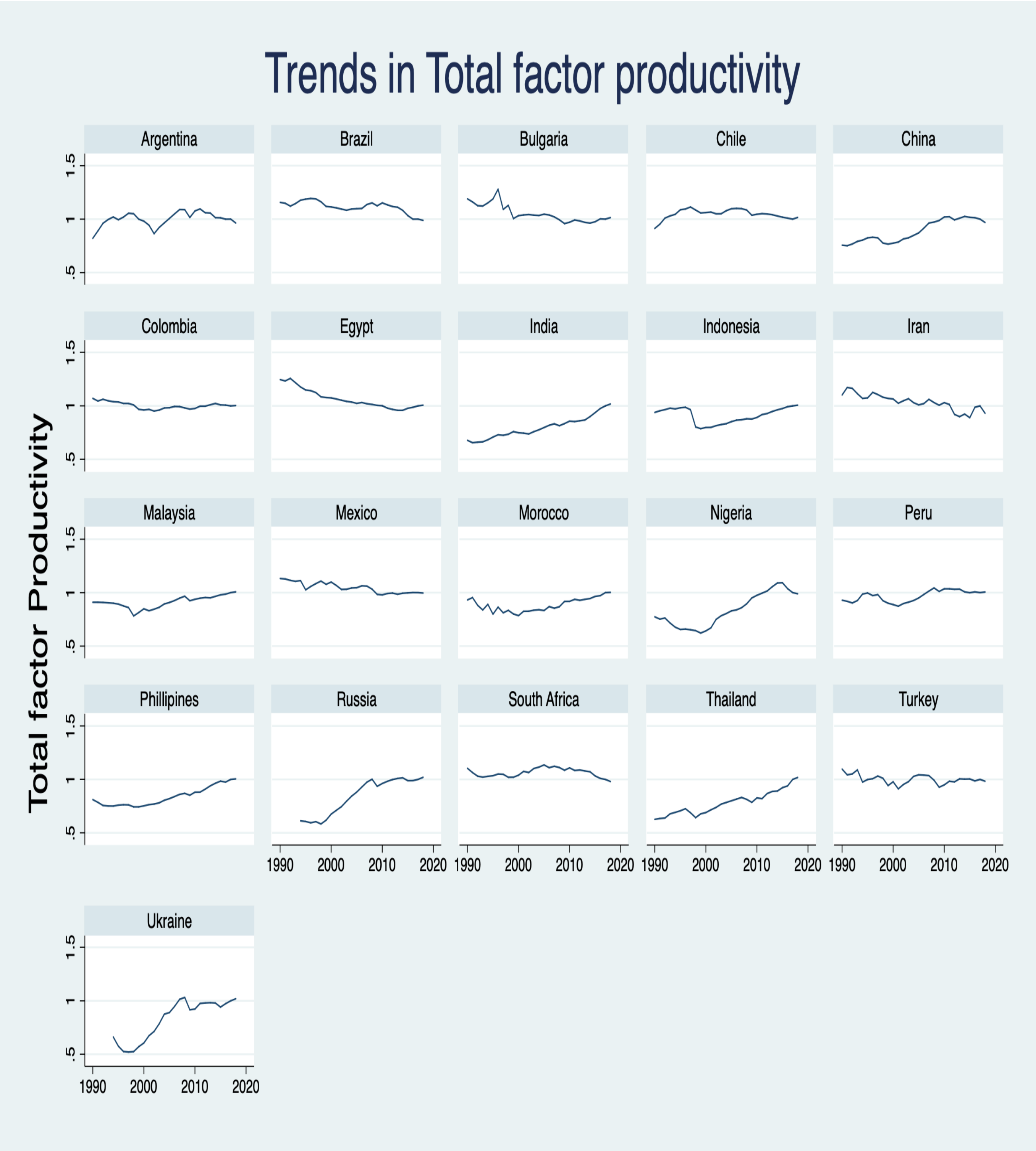
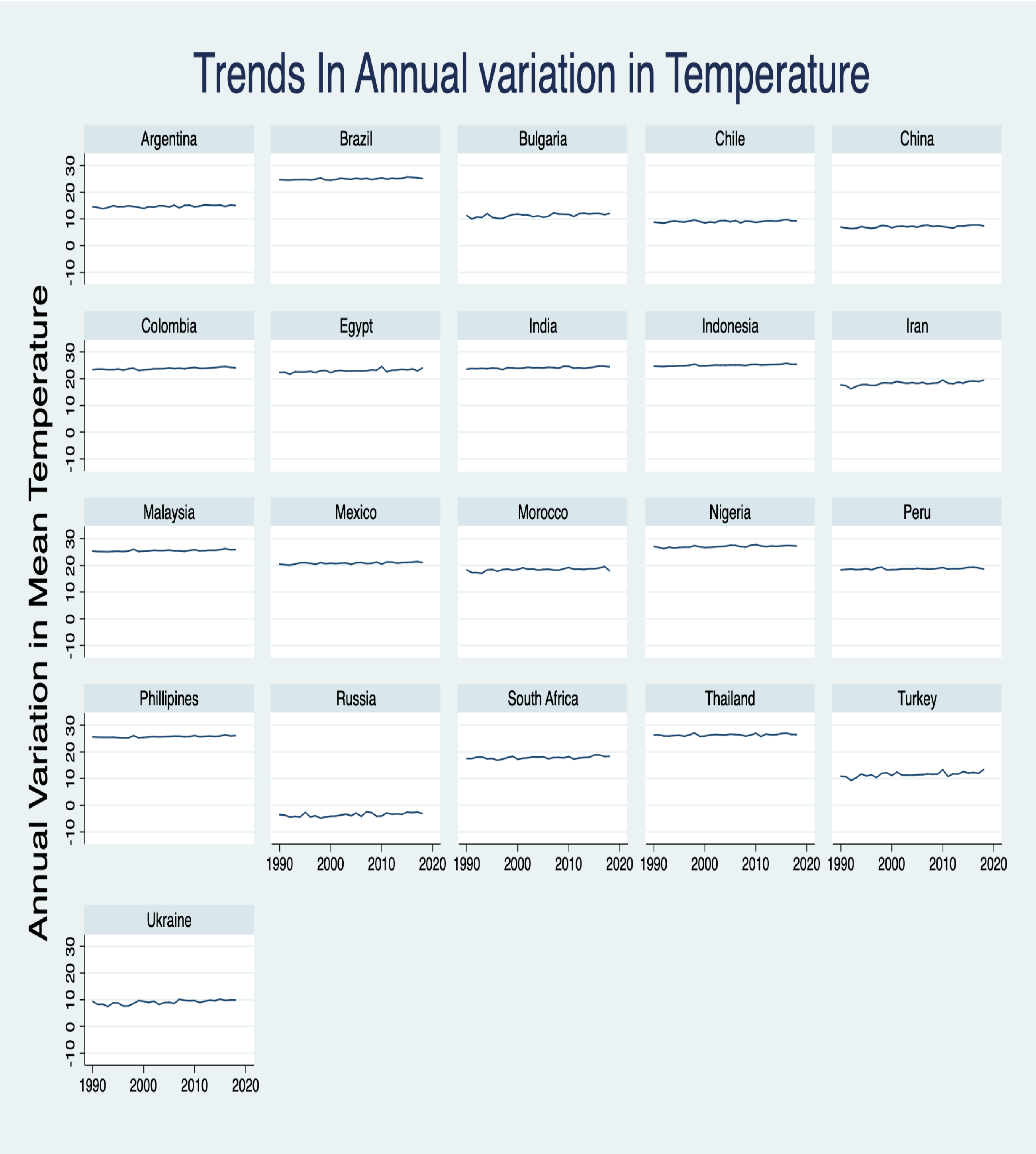


Figure (A.3) Trends in annual variation in temperature



A.3 Panel cointegration approach

A.3.1 Panel Cointegration test

If the linear combination of the I(1) Series is stationary, we say that process is cointegrated. Cointegration means that series move together and it has a long-term relationship. We used the following panel data model for I(1) dependant variable Y_{it} where i= 1,....N and t = 1....T denotes time

$$y_{it} = X'_{it}\beta_i + Z'_{it}\gamma_i + \epsilon_{it} \tag{5}$$

β_i represent cointegrating vector . Z_{it} controls for panel-specific mean and panel-specific linear trend. X_{it} each of the control vector is of order I(1).

A.3.2 Pedroni Panel cointegration test

It is a residual-based panel cointegration test. Pedroni allows for individual heterogeneous fixed effects and trends with two types of test statistics. Panel test statistics(within dimension based) are obtained by pooling the residual of individual regression is done along within the dimension of the panel. Group mean statistics were obtained by pooling the statistics between dimensions. We obtained seven test statistics. The Pedroni panel cointegration test is based on the regression equation for our analysis.

$$TFP_{it} = \alpha_i + \delta_{it} + \beta_i X_{it} + \epsilon_{it}$$

where i = 1.....N and t = 1......T . T is the number of observations over time . N denotes the number of countries in the panel. TFP_{it} is the total factor productivity for the ith country in period t. X_{it} is the explanatory variable determining productivity for country i. β_i is the slope coefficient (cointegrating vector) allowed to vary across cross-sections so that cointegrating vectors do not vary over time. α_i is country specific fixed effect and δ_i is the detrministic regression.

Above regression is estimated by OLS individually for each cross-section. Once we estimate the residual from above regression.

$$\widehat{L}^2_{11i} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\xi}^2_{it} + \frac{2}{T}\sum_{s=1}^{M_i}\left(1 - \frac{s}{Mi+1}\right)\sum_{t=s+1}^{T}\widehat{\xi}_{it}\widehat{\xi}_{i,t-s} \tag{6}$$

Pedroni defined seven test statistics using thses residual. Panel v Statistics

$$T^2N^{\frac{3}{2}}Z_{\widehat{v}NT} = T^2N^{\frac{3}{2}}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}^{-2}_{11i}\widehat{e}^2_{i,t-1}\right)^{-1} \tag{7}$$

Panel ρ Statistics

$$T\sqrt{N}Z_{\widehat{\rho}NT^{-1}} = T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{e}_{i,t-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(\widehat{e}_{i,t-1}\Delta\widehat{e}_{it} - \widehat{\lambda}_t) \tag{8}$$

Panel t Statistics(Semi-parametric)

$$Z_{tNT} = (\overline{\sigma}_{NT}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{e}_{i,t-1}^{2}\Big)^{-\frac{1}{2}}\sum_{i=1}^{N}\sum_{t=1}^{T}(\widehat{e}_{i,t-1}\Delta\widehat{e}_{it} - \widehat{\lambda}_t) \tag{9}$$

Panel t Statistics (Parametric)

$$Z_{tNT}^{*} = \left(\overline{s}_{NT}^{*2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{e}_{i,t-1}^{2}\right)^{-\frac{1}{2}}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{L}_{11i}^{-2}\widehat{e}_{i,t-1}\Delta\widehat{e}_{it} \tag{10}$$

Group ρ Statistics

$$TN^{-\frac{1}{2}}\overline{Z}_{\widehat{\rho}NT^{-1}} = TN^{-\frac{1}{2}}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T}\widehat{e}_{i,t-1}^{2}\right)^{-1}\sum_{t=1}^{T}(\widehat{e}_{i,t-1}\Delta\widehat{e}_{it} - \widehat{\lambda}_t)\right] \tag{11}$$

Group t statistics (Semi Parametric)

$$N^{-\frac{1}{2}}\overline{Z}_{tNT} = N^{-\frac{1}{2}}\sum_{i=1}^{N}\left[\left(\widehat{\sigma}_{i}^{2}\sum_{t=1}^{T}\widehat{e}_{i,t-1}^{2}\right)^{-\frac{1}{2}}\sum_{t=1}^{T}(\widehat{e}_{i,t-1}\Delta\widehat{e}_{it} - \widehat{\lambda}_t)\right] \tag{12}$$

Group t statistics (Parametric)

$$N^{-\frac{1}{2}}\overline{Z}_{tNT}^{*} = N^{-\frac{1}{2}}\sum_{i=1}^{N}\left[\left(\widehat{s}_{i}^{*2}\sum_{t=1}^{T}\widehat{e}_{i,t-1}^{2}\right)^{-\frac{1}{2}}\sum_{t=1}^{T}\widehat{e}_{i,t-1}\Delta\widehat{e}_{it}\right] \tag{13}$$

with

$$\widehat{\lambda}_i = \frac{1}{T}\sum_{s=1}^{M_i}\left(1 - \frac{s}{Mi+1}\right)\sum_{t=s+1}^{T}\widehat{u}_{it}\widehat{u}_{i,t-s}\ ,\widehat{s}_{i}^{2} = \frac{1}{T}\sum_{t=1}^{T}\widehat{u}_{it}^{2} \tag{14}$$

$$\widehat{\sigma}_{i}^{2} = \widehat{s}_{i}^{2} + 2\widehat{\lambda}_i\ ,\widehat{\sigma}_{NT}^{*2} = \frac{1}{N}\sum_{i=1}^{N}\widehat{L}_{11i}^{-2}\widehat{\sigma}_{i}^{2} \tag{15}$$

$$\widehat{s}_{i}^{*2} = \frac{1}{T}\sum_{t=1}^{T}\widehat{u}_{it}^{*2}\ ,\ \widehat{s}_{NT}^{*2} = \frac{1}{N}\sum_{i=1}^{N}\widehat{s}_{i}^{*2} \tag{16}$$

To obtain the panel v and parametric t-test statistics, we use difference regression ignoring the deterministic trend term of equation 5. Using these residuals, long-run variance is calculated. For calculating semi parametric statistics, we test the regression

$\hat{e}_{it} = \rho\hat{e}_{it-1} + \epsilon_{it}$ where ϵ_{it} is obtained from the equation 5. The parametric test statistics(panel t and group t) are obtained with the help of the residual ϵ_{it} from equation 5. Using regression equation $\hat{e}_{it} = \rho\hat{e}_{it-1} + \sum_{i=1}^{T} \gamma_i \hat{e}_{it-1} + \epsilon_{it}$ than simple and long run variance is calculated.

The first four statistics are obtained by adding the numerator and denominator over the N cross section individually. Between-dimension statistics are calculated by obtaining the ratio of each time series and then computing the standardised sum of the entire ratio over the N dimension of the panel.

Table (A.4) Panel cointegration test result

	Pedroni Panel co-integration test		Kao Panel co-integration test		
Test Statistics			Test Statistics		
Test Statistics	Statistics	P value	Test statistics	Statistics	p-value
Modified Philip perron test	-1.0789	0.1403	Modified dickey fuller-t	2.2109	0.0135
Philip perron t	-3.0379	0.0012	Dickey fuller-t	2.1512	0.0157
Augmented dickey fuller t	-2.8827	0.002	Augmented dickey fuller t	2.1923	0.0142
			Unadjusted modified dickey fuller t	1.2958	0.0975
			Unadjusted dickey fuller t	1.1252	0.1303

Notes: The null hypothesis for all tests is that there is no cointegration. The Kao and Pedroni tests' alternate hypothesis is that the variables are cointegrated in all panels . To avoid over-parametrization and the resulting loss of power, only one lag was included in the tests. In the Model, We test the cointegration between total factor productivity and mean temperature. **(***)(*) (**)Indicate rejection of the null hypothesis at the(1%) (5%) level (10%) level**

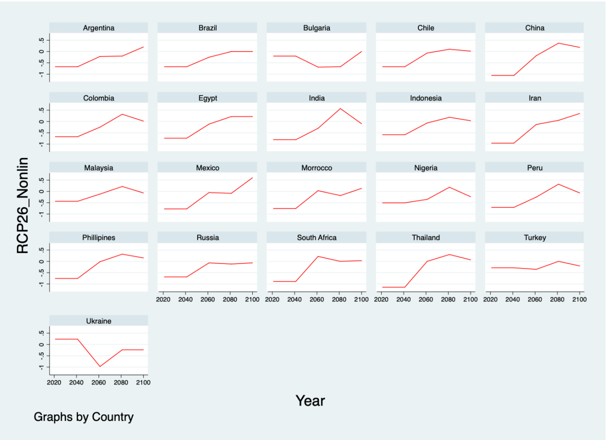
B Additional results on projected impact of temperature on TFP 2021-2100

Table (A.5) Level of TFP projections over the period 2020–2099(Non-linear projection estimate)

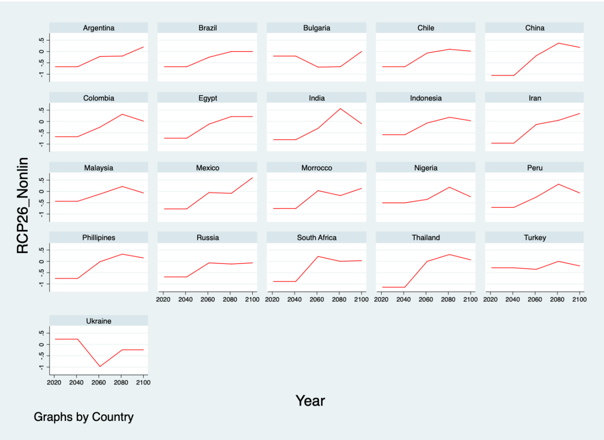
Scenario	2021-2041	2041-2061	2061-2081	2081-2100
Levels of log(TFP)				
RCP 2.6	-0.6552	-0.2016	0.1344	0.00672
RCP 4.5	-1.00296	-0.924	-0.672	-0.1344
RCP 6.0	-0.69888	-1.0584	-1.2096	-0.86856
RCP 8.5	-1.373736	-1.932	-1.9656	-2.14368

Notes: Positive (+) and Negative(-) sign indicates the magnitude of increase or decrease of the level of TFP in 2021-2100. RCP 2.6 - Low Emission Scenario, RCP 4.5 RCP 6.0- Intermediate emission scenario, RCP 8.5- Business as usual scenario

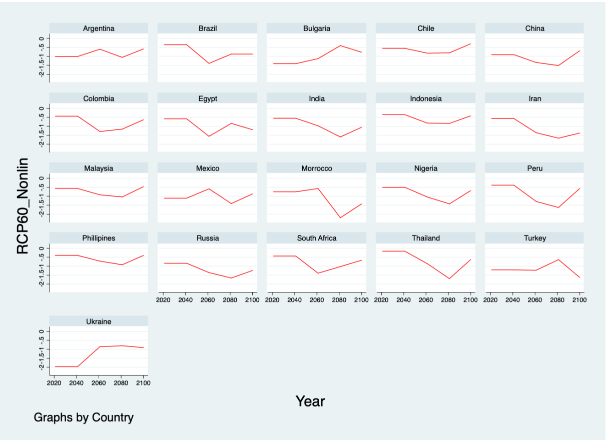
Figure (A.3) Level of TFP projections over the period 2020–2099(Non-Linear Projection Estimate)



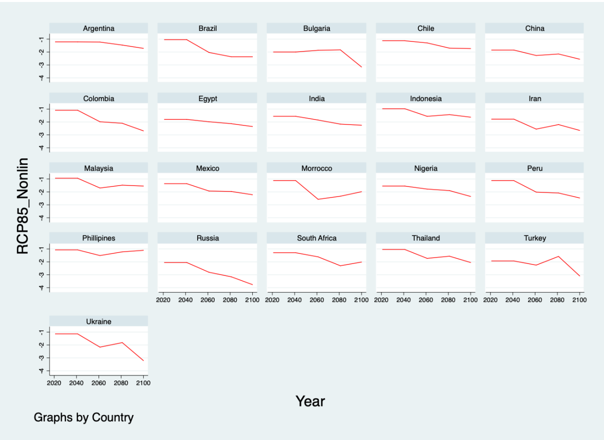
(a) RCP 2.6 - Low Emission Scenario



(b) RCP 4.5 Intermediate emission scenario



(c) RCP 6.0- Intermediate emission scenario



(d) RCP 8.5- Business as usual scenario

Magnitude of increase or decrease of the level of TFP in 2021-2100. RCP 2.6 - Low Emission Scenario, RCP 4.5 RCP 6.0- Intermediate emission scenario, RCP 8.5- Business as usual scenario

C Literature on impact of Human capital, trade openness, Institutional quality and total factor productivity

C.1 Trade openness

There is a significant body of literature suggesting that countries that are more open to trade are better positioned to benefit from technology diffusion. By fostering international exchange and exposing nations to foreign technology, trade openness can stimulate technological innovation and improve allocative efficiency. The research conducted by Miller and Upadhyay provides empirical support for this view, as their study found a positive relationship between trade openness and economic growth. Furthermore, the Melitz model, which examines the impact of trade on productivity, suggests that greater exposure to trade can lead to welfare gains.

C.2 Human Capital

According to [Islam et al., 2010], a study conducted on 99 countries, human capital has a positive impact on Total Factor Productivity (TFP) growth. This finding is corroborated by the results of [Wei and Hao, 2011], who also found a positive relationship between human capital and TFP growth.

C.3 Institutional Quality

The quality of institutions can have a significant impact on the economic incentives within a country. Specifically, a strong property rights system can encourage individuals to invest in physical and human capital, leading to increased output. Therefore, as institutional quality improves, productivity is likely to rise. This relationship between institutions and economic growth has been highlighted in the influential paper by Rodrik et al. [2004]. Additionally, several researchers have examined the relationship between institutional quality and economic development [North and Thomas, 1973, Law et al., 2013, Venard, 2013, Azam and Emirullah, 2014, Karimi and Heshmati Daiari, 2018]. North [1990] has argued that the institutional framework can create incentives and foster an environment conducive to economic growth. Acemoglu, Johnson, and Robinson [2004] also emphasised the importance of economic institutions for productivity.

C.4 foreign direct investment (FDI)

The inflow of foreign direct investment (FDI) has been shown to contribute to technology diffusion [Findlay, 1978] and technology spillover [Blalock and Gertler, 2009], which can affect the growth of total factor productivity (TFP) in host countries. Empirical studies have consistently found a positive relationship between FDI inflows and economic growth [Azman-Saini et al., 2010]. However, the impact of FDI on TFP growth remains a topic of debate. While some studies have found no significant impact [Alfaro et al., 2009], others have reported a negative relationship [De Mello, 1999]. Yet other studies have found a positive association between FDI and productivity growth [Woo, 2009, Baltabaev, 2014]. The mixed results suggest that the relationship between FDI inflows and TFP growth may depend on specific factors and contexts.

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