WP-2023-014

Temperature shock and economic growth: Does spillover effect hurt more?

Authors: Pratik Thakkar, Kausik Gangopadhyay and Rupayan Pal

Indira Gandhi Institute of Development Research, Mumbai
December 2023

Temperature shock and economic growth: Does spillover effect hurt more?

Authors: Pratik Thakkar, Kausik Gangopadhyay and Rupayan Pal

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

Abstract

In a trade-connected world, an adverse impact on economic growth on account of temperature shock in one economy may have a spillover effect on other economies. The current study quantitatively evaluates the impact of temperature shock on economic growth, during 1971--2019 for 168 economies, through direct and spillover channels. Our findings indicate that, while a temperature shock engenders an overall adverse effect on economic growth of all economies, only tropical economies experience a direct adverse effect, which is then transmitted to their non-tropical trade partners. The spillover effect is significant and more substantial for non-tropical economies than their direct effect. Among the sectors, the non-agriculture sector is sensitive to the spillover effect. Finally, the overall adverse effects on poor and rich economies hinge upon the direct and spillover effects, respectively. In our analysis, except for rich tropical economies, all experience an overall adverse effect.

Keywords: Temperature shock, Climate change, Direct effect, Spillover effect, Economic growth

JEL Code: F14, F18, O13, O14, Q54, Q56

Acknowledgements:

We gratefully acknowledge Dr. Manisha Jain from Indira Gandhi Institute of Development Research and participants of DSE Winter school 2023 conference for their valuable insights and comments, which greatly contributed to the refinement of this paper. However, any shortcomings in the paper are the sole responsibility of the authors.

Temperature shock and economic growth: Does spillover effect hurt more?

Pratik Thakkar[1*], Kausik Gangopadhyay[2] and Rupayan Pal[1]

[1]Indira Gandhi Institute of Development Research, Gen. AK Vaidya Marg, Mumbai, 400065, Maharashtra, India.
[2]Indian Institute of Management Kozhikode, IIMK Campus P.O., Kozikode, 673570, Kerala, India.

*Corresponding author(s). E-mail(s): pratikt@igidr.ac.in;
Contributing authors: kausik@iimk.ac.in; rupayan@igidr.ac.in;

Abstract

In a trade-connected world, an adverse impact on economic growth on account of temperature shock in one economy may have a spillover effect on other economies. The current study quantitatively evaluates the impact of temperature shock on economic growth, during 1971–2019 for 168 economies, through direct and spillover channels. Our findings indicate that, while a temperature shock engenders an overall adverse effect on economic growth of all economies, only tropical economies experience a direct adverse effect, which is then transmitted to their non-tropical trade partners. The spillover effect is significant and more substantial for non-tropical economies than their direct effect. Among the sectors, the non-agriculture sector is sensitive to the spillover effect. Finally, the overall adverse effects on poor and rich economies hinge upon the direct and spillover effects, respectively. In our analysis, except for rich tropical economies, all experience an overall adverse effect.

Keywords: Temperature shock, Climate change, Direct effect, Spillover effect, Economic growth

JEL Classification: F14 , F18 , O13 , O14 , Q54 , Q56

Acknowledgements: We gratefully acknowledge Dr. Manisha Jain from Indira Gandhi Institute of Development Research and participants of DSE Winter school 2023 conference for their valuable insights and comments , which greatly contributed to the refinement of this paper. However , any shortcomings in the paper are the sole responsibility of the authors.

The mean global surface temperature has increased by 1.09 [0.95 to 1.20]°Celsius from its value during 1850–1900 to the corresponding value during 2011—2020, as per the Sixth Assessment Report of the Intergovernmental Panel on Climate Change[1]. This temperature rise has diverse economic impacts across the world, with studies indicating both positive and negative effects of temperature shock on economic growth. It is observed that temperature shocks have a detrimental influence on economic outcomes in Africa[2–5] and Asia[6–11], although the association between temperature shocks and economic growth is less obvious in case of other countries[12–16].

Expectedly, any economic shock in one economy—in the globalised world—can have varying spillover effects on other economies' growth[17,18]. Trade literature[19–22] considers the impact of temperature shock on trade and observes that a temperature shock decreases exports for an economy. However, the cascading effects of a temperature shock on economic growth of trade partners due to changes in trade patterns remain unexplored. No study, to the best of our knowledge, quantifies the direct and spillover effects of a temperature shock on economic growth in a unified framework. In this study, we examine the impact of a localised temperature shock in one economy on other economies' economic growth in light of economic inter-dependencies from international trade.

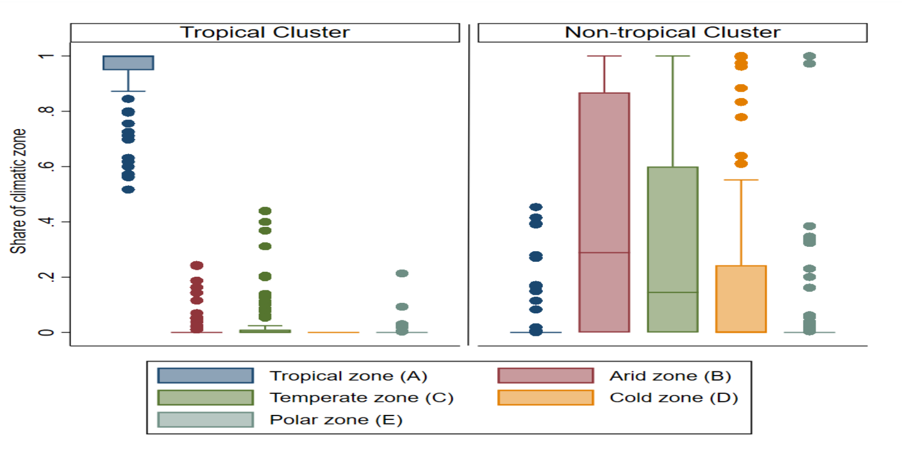
One pivotal determinant of the diverse repercussions of temperature shocks on economic growth across regions is their varied climatic zones[23]. Comprehensive studies[24–26] furnish evidence that temperature variation tends to favour colder regions while affecting warmer ones. Further investigation, in an African context, reveals that temperature shocks cause nonlinear effects on economic growth, contingent on climatic zones[27]. Another finding[28] in the same context notes that warmer regions are considerably more susceptible to temperature shocks. Understandably, the impact of temperature shocks on economic growth for an economy necessitates an exploration rooted in the climatic attributes of that economy.

Another strand of literature[29,30] shows that poor economies are more affected by temperature shocks compared to their richer counterparts. Other studies[24,25,31,32], however, imply that both rich and poor economies are vulnerable to temperature shocks. Given these findings, we advance this strand of literature by a thorough analysis of the impact of a temperature shock on economic growth of rich economies vis-à-vis their poorer counterparts in the context of spillover effects originating from a partner economy.

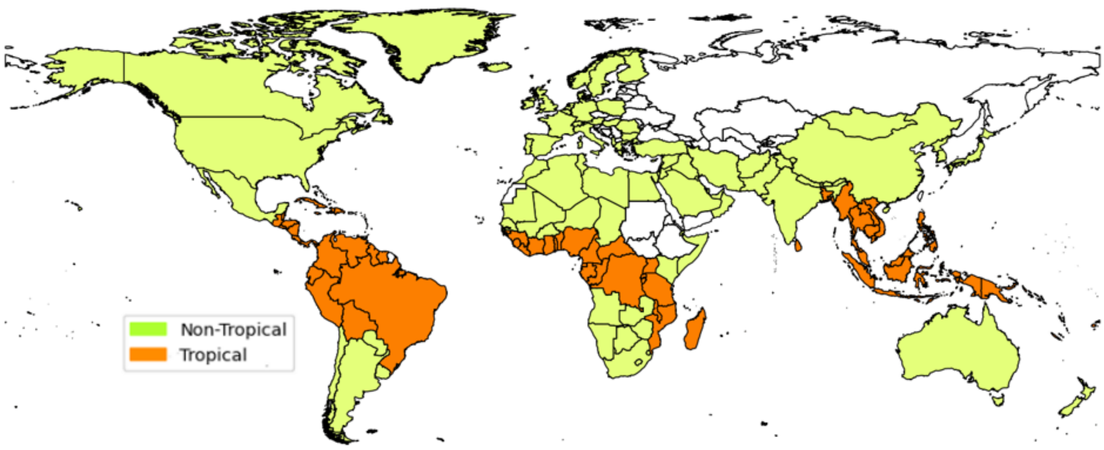
We perform our analysis considering three critical pathways: geo-climatic features of different economies, subsequent spillovers on trading partners, and the precise economic sectoral paths through which the spillover effect ultimately benefits (or hurts) partner economies. Our analysis has two distinct features. First, our study estimates the differential impacts on account of the direct and the spillover effects, which potentially, depend on climatic zones and income levels. Second, the analysis critically engenders a complex interaction between temperature shock and economic variables and, hence, its economic consequences on a regional and global scale.

In our paper, as a preliminary step, we classify economies based on comparable climatic zones to produce two broad clusters: the tropical economies and the non-tropical ones. For this, we utilise a 0.5° (approximately 50 km) resolution of global classification of the Köppen-Geiger climatic zones[33] and focus on five broad categories, that is, tropical, arid, temperate, cold, and polar zone (refer to Table S1 in the supplementary material). We classify economies based on their climate zone share by employing K-means clustering algorithm[34] (refer to panel (a) and (b) of Fig. 1 for classification). These climate zone classifications are based on a multivariate analysis of the weather as opposed to a temperature-based one. Therefore, our clustering differs, decidedly, from the typical hot/cold characterisation—that is widely followed in the literature—based on the median temperature of the economies in a particular year.

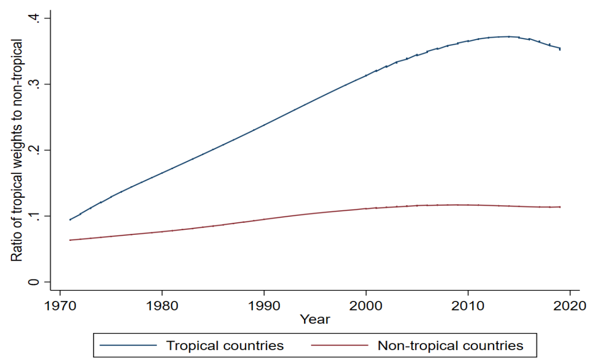
Next, we define a time-variant spillover temperature shock variable for each economy, which is the weighted average of temperature shocks experienced by its trade partners (refer to 'Results' for a detailed explanation). We use this spillover variable



(a) **Distribution of climatic zone share in each cluster:** The share of climatic zone ($S_i(CZ)$) in the economy's geography is computed as $S_i(CZ) = \frac{\#\ of\ grids\ in\ CZ}{\#\ of\ grids\ in\ economy\ i}$, where, CZ refers to climatic zone. The boxplot graphs the distributions of the share of climate zones within the clusters. Clusters are distinguished based on the share of tropical zones in the economy. There are 82 economies in the tropical cluster and 86 economies in the non-tropical cluster.



(b) **Global mapping of cluster:** The map presents visually the distribution of 168 economies of our consideration into two clusters of tropical (82 economies) and non-tropical (86 economies). The economies in the tropical cluster are observed to be near the equatorial line.



(c) **Trade openness trend:** We plot the ratio of trade weights of tropical partners to non-tropical partners using the Locally Weighted Scatterplot Smoothing (LOWESS) technique. The trade openness is obtained from the Direction of Trade Statistics database.

Fig. 1: Climatic zone classification of economies

to estimate the impact of a tropical and non-tropical trade partner's temperature shock on the home country's economic growth through trade dependency. Finally, we employ the Panel Vector Autoregression (PVAR) model[35] that considers the endogeneity (interrelationship) between sectors while estimating the impact of temperature shocks, both direct and spillover, on each sector. This analysis offers a deep insight into understanding how the impact on each sector, albeit individually insignificant, can turn out to be significant when combined at the economy level.

Results

Our investigation begins with assessing the effect of direct temperature shock on economic growth (defined as 'Closed economy' models). Following that, we examine both direct and spillover consequences of temperature shock in the presence of international trade interconnection (defined as 'Open economy' models). Finally, we extend the open economy model by integrating income-level bifurcation to quantify the effects of temperature shocks on poor and rich economies.

Closed economy: Direct impact of temperature shock

We commence our analysis by testing the null hypothesis that temperature shock does not have any effect on growth rate of gross value added (henceforth, GVA) per capita for an economy. We employ a PVAR model with three lags comprising of two endogenous variables: growth rate of per capita GVA and per capita GVA growth rate from the agriculture sector. We have discussed the rationale for the choice of the variables along with their precise definitions in the 'Online methods'. Our model controls for precipitation shock, country-level fixed effects, and regional-level trends (based on World Bank classification).

We appeal to the System-Generalised Method of Moments technique for the estimation of the model. As this technique is sensitive to the presence of outliers, we address this issue by censoring the endogenous variables at both ends—at the 0.5^{th} and the 99.5^{th} percentiles (refer to the supplementary material for the robustness exercise). Since this initial version of our model does not consider the spillover effect, we define this model as the 'closed economy' version of our model. As an extension to this 'closed economy' version, we interact the temperature shock variable with the *tropical dummy* and call it the 'Closed with interaction' version. The *tropical dummy* takes the value one if an economy is in the tropical cluster and zero otherwise. This interaction allows us to estimate the additional impact of temperature shock on economic growth of tropical economies.

Columns (1) and (2) of Table 1 present the marginal effect of one standard deviation (one-SD) shock to direct temperature—ranging from 0.30°Celsius to 0.56°Celsius (refer to Table S3 and S4 of the supplementary materials) depending on the cluster to which an economy belongs—estimated using both 'closed economy' and 'closed with interaction' models. For marginal effects of one-SD shock, we multiply the standard deviation of temperature shock by the coefficient obtained as PVAR model estimate—refer to Table S10 in the supplementary material for computation.

Panel (a) of column (1) indicates that one-SD temperature shock exerts a weakly significant (at 10% level) negative impact on per capita GVA growth rate. The agriculture sector is the key driver of this negative impact (-0.084 $\pm$ 0.029 pp, i.e. mean $\pm$ 1.96 $\times$ standard errors)—refer to panel (b). The inclusion of the above-mentioned interaction term [Column (2), Panel (a)] shows that though overall, the figures are weakly significant, that impact (-0.219 $\pm$ 0.163 pp) is duly significant for tropical economies but not for their non-tropical counterparts. Remarkably, for both tropical and non-tropical economies, we observe an adverse effect of very similar magnitude on the agriculture sector [refer to panel (b)]. Incontrovertibly, this effect represents the general reliance of the agriculture sector on weather conditions.

Table 1: Marginal estimates for a global sample at one standard deviation shock to temperature

	(1) Closed economy	(2) Closed with interaction		(3) Open economy		(4) Open with interaction	
	All	**Topical**	**Non Tropical**	**Topical**	**Non Tropical**	**Topical**	**Non Tropical**
Panel (a): Dependent variable - Per capita GVA growth rate (in pp)							
Direct temperature	-0.103*	-0.219***	-0.050	-0.119	-0.028	-0.180	0.015
	(0.053)	(0.083)	(0.072)	(0.106)	(0.082)	(0.114)	(0.087)
Tropical spillover				-0.114*		-0.075	-0.178**
				(0.068)		(0.101)	(0.090)
Non-tropical spillover				-0.037		0.018	-0.089
				(0.061)		(0.091)	(0.083)
Panel (b): Dependent variable: Per capita GVA growth rate from agriculture (in pp)							
Direct temperature	-0.084***	-0.084***	-0.087***	-0.074**	-0.079***	-0.089**	-0.089***
	(0.015)	(0.027)	(0.020)	(0.035)	(0.023)	(0.037)	(0.024)
Tropical spillover				-0.007		0.018	-0.025
				(0.023)		(0.030)	(0.038)
Non-tropical spillover				-0.016		-0.059*	0.025
				(0.019)		(0.031)	(0.024)
Panel (c): Dependent variable: Per capita GVA growth rate from non-agriculture (in pp)							
Direct temperature	-0.019	-0.135*	0.037	-0.045	0.051	-0.091	0.104
	(0.048)	(0.074)	(0.066)	(0.095)	(0.075)	(0.102)	(0.080)
Tropical spillover				-0.107*		-0.093	-0.153**
				(0.063)		(0.095)	(0.078)
Non-tropical spillover				-0.021		0.077	-0.113
				(0.054)		(0.078)	(0.076)
Trade Openness	No	No		Yes		Yes	

All models include direct precipitation shock, economy fixed effects, and regional trend as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector. Additional controls, in case of open economy model, includes spillover precipitation and *autarky dummy*. Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate.
Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–refer to the online methods for details.
Column (1) includes direct temperature shock; Column (2) interacts direct temperature shock with the *tropical dummy*; Column (3) includes spillover shock variable; and Column (4) interacts spillover shock variable with the *tropical dummy*. We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Open economy: Direct and spillover impacts of temperature shock

As a next step, we posit that a temperature shock in a tropical economy spills over to other economies, affecting their economic growth. The trade-climate literature estimates that a temperature shock significantly reduces exports but not imports for an economy[19−22]. Even though the direct effect of a temperature shock on the total imports of an economy is insignificant, nevertheless Acemoglu et al. (2012)[36] have demonstrated that a specific shock to even one particular firm could have a significant impact on other sectors through input-output channels. Thus, the direct effect of a temperature shock on trade can affect partner economies' import-led or export-led economic growth.

We create a cluster-level spillover variable based on trade connectivity inspired by the Global Vector Autoregressive (GVAR) literature[31,37,38] to capture the effects of shocks on partner economies at the cluster level. Specifically speaking, we define the variable 'trade openness weight' (denoted as w_{ijt}) as the ratio of the sum of exports and imports between a given home economy 'i' and its partner economy 'j' in year ‘t’, relative to the sum of exports and imports for the home economy ’i’ in the year ‘t’ with all partner economies. To further refine our analysis, we calculate the three-year simple moving average of w_{ijt} and represent it as $\tilde{w}_{ijt}$ and compute the spillover temperature shock as follows:

$$ST_{k,it} = \sum_{j \in k} \tilde{w}_{ijt-1} \times \Delta T_{jt}$$

where ΔT_{jt} is the temperature shock in partner ‘j’ in the year ‘t’, and ‘k’ represents one of the two clusters of tropical and non-tropical economies.

By our construction, the spillover variable indicates the trade-weighted average spillover of temperature shock from the partner economies in a cluster to the home economy. Moreover, to ensure weak exogeneity of the spillover variable to the dependent variables of our interest, we consider the lagged values of the trade openness weight variable ($\tilde{w}_{ijt-1}$) in constructing the spillover temperature shock. Our construction differs from that discussed by the GVAR literature in two ways. Firstly, our variable accounts for the influence of the *temperature shocks* in the partner economies on the home economy instead of economic shocks. Secondly, the GVAR literature assumes constant trade-weights across years against our empirically observed year-wise trade openness weights, increasing over time, towards the tropical economies [refer to panel (c) of Fig. 1].

For the ‘open economy’ version of our model, we incorporate the spillover temperature shock variable and also interact it with the *tropical dummy* in the ‘Open with interaction’ version to understand the differential impact on tropical home economies. We also augment our list of control variables by adding a spillover precipitation shock variable and an *autarky dummy* variable for representing trade connectivity among countries. The endogenous variables remain, expectedly, unchanged. That the spillover temperature shock has no effect on home economy’s per capita GVA growth rate is the null hypothesis for this model version.

The results presented in columns (3) and (4) of panel (a) of Table 1 shed light on the propagation of adverse effects, from a home economy to its partner economies, of a one-SD temperature shock which, incidentally, varies between 0.03°Celsius and 0.32°Celsius (refer to Table S3 and Table S4 of the supplementary material). In particular, column (3) indicates a weak negative spillover effect originating from tropical partners. It is noteworthy that the significant impact of a tropical home economy’s temperature—illustrated in column (2)—loses significance in the open economy version, which strengthens the argument for considering the transmission mechanism, as also observed in Ahmadi et al. (2022)[31]. ‘Open with interaction’ version [Column (4)] provides the *prominent evidence* of such a transmission mechanism, as a one-SD temperature shock on tropical economies spills over to a non-tropical economy, with an average negative impact of -0.178 $\pm$ 0.176 pp on economic growth.

A one-SD shock in direct temperature significantly affect economic growth in the agriculture sector [Panel (b), Table 1] as observed by Dell et al. (2012)[30], unlike the case with the non-agriculture sector [Panel (c), Table 1]. As the non-agriculture sector is more internationally connected than the agriculture sector—as per World Input-Output Database[39]—we expect the spillover effects to transmit mainly through the non-agriculture sector. Accordingly, the temperature shock of tropical partners spills over to affect per capita GVA growth rate of a non-tropical economy through the non-agriculture sector by a magnitude of -0.153 $\pm$ 0.152 pp [Panel (c), Table 1].

We compute the total direct, spillover and overall impact of a temperature shock on economic growth (refer to the online methods for computation). A temperature shock, not unexpectedly, engenders an overall negative impact on economic growth [Panel (a) of Fig. 2]. Moreover, a group mean comparison using a t-test signifies no differential overall impact of a temperature shock on economic growth between the tropical and non-tropical economies. Interestingly, a tropical economy is affected by both the direct and the spillover impact of a temperature shock, whereas a non-tropical economy is primarily affected by the spillover effect alone.

It may be interesting to understand why the spillover effect of a temperature shock may be more than the direct effect. A direct shock for an economy may or may not be large enough. However, a spillover temperature shock can affect its trade partners directly and significantly. Consequently, the imports for the economy-in-question become expensive while having no considerable effect on its exports. Invoking the Marshall-Lerner condition[46], one may conclude that the economy-in-question will have a stronger spillover effect than the direct effect.

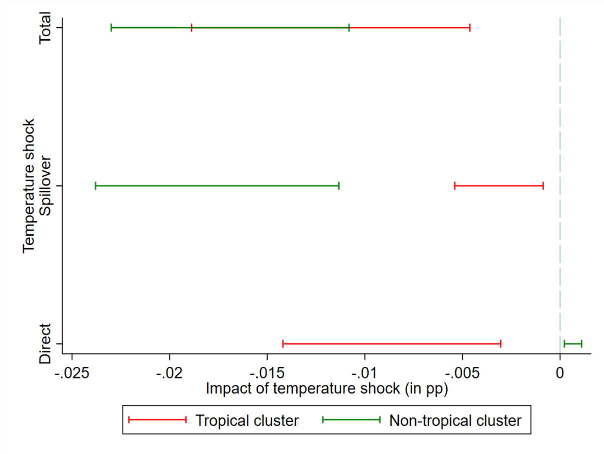
We separately compute the tropical spillover effect and its non-tropical counterpart. The distribution of the spillover's impact on economic growth is plotted in panel (b) of Fig. 2 for all country-year observations, grouped into two clusters. From the figure, we observe that there is more diverse impact for non-tropical economies compared to their tropical counterparts.

Turning our attention to the sectoral transmission channel, we discover that, for both clusters, economic growth is affected through the agriculture channel, as shown in panel (c) of Fig. 2. In the case of the non-agriculture channel, while the non-tropical cluster registers a significant negative impact, the impact on its tropical counterpart is ambiguous. Notably, the spillover effect affects both the non-tropical and tropical clusters but through different channels—the agriculture and the non-agriculture, respectively. These findings provide insight into the sensitivity of sectors to the direct as well as spillover temperature shocks in tropical and non-tropical economies.

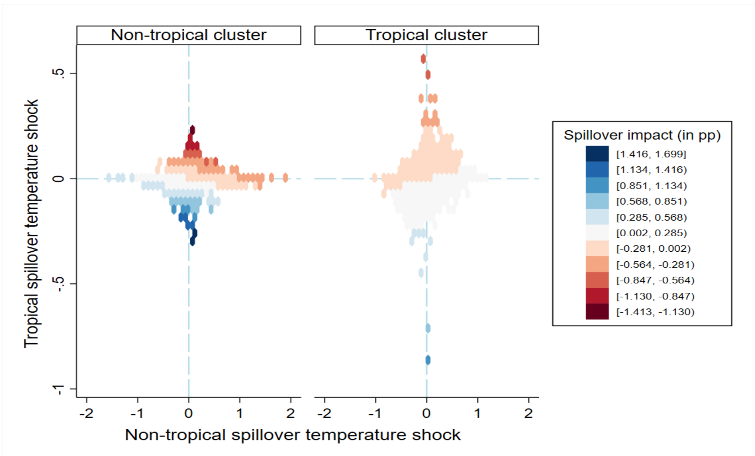
Differentiated impact on poor and rich

Following the literature, we compute the impact of a temperature shock on poor and rich economies by considering the *poor dummy*—indicative of per capita GVA being less than that of the world median in 1970—interacted with the temperature shock, both direct and spillover. We further augment our model by adding the interaction of temperature shocks with the *tropical dummy*. We refer to these two models as 'Open with poor interaction' and 'Open with all interactions', respectively.

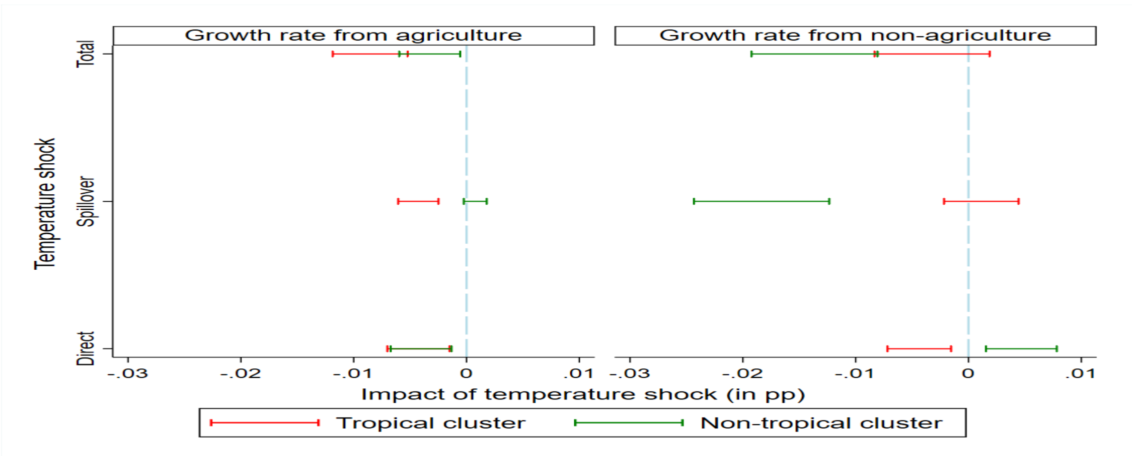
The impact of one-SD shock on economic growth is tabulated in the supplementary material (refer to Table S11). We determine that economic growth of poor economies is significantly affected by a direct temperature shock (-0.265 $\pm$ 0.180 pp), whereas tropical partners' spillover temperature affects economic growth of rich economies (-0.193 $\pm$ 0.157 pp). Further bifurcating poor and rich economies into the tropical and non-tropical clusters, we find that the adverse effects of direct and spillover temperature shocks are borne by poor tropical and rich non-tropical economies, respectively.



(a) **Impact on overall economic growth:** The total impact from each temperature shock is computed using PVAR estimates and values of temperature shocks from data. We perform a t-test on computed values and plot the 95% confidence bands for each group.



(b) **Spillover Impact:** The spillover impact, plotted above in the hexplot, is computed using PVAR estimates and values of spillover temperature variables from data. These values are plotted against the spillover temperature shock of tropical and non-tropical partner groups for all economy-year observations.



(c) **Sectoral channel of total impact:** The total impact from each temperature variable is computed using PVAR estimates and values of spillover temperature variables from data. We perform a t-test on computed values and plot the 95% confidence bands for each group at the sector level.

Fig. 2: Total impact of temperature shock on economic growth

We compute the overall direct, spillover and total impact of temperature shocks on economic growth using a similar method discussed in the previous section. In column (1) of Table 2, we observe a clear pattern: only poor economies suffer negative effects from their direct temperature shocks, a finding supported by Dell et al. (2012)[30] and Acevedo et al. (2020)[29]. Remarkably, a thorough analysis that considers the spillover effect presents a different picture: Not only the poor ones but all economies are negatively affected by temperature shocks. This underscores the importance of spillover temperature shocks, as due to spillover effects, temperature shock ultimately affects economies across the income spectrum.

We discover from the 'Open with all interactions' version of our model, presented in column (2), Table 2, that the detrimental impact of a temperature shock does not affect rich economies equally. Notably, poor economies and rich non-tropical economies experience the worst effects of these shocks, with the spillover effects being larger than the direct effects for non-tropical economies. These results emphasise that the division of economies into poor and rich masks the heterogeneity of the impact of temperature shock on these economies due to their climatic zones.

Table 2: Differential impact of temperature shock in poor and rich economies

	(1) Open with poor interaction		**(2) Open with all interactions**			
	All economies		**Tropical**		**Non-tropical**	
	Poor	**Rich**	**Poor**	**Rich**	**Poor**	**Rich**
Direct Impact (in pp)	-0.011***	0.004***	-0.011**	-0.002**	-0.010	0.006**
	(0.004)	(0.001)	(0.005)	(0.001)	(0.007)	(0.002)
Spillover Impact (in pp)	-0.010***	-0.013***	-0.002***	-0.008	-0.025***	-0.016***
	(0.002)	(0.003)	(0.000)	(0.006)	(0.006)	(0.004)
Total Impact (in pp)	**-0.021*** **	**-0.009*** **	**-0.013** **	**-0.010**	**-0.035*** **	**-0.010** **
	(0.005)	**(0.003)**	**(0.005)**	**(0.007)**	**(0.010)**	**(0.004)**
Observations	4116	4116	2548	1470	1568	2646

The impact is computed using PVAR estimates and values of temperature shocks from data, and a t-test is employed for significance. Column (1) includes only poor and rich classification, whereas Column (2) includes further bifurcation into tropical and non-tropical economies. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Discussion

A growing body of research has revealed the significant impact of temperature shocks on an economy's potential for economic growth. Given the complex economic inter-dependencies resulting from international trade, our study adds to this stream of research by supplying empirical evidence in support of the notion that the idiosyncratic risks associated with temperature shocks in one economy may impact other economies' growth.

Our analysis demonstrates a differential adverse impact of temperature shocks on economic growth of tropical and non-tropical economies. Direct and spillover temperature shocks negatively impact economic growth of tropical economies. In contrast, the non-tropical economies are predominantly affected by spillover temperature shocks. While the agriculture sector of all economies experiences adverse economic effects from the direct temperature shock, the non-agriculture sector of non-tropical economies too experiences hurdles due to the spillover effect of temperature shocks.

Importantly, our research also shows that the harmful impacts of temperature shocks do not consistently affect various rich economies, demonstrating differences in vulnerability within this group. This indicates that the disparity in the effects of temperature shock on rich and poor economies due to their varying climatic zones is hidden by the income categorisation of economies. It is, therefore, imperative that the differential impacts of temperature shocks on poor and rich economies should be considered under the light of the climatic attributes of the economies.

Our results demonstrate the relevance of trade policies in understanding the actual effects of an increase in the mean global temperature. For example, trade policies can, definitely, provide viable adaptation methods towards the negative impact of climate change. Economies may provide subsidies to their direct temperature-shock-affected sector to make it competitive in the international market. They may also substitute a temperature-shock-affected trade partner for a temperature-shock-neutral one.

There is an ongoing debate on the reliability of the damage function considered for the computation of economic damages due to climate change in global climate models (like RICE/DICE, FACE). While these models consider only direct temperature shock in their damage function, our results indicate that the inclusion of spillover temperature shock in the damage function is crucial to understanding the real effect, necessitating substantial modification of global climate models.

References:

1. IPCC, A. W. (2021). *AR6 climate change 2021: The physical science basis*. Sixth Assessment Report: Working Group I.
2. Ayinde, O.E., Muchie, M., & Olatunji, G.B. (2011). Effect of climate change on agricultural productivity in Nigeria: a co-integration model approach. *Journal of Human Ecology, 35*, 189-194, https://doi.org/10.1080/09709274.2011.11906406
3. Abidoye, B.O., & Odusola, A.F. (2015, 3). Climate change and economic growth in Africa: An econometric analysis. *Journal of African Economies, 24*, 277-301, https://doi.org/10.1093/jae/eju033
4. Barrios, S., Ouattara, B., & Strobl, E. (2008, 8). The impact of climatic change on agricultural production: Is it different for Africa? *Food Policy, 33*, 287-298, https://doi.org/10.1016/j.foodpol.2008.01.003
5. Kotir, J.H. (2011, 6). Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability, 13*, 587-605, https://doi.org/10.1007/s10668-010-9278-0
6. Birthal, P.S., Hazrana, J., & Negi, D.S. (2021, 11). Impacts of climatic hazards on agricultural growth in India. *Climate and Development, 13*, 895-908, https://doi.org/10.1080/17565529.2020.1867045
7. Guiteras, R. (2009). *The impact of climate change on Indian agriculture*, Manuscript, Department of Economics, University of Maryland, College Park, Maryland
8. Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy, 129*, 1797-1827, https://doi.org/10.1086/713733
9. Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., & Zhang, L. (2009, 5). The impact of climate change on China's agriculture. *Agricultural Economics, 40*, 323-337, https://doi.org/10.1111/j.1574-0862.2009.00379.x
10. Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018, 3). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese

manufacturing plants. *Journal of Environmental Economics and Management, 88*, 1-17, https://doi.org/10.1016/j.jeem.2017.11.001
11. Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture, 13*, 660-665, https://doi.org/10.1016/S2095-3119(13)60701-7
12. Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review, 97*, 354-385, https://doi.org/10.1257/aer.97.1.354
13. Donadelli, M., Jüppner, M., Riedel, M., & Schlag, C. (2017, 9). Temperature shocks and welfare costs. *Journal of Economic Dynamics and Control, 82*, 331-355, https://doi.org/10.1016/j.jedc.2017.07.003
14. Schlenker, W., & Roberts, M.J. (2009, 9). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences, 106*, 15594-15598, https://doi.org/10.1073/pnas.0906865106
15. Gallic, E., & Vermandel, G. (2020, 5). Weather shocks. *European Economic Review, 124*, 103409, https://doi.org/10.1016/j.euroecorev.2020.103409
16. Aaheim, A., Amundsen, H., Dokken, T., & Wei, T. (2012, 10). Impacts and adaptation to climate change in European economies. *Global Environmental Change, 22*, 959-968, https://doi.org/10.1016/j.gloenvcha.2012.06.005
17. Forbes, K. J. (2004). The Asian flu and Russian virus: the international transmission of crises in firm-level data. *Journal of International Economics, 63(1)*, 59-92, https://doi.org/10.1016/S0022-1996(03)00044-8
18. Cravino, J., & Levchenko, A. A. (2017). Multinational firms and international business cycle transmission. *The Quarterly Journal of Economics, 132(2)*, 921-962, https://doi.org/10.1093/qje/qjw043
19. Jones, B.F., & Olken, B.A. (2010, 5). Climate shocks and exports. *American Economic Review, 100*, 454-459, https://doi.org/10.1257/aer.100.2.454
20. Dallmann, I. (2019). Weather variations and international trade. *Environmental and Resource Economics, 72*, 155-206, https://doi.org/10.1007/s10640-018-0268-2
21. Li, C., Xiang, X., & Gu, H. (2015, 10). Climate shocks and international trade: Evidence from China. *Economics Letters, 135*, 55-57, https://doi.org/10.1016/j.econlet.2015.07.032
22. Karlsson, J. (2021, 10). Temperature and exports: Evidence from the United States. *Environmental and Resource Economics, 80*, 311-337, https://doi.org/10.1007/s10640-021-00587-5
23. Gallup, J.L., Sachs, J.D., & Mellinger, A.D. (1999). Geography and economic development. *International regional science review, 22(2)*, 179–232, https://doi.org/10.1177/016001799761012334
24. Burke, M., Hsiang, S.M., & Miguel, E. (2015, 11). Global non-linear effect of temperature on economic production. *Nature, 527*, 235-239, https://doi.org/10.1038/nature15725
25. Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management, 103*, 102360, https://doi.org/10.1016/j.jeem.2020.102360
26. Nordhaus, W.D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences, 103(10)*, 3510–3517, https://doi.org/10.1073/pnas.0509842103
27. Zhao, Y., & Liu, S. (2023). Effects of climate change on economic growth: A perspective of the heterogeneous climate regions in Africa. *Sustainability, 15(9)*, 7136, https://doi.org/10.3390/su15097136

28. Helman, D., & Zaitchik, B.F. (2020). Temperature anomalies affect violent conflicts in African and middle eastern warm regions. *Global Environmental Change, 63*, 102118, https://doi.org/10.1016/j.gloenvcha.2020.102118
29. Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics, 65*, 103207, https://doi.org/10.1016/j.jmacro.2020.103207
30. Dell, M., Jones, B.F., & Olken, B.A. (2012, July). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics, 4(3)*, 66-95, https://doi.org/10.1257/mac.4.3.66
31. Ahmadi, M., Casoli, C., Manera, M., & Valenti, D. (2022). *Modelling the effects of climate change on economic growth: a bayesian structural global vector autoregressive approach*, FEEM Working Paper 46
32. Kahn, M.E., Mohaddes, K., Ng, R.N.C., Pesaran, M.H., Raissi, M., & Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics, 104*, 105624, https://doi.org/10.1016/j.eneco.2021.105624
33. Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., & Wood, E.F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data, 5*, 180214, https://doi.org/10.1038/sdata.2018.214
34. Rencher, A.C. (2002). *Methods of multivariate analysis*. J. Wiley.
35. Abrigo, M.R.M., & Love, I. (2016). Estimation of panel vector autoregression in stata. *The Stata Journal, 16(3)*, 778-804, https://doi.org/10.1177/1536867X1601600314
36. Acemoglu, D., Carvalho, V.M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica, 80*, 1977-2016, https://doi.org/10.3982/ECTA9623
37. Dees, S., Mauro, F.D., Pesaran, M.H., & Smith, L.V. (2007, 1). Exploring the international linkages of the Euro area: A global var analysis. *Journal of Applied Econometrics, 22*, 1-38, https://doi.org/10.1002/jae.932
38. Pesaran, M.H., Schuermann, T., & Weiner, S.M. (2004, 4). Modeling regional interdependences using a global error-correcting macroeconometric model. *Journal of Business and Economic Statistics, 22*, 129-162, https://doi.org/10.1198/073500104000000019
39. Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G.J. (2015, 8). An illustrated user guide to the world input-output database: The case of global automotive production. *Review of International Economics, 23*, 575-605, https://doi.org/10.1111/roie.12178
40. Holtz-Eakin, D., Newey, W., & Rosen, H.S. (1988). Estimating vector autoregressions with panel data. *Econometrica, 56*, 1371-1395, https://doi.org/10.2307/1913103
41. Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies, 58*, 277-297, https://doi.org/10.2307/2297968
42. Im, K.S., Pesaran, M.H., & Shin, Y. (2003, 7). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*, 53-74, https://doi.org/10.1016/S0304-4076(03)00092-7
43. Hamilton, J.D. (2020). *Time series analysis*. Princeton university press.
44. Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science Business Media.
45. Hansen, L.P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 1029-1054, https://doi.org/10.2307/1912775

46. Krugman, P. R., & Obstfeld, M. (2009). *International economics: Theory and policy*. Pearson Education.

Online methods

Data: We use economic activity-level value-added data at constant (2015) prices in US dollars from the United Nations data portal and combine economic activities of International Standard Industrial Classification codes from A to B as Agriculture and the rest as non-agriculture. Additionally, we obtain population information from the World Bank database and calculate the per-capita value-added. For trade openness, we obtain annual pair-wise trade exports and imports from the Direction of Trade Statistics. The Climate Change Knowledge Portal provides the grid-level annual average temperature and precipitation. The grid level climatic zone data is provided by Beck et al. (2018)[33]. Accordingly, we have balanced panel data with 168 countries from 1971 to 2019. The descriptive statistics are provided in the supplementary material (refer to Table S3–S7).

Clustering: We consider five broad classifications of climate zones from Beck et al. (2018)[33] data, i.e. A (Tropical), B (Arid), C (Temperate), D (Cold) and E (Polar) (refer to Table S1 in the supplementary material). Due to the unavailability of higher-resolution data pertaining to international trade and economic sector composition, we aggregate the climatic zone data at the country level by calculating the proportion of each climatic zone in the economy's geographical area. Accordingly, we compute the share of each climatic zone $[S_i(CZ)]$ in the country's geography as follows, where 'CZ' refers to climatic zones:

$$S_i(CZ) = \frac{\#\ of\ grids\ in\ CZ}{\#\ of\ grids\ in\ country\ i} \tag{1}$$

We use the Silhouette score and elbow method to determine the optimal number of clusters to group the countries based on their similar climatic characteristics. Accordingly, we consider $S_i(CZ)$ as input and compute two groups of countries using K-means clustering algorithm[34]. We define the *tropical dummy* $(Trop_i)$ as one if the economy is in a tropical cluster; otherwise, zero.

Spillover variable: We create a cluster-level spillover variable based on trade connectivity inspired by the Global Vector Autoregressive (GVAR) literature[31,37,38] to capture the effects of shocks on partner economies at the cluster level. Specifically speaking, we define the variable 'trade openness weight' (denoted as w_{ijt}) as the ratio of the sum of exports and imports between a given home economy 'i' and its partner economy 'j' in year 't', relative to the sum of exports and imports for the home economy 'i' in the year 't' with all partner economies. To further refine our analysis, we calculate the three-year simple moving average of w_{ijt} and represent it as $\tilde{w}_{ijt}$ and compute the spillover temperature shock as $ST_{k,it} = \sum_{j \in k} \tilde{w}_{ijt-1} \times \Delta T_{jt}$, where, ΔT_{jt} is the temperature shock in partner 'j' in the year 't', and 'k' represents one of the two different clusters of tropical and non-tropical economies.

Empirical approach: We employ the following PVAR model with three lags incorporating per-capita GVA growth rates (overall and from the agriculture sector) as endogenous variables for the studies discussed in the paper.

$$\begin{aligned} Y_{it} = &\sum_{l=1}^{3} A_l Y_{it-l} + \tau\left(\Delta T_{it}, ST_{kit}\right) + \sigma\left(\Delta P_{it}, SP_{kit}\right) \\ &+ \alpha_r tr_t + Autarky_{it} + u_i + \epsilon_{it} \end{aligned} \tag{2}$$

where Y_{it} is a vector of endogenous variables and A_l is corresponding coefficient of endogenous variables with lag 'l'. $\tau\left(\Delta T_{it}, ST_{kit}\right)$ and $\sigma\left(\Delta P_{it}, SP_{kit}\right)$ are the functional forms of the exogenous temperature and precipitation variables, respectively. ΔT_{it} (ΔP_{it}) represents the temperature (precipitation) shock to economy 'i' in the year 't' whereas ST_{kit} (SP_{kit}) refers to the spillover temperature (precipitation) shock experienced by economy 'i' from trade partner cluster $k \in \{Tropical\ (`Tr'),\ Non-tropical\ (`NonTr')\}$ in the year 't'. tr_t are regional-level time trends, u_i are country-level fixed effects, and ϵ_{it} are idiosyncratic errors for country 'i' in year 't'. We define the *autarky dummy* ('$Autarky_{it}$') for open versions of our model, which takes the value of one for not trade-connected economy 'i' during a particular year 't'. We assume the homogeneous independent error structure, that is, $E\left(\epsilon_{it}\epsilon_{it}'\right) = \Sigma\ \forall\ i,\ t$ where Σ is a symmetric full rank matrix.

We bifurcate per capita GVA growth rate into per capita GVA growth rates from agriculture and that from non-agriculture sector as follows: we consider the national identity equation: $y_{it} = a_{it} + na_{it}$, where a_{it}, na_{it} and y_{it} are per-capita agriculture sector, non-agriculture sector and economy GVA, respectively, for country 'i' in year 't'. Taking the log and differentiating wrt 't', we get:

$$\dot{y}_{it} = w_{a,it} \times \dot{a}_{it} + w_{na,it} \times \dot{na}_{it} \tag{3}$$

where $\dot{y}_{it}$, $\dot{a}_{it}$ and $\dot{na}_{it}$ are per-capita GVA growth rates of economy, agriculture sector and non-agriculture sector, respectively: whereas, $w_{m,it}$ is share of sector 'm' where 'm' being agriculture ('a') or non-agriculture ('na'). The first term on the right-hand side of the Equation (3) is per capita economy GVA growth from the agriculture sector ($w_{a,it} \times \dot{a}_{it} = \bar{A}_{it}$), and the second term corresponds to that from the non-agriculture sector ($w_{na,it} \times \dot{na}_{it} = \bar{NA}_{it}$). We use $Y_{it} = [\dot{y}_{it}\quad \bar{A}_{it}]'$ as endogenous variables and compute impact on $\bar{NA}_{it}$ using linear combination hypothesis.

Finally, we consider the following functional forms of the temperature shock variables. Equations (4)–(5) are employed for the closed economy versions of our model, whereas Equations (6)–(7) are for open economy versions for results in Table 1. Finally, Equations (8)–(9) are employed for the estimates of differentiated impact on poor and rich economies in Table 2, where $Poor_i$ is the *poor dummy* taking value one if the economy 'i' has per capita GVA less than that of world median in 1970. A similar specification is considered for the precipitation shock. For marginal effects of one-SD shock, we multiply standard deviations of temperature shocks with coefficients obtained from Equations (4)–(9). We have tabulated the computation strategy of marginal effect for each cluster and income group in Table S10 in the supplementary material.

$$\tau\left(.\right) = \beta_1 \Delta T_{it} \tag{4}$$

$$\tau\left(.\right) = \beta_1 \Delta T_{it} + \beta_{11} \Delta T_{it} \times Trop_i \tag{5}$$

$$\tau\left(.\right) = \beta_1 \Delta T_{it} + \beta_{11} \Delta T_{it} \times Trop_i + \beta_2 ST_{Tr,it} + \beta_3 ST_{NonTr,it} \tag{6}$$

$$\begin{aligned} \tau\left(.\right) = {} & \beta_1 \Delta T_{it} + \beta_{11} \Delta T_{it} \times Trop_i \\ & + \beta_2 ST_{Tr,it} + \beta_{21} ST_{Tr,it} \times Trop_i \\ & + \beta_3 ST_{NonTr,it} + \beta_{31} ST_{NonTr,it} \times Trop_i \end{aligned} \tag{7}$$

$$\begin{aligned} \tau\left(.\right) = {} & \beta_1 \Delta T_{it} + \beta_{12} \Delta T_{it} \times Poor_i \\ & + \beta_2 ST_{Tr,it} + \beta_{22} ST_{Tr,it} \times Poor_i \\ & + \beta_3 ST_{NonTr,it} + \beta_{32} ST_{NonTr,it} \times Poor_i \end{aligned} \tag{8}$$

$$\tau(.) = \beta_1 \Delta T_{it} + \beta_{11} \Delta T_{it} \times Trop_i + \beta_{12} \Delta T_{it} \times Poor_i + \beta_2 ST_{Tr,it} + \beta_{21} ST_{Tr,it} \times Trop_i + \beta_{22} ST_{Tr,it} \times Poor_i + \beta_3 ST_{NonTr,it} + \beta_{31} ST_{NonTr,it} \times Trop_i + \beta_{32} ST_{NonTr,it} \times Poor_i \quad (9)$$

The direction and magnitude of temperature shocks of various kinds—direct, tropical spillover and non-tropical spillover—vary across country-year observations. For Fig. 2, we compute the impact of different temperature shocks on economic growth for each country-year observation. For that purpose, we multiply the coefficient estimates (refer to Table S9 in supplementary material) with the actual value of the temperature shocks. This methodology assumes that the marginal effect of a temperature shock is constant across time for each cluster and income group. Nevertheless, the total impact will differ as the direction and magnitude of direct and spillover temperature shocks are different.

Pre-estimation and post-diagnostic tests: We employ the system-GMM estimator to estimate the PVAR model[40]. We apply Arellano and Bond statistics[41] to determine whether a second-order serial correlation exists in the initial differenced residuals. We select lags such that the condition of the non-existence of second-order serial correlation is satisfied to ensure consistency of results. Further, we perform a panel unit root test[42] to check for stationarity of each variable considered in the PVAR model, and the unit roots do not exist at 1% significance (refer to Table S8 in the supplementary material). As part of the post-diagnostic tests, we check the model's stability, ensuring each eigenvalue's modulus lies within a unit circle[43,44]. Further, we check the overidentifying restrictions[45] to ensure the instruments are valid in the model. Using asymptotically χ^2-distributed Wald statistic, we test the null hypothesis of no impact of the temperature shock on per capita GVA growth rate.

Robustness checks: We use the same model specification for different censoring levels ranging from 2% to 5%, as opposed to the baseline model of 1% censoring (refer to Table S12 and S16). Additionally, we test for robustness of results using different trade openness weights—compared to the baseline case of a three-year simple moving average—which include simple moving averages of five-year, four-year and two-year duration as well as the last year and the contemporaneous values as weight (refer to Table S13 and S17).

We also consider a two, four and five year lag order of endogenous variables to assess the results' reliability (refer to Table S14 and S18). Further, we calculate the results, taking alternative endogenous variables into account because the different endogenous variables may impact the outcomes. Moreover, we consider a non-linear model of direct temperature shock [as suggested by Burke et al. (2015)[24]]. Finally, we also consider K-median clustering, country trends and clustered standard errors for robustness (refer to Table S15 and S19).

Supplementary Material

Literature review:

Apart from the global studies on the impact of temperature shock on economic growth, various country-level and regional-level studies talk about the impact of temperature shock. The country-level studies identify a negative impact on developing countries[1−6] but ambiguous impact on developed countries[7−10]. Further, the regional-level studies observe a negative impact of temperature shock on the countries from the African region[11−13] and ones from the Asian continent[14] but find both positive and negatives impacts in case of countries from the European region[15]. These studies are silent about the impact of temperature shock on economic growth through trade channels.

The trade-climate literature estimates that a temperature shock significantly reduces a country's exports, whereas imports are insignificantly affected. Jones and Olken (2010)[16] find that the temperature shocks in the poor countries decrease their exports with no impact for rich countries. Using 134 counties for period 1992-2014, Dallman (2019)[17] observes that the temperature shock affects export patterns negatively, whereas a temperature shock in a partner country do not affect exports. In the context of China, Li et al. (2015)[18] find that a temperature shock substantially affect China's exports. Similar results are observed by Karlsson (2021)[19] in the case of United States.

This initial impact on trade can affect the partner countries' import or export-led growth. Even if the initial impact of temperature shock on trade is insignificant, Acemoglu et al. (2012)[20] demonstrate that an atypical shock to just one firm may significantly impact other sectors through input-output channels. This channel is studied for understanding the aggregate national and global level impact of extreme weather events like floods[21−24].

Ahmadi et al. (2022)[25] partially explore the spillover effect of a temperature shock. Using Bayesian Global VAR, the authors demonstrate that the magnitude of temperature shock changes in the presence of trade. While this finding reveals that a country transfers its climate risks/returns to partner countries, nevertheless, this study does not comment on how economic growth of partner countries is affected because of the transmission of climate risks. We address all these shortcomings in our work.

Clustering Analysis

We consider five broad classifications of climate zones from Beck et al. (2018)[26] data, i.e. A (Tropical), B (Arid), C (Temperate), D (Cold) and E (Polar) (refer to Table S1). This data provides approx. 50 km resolution map for climatic zones for all economies. Extracting this data, we compute the share of each zone $[S_i(CZ) = \frac{\#\ of\ grids\ of\ CZ}{\#\ of\ grids\ of\ economy\ i}]$ for the economy 'i', where 'CZ' represents the climatic zone. We use the Silhouette score and the elbow method to determine the optimal number of clusters to group the economies based on their similar climatic characteristics. Fig. 3 demonstrates that the optimal number of clusters is two, given that the silhouette score is highest and the elbow method shows an elbow bend at point two.

Accordingly, we consider $S_i(CZ)$ as input and compute two groups of economies

Table S1: Classification of climate zones

Zones	Description	Criterion
A	Tropical	The air temperature of the coldest month is greater than 18°C
B	Arid	Mean annual precipitation <10×Threshhold(P) where, Threshhold(P) = 2×Mean annual temperature (if >70% precipitation falls in winter) Threshhold(P) = 2×Mean annual temperature + 28 (if >70% precipitation falls in summer)
C	Temperate	The air temperature of the warmest month is greater than 10°C and the air temperature of the coldest month is (0°C,18°C)
D	Cold	The air temperature of the warmest month is less than 10°C and the air temperature of the coldest month is less than 0°C
E	Polar	The air temperature of the warmest month is less than 0°C

It is initially decided whether or not the grid's climatic zone is B. If not, additional zones are assigned to it.

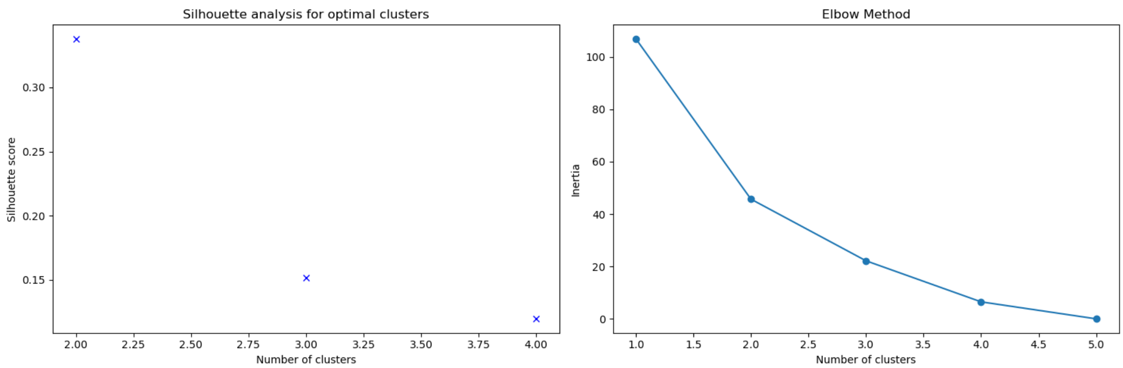


Fig. 3: Optimal number of clusters

using K-means clustering algorithm[27]. Table S2 provides summary statistics on the share of different climatic zones for each cluster.

Table S2: Summary statistics of climate zones

Zones	All	Cluster 1	Cluster 2
Tropical (A)	0.4742	0.9359	0.0340
	(0.4652)	(0.1292)	(0.0987)
Arid (B)	0.2202	0.0172	0.4138
	(0.3590)	(0.0499)	(0.4154)
Temperate (C)	0.1858	0.0424	0.3225
	(0.3118)	(0.1002)	(0.3769)
Cold (D)	0.0919	-	0.1795
	(0.2494)	(-)	(0.3253)
Polar (E)	0.0279	0.0044	0.0503
	(0.1217)	(0.0257)	(0.1652)

Standard deviations are in parenthesis

Descriptive statistics

Tables S3–S7 provide the descriptive statistics for the economic and climatic variables for the 168 economies across the period 1971-2019, as available in our dataset.

Table S3: Descriptive statistics of all economies

	Mean	Std. Dev.	Median	Minimum	Maximum
GVA Growth Rate ($\dot{g}_{it}$) in pp	1.562	6.409	1.929	-109.418	67.279
Agriculture Channel ($\bar{A}_{it}$) in pp	0.094	1.984	0.030	-25.815	34.126
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	1.525	5.757	1.759	-96.834	68.597
Direct Temperature (ΔT_{it})	0.020	0.453	0.020	-3.023	2.756
Tropical Spillover Temperature ($ST_{Tr,it}$)	0.003	0.049	0.000	-0.862	0.570
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	0.026	0.292	0.000	-1.545	1.871
Direct Precipitation (ΔP_{it})	-0.010	2.885	0.000	-34.201	26.450
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-0.008	0.409	0.000	-4.898	6.572
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	0.005	0.561	0.000	-3.687	3.999

The statistics are for all economies. There are 8,232 country-year observations.

Table S4: Descriptive statistics for clusters

	Mean	Std. Dev.	Median	Minimum	Maximum
GVA Growth Rate ($\dot{g}_{it}$) in pp	1.467	6.241	1.926	-60.102	67.279
	(1.653)	(6.564)	(1.931)	(-109.418)	(65.766)
Agriculture Channel ($\bar{A}_{it}$) in pp	0.110	2.204	0.058	-25.815	34.126
	(0.078)	(1.749)	(0.017)	(-22.078)	(18.533)
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	1.418	5.401	1.656	-47.142	68.597
	(1.628)	(6.075)	(1.803)	(-96.834)	(64.947)
Direct Temperature (ΔT_{it})	0.015	0.304	0.016	-1.272	1.286
	(0.025)	(0.559)	(0.030)	(-3.023)	(2.756)
Tropical Spillover Temperature ($ST_{Tr,it}$)	0.004	0.063	0.000	-0.862	0.570
	(0.002)	(0.029)	(0.000)	(-0.284)	(0.232)
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	0.023	0.253	0.000	-0.979	1.196
	(0.029)	(0.324)	(0.000)	(-1.545)	(1.871)
Direct Precipitation (ΔP_{it})	-0.030	3.806	0.000	-34.201	26.45
	(0.008)	(1.564)	(0.017)	(-10.565)	(13.321)
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-0.014	0.559	0.000	-4.898	6.572
	(-0.003)	(0.169)	(0.000)	(-1.435)	(1.398)
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	0.007	0.527	0.000	-3.687	3.067
	(0.004)	(0.592)	(0.000)	(-3.584)	(3.999)

The statistics are for tropical clusters and the ones in the parenthesis are for non-tropical cluster. There are 8,232 country-year observations.

Estimates of PVAR model

We perform panel unit root tests[28] to ensure stationarity of variables in the model. We assume three lags and trend before employing the Augmented Dickey Fuller regressions for tests (refer to Table S8 for results). The results are consistent across models with different numbers of lag.

The estimates for the PVAR models presented in the main paper are shown in Table S9. The fuller version of the results that we have described in columns (1)–(4) of Table 1 and for Fig. 2 in the main paper, are available in columns (1)–(4) in Table S9. Similarly, the fuller versions of the results in the columns (1) and (2) in

Table S5: Descriptive statistics for income groups

	Mean	Std. Dev.	Median	Minimum	Maximum
GVA Growth Rate ($\dot{g}_{it}$) in pp	1.821	6.259	2.230	-60.102	65.238
	(1.303)	(6.546)	(1.646)	(-109.418)	(67.279)
Agriculture Channel ($\bar{A}_{it}$) in pp	0.155	2.727	0.154	-25.815	34.126
	(0.323)	(0.653)	(0.008)	(-12.584)	(8.560)
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	1.758	5.104	1.860	-47.142	48.177
	(1.292)	(6.335)	(1.641)	(-96.834)	(68.597)
Direct Temperature (ΔT_{it})	0.015	0.383	0.019	-2.108	1.673
	(0.025)	(0.513)	(0.023)	(-3.023)	(2.756)
Tropical Spillover Temperature ($ST_{Tr,it}$)	0.003	0.057	0.000	-0.862	0.570
	(0.003)	(0.039)	(0.001)	(-0.319)	(0.257)
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	0.025	0.262	0.000	-0.979	1.196
	(0.027)	(0.319)	(0.000)	(-1.545)	(1.871)
Direct Precipitation (ΔP_{it})	-0.011	2.897	0.000	-22.568	21.809
	(-0.010)	(2.873)	(0.013)	(-34.201)	(26.450)
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-0.007	0.474	0.000	-4.898	6.572
	(-0.009)	(0.330)	(0.000)	(-2.665)	(2.585)
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	0.006	0.564	0.000	-3.687	2.761
	(0.005)	(0.559)	(0.000)	(-3.585)	(3.999)

The statistics are for poor economies and the ones in the parenthesis are for rich economies. There are 8,232 country-year observations.

Table S6: Descriptive statistics for clusters in poor economies

	Mean	Std. Dev.	Median	Minimum	Maximum
GVA Growth Rate ($\dot{g}_{it}$) in pp	1.615	6.436	2.097	-60.102	65.238
	(2.155)	(5.947)	(2.488)	(-36.172)	(46.947)
Agriculture Channel ($\bar{A}_{it}$) in pp	0.153	2.710	0.143	-25.815	34.126
	(0.158)	(2.756)	(0.173)	(-22.078)	(18.533)
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	1.544	5.233	1.697	-47.142	48.177
	(2.105)	(4.870)	(2.140)	(-22.929)	(43.105)
Direct Temperature (ΔT_{it})	0.013	0.302	0.015	-1.250	1.087
	(0.020)	(0.489)	(0.030)	(-2.108)	(1.673)
Tropical Spillover Temperature ($ST_{Tr,it}$)	0.004	0.066	0.000	-0.862	0.570
	(0.002)	(0.037)	(0.000)	(-0.284)	(0.232)
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	0.024	0.257	0.000	-0.979	1.196
	(0.026)	(0.270)	(0.000)	(-0.867)	(1.007)
Direct Precipitation (ΔP_{it})	-0.021	3.509	0.000	-22.568	21.809
	(0.005)	(1.427)	(0.001)	(-6.613)	(5.896)
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-0.011	0.563	0.000	-4.898	6.572
	(-0.002)	(0.192)	(0.000)	(-1.435)	(1.112)
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	0.007	0.563	0.000	-3.687	2.593
	(0.004)	(0.565)	(0.000)	(-2.844)	(2.761)

The statistics are for tropical clusters and the ones in the parenthesis are for non-tropical cluster. All the statistics are for the poor economies. There are 8,232 country-year observations.

Table 2 of the main paper, are described in Columns (5) and (6) in Table S9.

Table S10 presents the computations for the marginal effect of a one-standard-deviation (one-SD) temperature shock. We illustrate an example here. The marginal effect of a tropical spillover temperature shock on non-tropical economies—in the case of the 'Open with interaction' version of our model—is computed by multiplying the standard deviation of the non-tropical cluster (0.029°C, Table S4) with the coefficients β_2 (-6.039 pp, Table S9) in Equation (7) highlighted in the online methods. Finally, Table S11 showcases the marginal effects for a one-SD temperature shock, utilizing the estimates from columns (5) and (6) in Table S9.

Table S7: Descriptive statistics for clusters in rich economies

	Mean	**Std. Dev.**	**Median**	**Minimum**	**Maximum**
GVA Growth Rate ($\dot{g}_{it}$) in pp	1.209	5.881	1.584	-36.07	67.279
	(1.356)	(6.888)	(1.676)	(-109.418)	(65.766)
Agriculture Channel ($\bar{A}_{it}$) in pp	0.035	0.733	0.015	-4.422	8.561
	(0.031)	(0.604)	(0.007)	(-12.584)	(4.872)
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	1.198	5.677	1.561	-31.688	68.597
	(1.345)	(6.673)	(1.674)	(-96.834)	(64.947)
Direct Temperature (ΔT_{it})	0.018	0.307	0.020	-1.272	1.286
	(0.028)	(0.597)	(0.030)	(-3.023)	(2.756)
Tropical Spillover Temperature ($ST_{Tr,it}$)	0.004	0.057	0.001	-0.319	0.257
	(0.002)	(0.024)	(0.001)	(-0.192)	(0.128)
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	0.022	0.246	0.000	-0.852	0.889
	(0.030)	(0.353)	(0.002)	(-1.545)	(1.871)
Direct Precipitation (ΔP_{it})	-0.046	4.275	0.000	-34.201	26.450
	(0.011)	(1.640)	(0.024)	(-10.565)	(13.321)
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-0.020	0.513	0.000	-2.665	2.585
	(-0.003)	(0.153)	(0.000)	(-1.091)	(1.398)
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	0.006	0.460	0.000	-3.445	3.067
	(0.004)	(0.607)	(0.000)	(-3.585)	(3.999)

The statistics are for tropical clusters and the ones in the parenthesis are for non-tropical cluster. All the statistics are for the rich economies. There are 8,232 country-year observations.

Table S8: Panel unit root tests

Variables	**Test Statistics**
GVA Growth Rate ($\dot{g}_{it}$) in pp	-21.202***
Agriculture Channel ($\bar{A}_{it}$) in pp	-26.510***
Non-Agriculture Channel ($\bar{NA}_{it}$) in pp	-20.361***
Direct Temperature (ΔT_{it})	-48.646***
Tropical Spillover Temperature ($ST_{Tr,it}$)	-53.266***
Non-tropical Spillover Temperature ($ST_{NonTr,it}$)	-42.958***
Direct Precipitation (ΔP_{it})	-50.202***
Tropical Spillover Precipitation ($SP_{Tr,it}$)	-54.371***
Non-Tropical Spillover Precipitation ($SP_{NonTr,it}$)	-46.650***

There are 8,232 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S9: Estimates of PVAR model in the main paper

	(1) Closed economy		(2) Closed with interaction		(3) Open economy		(4) Open with interaction		(5) Open with poor interaction		(6) Open with all interaction	
	GVA growth	Agri. sector	GVA growth	Agri. sector	GVA growth	Agri. sector	GVA growth	Agri. sector	GVA growth	Agri. sector	GVA growth	Agri. sector
Direct temperature	-0.227*	-0.186***	-0.0897	-0.156***	-0.0506	-0.142***	0.0262	-0.160***	0.152	-0.0338	0.217	-0.0442*
	(0.117)	(0.0341)	(0.129)	(0.0355)	(0.147)	(0.0411)	(0.156)	(0.0424)	(0.179)	(0.0214)	(0.183)	(0.0268)
Interacted with												
Tropical dummy			-0.631**	-0.121	-0.340	-0.101	-0.620	-0.134			-0.335	0.0284
			(0.301)	(0.0963)	(0.367)	(0.121)	(0.405)	(0.128)			(0.432)	(0.137)
Poor dummy									-0.843***	-0.424***	-0.742**	-0.416***
									(0.299)	(0.107)	(0.318)	(0.113)
Tropical spillover temperature					-2.335*	-0.140	-6.039**	-0.863	-4.984**	-1.119***	-7.224**	-1.176
					(1.406)	(0.466)	(3.039)	(1.283)	(2.063)	(0.275)	(3.406)	(1.101)
Interacted with												
Tropical dummy							4.840	1.152			3.042	0.227
							(3.443)	(1.368)			(3.563)	(1.421)
Poor dummy									4.282*	1.878***	4.138	1.717**
									(2.526)	(0.634)	(2.703)	(0.735)
Non-tropical spillover temperature					-0.127	-0.0552	-0.273	0.0757	-0.0160	0.0194	-0.173	0.0786
					(0.211)	(0.0662)	(0.257)	(0.0743)	(0.264)	(0.0394)	(0.282)	(0.0551)
Interacted with												
Tropical dummy							0.344	-0.309**			0.645	-0.222
							(0.441)	(0.143)			(0.483)	(0.157)
Poor dummy									-0.323	-0.220	-0.566	-0.140
									(0.438)	(0.145)	(0.476)	(0.157)

All models include direct precipitation shock, economy fixed effects, and regional trend as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector. Additional controls, in case of open economy model, includes spillover precipitation and *autarky dummy*.

Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.

Column (1) includes direct temperature shock; Column (2) interacts direct temperature shock with the *tropical dummy*; Column (3) includes spillover shock variable; Column (4) interacts spillover shock variable with the *tropical dummy*; Column (5) interacts temperature shock variable with the *poor dummy*; and Column (6) interacts temperature shock variable with the *tropical dummy* and the *poor dummy*. We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S10: Computation of marginal effects of one-SD temperature shock

PVAR Model	**Economies**	**Temperature shock**	**Standard Deviations**	**Coefficients**	**Equation in online methods**
Closed economy	All	Direct	Table S3	β_1	Equation (4)
Closed with interaction	Tropical	Direct	Table S4	$\beta_1 + \beta_{11}$	Equation (5)
	Non-tropical	Direct	Table S4	β_1	
Open economy	Tropical	Direct	Table S4	$\beta_1 + \beta_{11}$	Equation (6)
	Non-tropical	Direct	Table S4	β_1	
	All	Tropical spillover	Table S3	β_2	
	All	Non-tropical spillover	Table S3	β_3	
Open with interaction	Tropical	Direct	Table S4	$\beta_1 + \beta_{11}$	Equation (7)
		Tropical spillover	Table S4	$\beta_2 + \beta_{21}$	
		Non-tropical spillover	Table S4	$\beta_3 + \beta_{31}$	
	Non-tropical	Direct	Table S4	β_1	
		Tropical spillover	Table S4	β_2	
		Non-tropical spillover	Table S4	β_3	
Open with poor interaction	Poor	Direct	Table S5	$\beta_1 + \beta_{12}$	Equation (8)
		Tropical spillover	Table S5	$\beta_2 + \beta_{22}$	
		Non-tropical spillover	Table S5	$\beta_3 + \beta_{32}$	
	Rich	Direct	Table S5	β_1	
		Tropical spillover	Table S5	β_2	
		Non-tropical spillover	Table S5	β_3	
Open with all interactions	Poor-Tropical	Direct	Table S6	$\beta_1 + \beta_{11} + \beta_{12}$	Equation (9)
		Tropical spillover	Table S6	$\beta_2 + \beta_{21} + \beta_{22}$	
		Non-tropical spillover	Table S6	$\beta_3 + \beta_{31} + \beta_{32}$	
	Poor-Nontropical	Direct	Table S6	$\beta_1 + \beta_{12}$	
		Tropical spillover	Table S6	$\beta_2 + \beta_{22}$	
		Non-tropical spillover	Table S6	$\beta_3 + \beta_{32}$	
	Rich-Tropical	Direct	Table S7	$\beta_1 + \beta_{11}$	
		Tropical spillover	Table S7	$\beta_2 + \beta_{21}$	
		Non-tropical spillover	Table S7	$\beta_3 + \beta_{31}$	
	Rich-Nontropical	Direct	Table S7	β_1	
		Tropical spillover	Table S7	β_2	
		Non-tropical spillover	Table S7	β_3	

The marginal effects are computed by multiplying the respective standard deviations of the economies with the values obtained from the coefficients of the PVAR models.

Table S11: Marginal estimates for a global sample at one standard deviation shock to temperature on poor and rich

	(1)		(2)			
	All		Tropical		Non-Tropical	
	Poor	Rich	Poor	Rich	Poor	Rich
Dependent variable: GVA per capita growth rate (in pp)						
Direct temperature	-0.265***	0.078	-0.259**	-0.036	-0.256*	0.129
	(0.092)	(0.092)	(0.116)	(0.136)	(0.134)	(0.109)
Tropical spillover temperature	-0.040	-0.193**	-0.003	-0.237	-0.115	-0.170**
	(0.082)	(0.080)	(0.110)	(0.154)	(0.125)	(0.080)
Non-tropical spillover temperature	-0.089	-0.005	-0.024	0.116	-0.199	-0.061
	(0.091)	(0.084)	(0.103)	(0.115)	(0.121)	(0.100)
Dependent variable: GVA per capita growth rate from agriculture (in pp)						
Direct temperature	-0.176***	-0.017	-0.130***	-0.005	-0.225***	-0.026*
	(0.040)	(0.011)	(0.041)	(0.039)	(0.056)	(0.016)
Tropical spillover temperature	0.043	-0.043***	0.051	-0.054	0.020	-0.027
	(0.032)	(0.011)	(0.037)	(0.035)	(0.056)	(0.026)
Non-tropical spillover temperature	-0.053	0.006	-0.073*	-0.035	-0.017	0.028
	(0.036)	(0.013)	(0.039)	(0.032)	(0.031)	(0.019)
Dependent variable: GVA per capita growth rate from non-agriculture (in pp)						
Direct temperature	-0.090	0.095	-0.129	-0.032	-0.032	0.156
	(0.075)	(0.089)	(0.101)	(0.125)	(0.112)	(0.105)
Tropical spillover temperature	-0.083	-0.150*	-0.053	-0.183	-0.136	-0.142*
	(0.074)	(0.078)	(0.103)	(0.145)	(0.107)	(0.073)
Non-tropical spillover temperature	-0.036	-0.011	0.049	0.151	-0.183*	-0.089
	(0.075)	(0.081)	(0.086)	(0.105)	(0.103)	(0.095)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
Column (1) interacts temperature shock variable with the *poor dummy*; and Column (2) interacts temperature shock variable with the *tropical dummy* and the *poor dummy*. We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Robustness checks:

Direct and spillover impact of temperature shock

Tables S12–S15 present robustness checks for results concerning direct and spillover impact on the tropical and non-tropical economies. Table S12 presents results with different levels of censoring, that is, 2% to 5% as compared to the baseline 1% level. Table S13 considers notion for calculating different trade openness weight for the spillover temperature variable. These notions include using (a) contemporaneous trade openness [Column (2)], (b) one-year lag [Column (3)], (c) two-year simple moving average [Column (4)], (d) four-year simple moving average [Column (5)], and (e) five-year simple moving average [Column (6)].

Since the PVAR model is potentially sensitive to different lag orders, we consider two-year lag [Column (2)], four-year lag [Column (3)] and five-year lag [Column (4)] and present the corresponding results in Table S14 to vindicate the robustness of our exercise.

Finally, Table S15 presents other robustness checks. We use the K-median clustering technique instead of K-means in column (2). We use standard errors clustered at the economy level instead of robust standard errors in column (3). Column (4) considers quadratic terms for direct temperature and precipitation variables as Burke et al. (2015)[29] have considered. Columns (5) and (6) consider different vectors of endogenous variables. Column (5) considers $\bar{A}_{it}$ and $\bar{NA}_{it}$ as endogenous variables and presents impacts on per capita GVA growth rate using linear hypothesis test. Column (6) considers GVA, agricultural value added and non-agriculture value added growth rate instead of $\bar{A}_{it}$ and $\bar{NA}_{it}$. Finally, we consider country trends instead of regional trends in column (7). We find the robustness of our main results from these various robustness checks.

Table S12: Robustness checks: Different level of censoring for endogenous variables

	(1) Baseline 1%	(2) Censor 2%	(3) Censor 3%	(4) Censor 4%	(5) Censor 5%
Direct temperature	0.0262	-0.00123	-0.0245	-0.0446	-0.0541
	(0.156)	(0.145)	(0.137)	(0.133)	(0.129)
Interacted with					
Tropical dummy	-0.620	-0.572	-0.527	-0.464	-0.440
	(0.405)	(0.383)	(0.363)	(0.350)	(0.340)
Tropical spillover temperature	-6.039**	-6.136**	-5.991**	-5.740**	-5.582**
	(3.039)	(2.939)	(2.827)	(2.776)	(2.732)
Interacted with					
Tropical dummy	4.840	4.992	4.928	4.642	4.536
	(3.443)	(3.302)	(3.159)	(3.090)	(3.034)
Non-tropical spillover temperature	-0.273	-0.228	-0.197	-0.159	-0.125
	(0.257)	(0.240)	(0.227)	(0.221)	(0.215)
Interacted with					
Tropical dummy	0.344	0.274	0.200	0.151	0.101
	(0.441)	(0.412)	(0.388)	(0.376)	(0.365)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S13: Robustness checks: Spillover weights

	(1) Baseline 3yr-SMA	(2) Current year	(3) One year lag	(4) 2 year SMA	(5) 4 year SMA	(6) 5 year SMA
Direct temperature	0.0262	0.0199	0.0122	0.00901	0.0248	0.0234
	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)
Interacted with						
Tropical dummy	-0.620	-0.572	-0.615	-0.618	-0.619	-0.591
	(0.405)	(0.407)	(0.411)	(0.407)	(0.405)	(0.404)
Tropical spillover temperature	-6.039**	-6.121**	-5.253*	-5.814*	-6.409**	-6.279**
	(3.039)	(2.838)	(2.950)	(2.997)	(3.074)	(3.064)
Interacted with						
Tropical dummy	4.840	4.654	4.250	4.785	5.155	4.788
	(3.443)	(3.278)	(3.397)	(3.412)	(3.476)	(3.472)
Non-tropical spillover temperature	-0.273	-0.223	-0.232	-0.212	-0.256	-0.256
	(0.257)	(0.255)	(0.257)	(0.256)	(0.258)	(0.258)
Interacted with						
Tropical dummy	0.344	0.253	0.232	0.261	0.381	0.399
	(0.441)	(0.443)	(0.441)	(0.443)	(0.438)	(0.435)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S14: Robustness checks: Lag order

	(1) Baseline - lag 3	(2) Order - lag 2	(3) Order - lag 4	(4) Order - lag 5
Direct temperature	0.0262	0.0384	0.0241	-0.0204
	(0.156)	(0.155)	(0.157)	(0.158)
Interacted with				
Tropical dummy	-0.620	-0.670	-0.403	-0.383
	(0.405)	(0.411)	(0.407)	(0.408)
Tropical spillover temperature	-6.039**	-7.076**	-5.743*	-5.359*
	(3.039)	(3.094)	(3.016)	(3.012)
Interacted with				
Tropical dummy	4.840	6.129*	3.841	3.455
	(3.443)	(3.502)	(3.416)	(3.412)
Non-tropical spillover temperature	-0.273	-0.233	-0.287	-0.209
	(0.257)	(0.254)	(0.256)	(0.258)
Interacted with				
Tropical dummy	0.344	0.545	0.329	0.302
	(0.441)	(0.436)	(0.442)	(0.443)
Observations	7560	7728	7392	7224

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S15: Robustness checks: Others

	(1) Baseline	(2) Clustering K-median	(3) Errors Country	(4) Non-linear Temp	(5) Endo. var. Channel	(6) Endo. var. Growth rate	(7) Country Trend
Direct temperature	0.026	0.021	0.023	0.031	0.022	0.022	0.017
	(0.156)	(0.155)	(0.210)	(0.156)	(0.154)	(0.155)	(0.156)
Interacted with							
Tropical dummy	-0.620	-0.600	-0.619	-0.610	-0.609	-0.583	-0.602
	(0.405)	(0.409)	(0.422)	(0.406)	(0.401)	(0.405)	(0.409)
Direct temperature (Sq.)				0.243*			
				(0.142)			
Interacted with							
Tropical dummy				-0.870			
				(0.700)			
[1em] Tropical spillover temperature	-6.039**	-5.528**	-6.130***	-6.125**	-5.753*	-5.600*	-6.209**
	(3.039)	(2.633)	(2.357)	(3.051)	(3.011)	(3.016)	(2.989)
Interacted with							
Tropical dummy	4.840	4.280	4.916*	4.666	4.537	4.383	4.966
	(3.443)	(3.120)	(2.745)	(3.470)	(3.404)	(3.423)	(3.382)
Non-tropical spillover temperature	-0.273	-0.286	-0.256	-0.304	-0.217	-0.258	-0.244
	(0.257)	(0.256)	(0.309)	(0.257)	(0.253)	(0.257)	(0.256)
Interacted with							
Tropical dummy	0.344	0.376	0.346	0.409	0.281	0.332	0.342
	(0.441)	(0.442)	(0.463)	(0.441)	(0.441)	(0.438)	(0.444)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Differentiated impact on poor and rich

Tables S16–S19 present robustness checks for results concerning direct and spillover impact on the tropical and non-tropical economies. Table S16 presents results with different levels of censoring, that is, 2% to 5% as compared to the baseline 1% level. Table S17 considers notion for calculating different trade openness weight for the spillover temperature variable. These notions include using (a) contemporaneous trade openness [Column (2)], (b) one-year lag [Column (3)], (c) two-year simple moving average [Column (4)], (d) four-year simple moving average [Column (5)], and (e) five-year simple moving average [Column (6)].

Since the PVAR model is potentially sensitive to different lag orders, we consider two-year lag [Column (2)], four-year lag [Column (3)] and five-year lag [Column (4)] and present the corresponding results in Table S18 to vindicate the robustness of our exercise.

Finally, Table S19 presents other robustness checks. We use the K-median clustering technique instead of K-means in column (2). We use standard errors clustered at the economy level instead of robust standard errors in column (3). Column (4) considers quadratic terms for direct temperature and precipitation variables as Burke et al. (2015)[29] have considered. Columns (5) and (6) consider different vectors of endogenous variables. Column (5) considers $\bar{A}_{it}$ and $N\bar{A}_{it}$ as endogenous variables and presents impacts on per capita GVA growth rate using linear hypothesis test. Column (6) considers GVA, agricultural value added and non-agriculture value added growth rate instead of $\bar{A}_{it}$ and $N\bar{A}_{it}$. Finally, we consider country trends instead of regional trends in column (7). We find the robustness of our main results from these various robustness checks.

Table S16: Robustness checks: Different level of censoring for endogenous variables

	(1) Baseline 1%	(2) Censor 2%	(3) Censor 3%	(4) Censor 4%	(5) Censor 5%
Direct temperature	0.217	0.178	0.147	0.124	0.111
	(0.183)	(0.168)	(0.157)	(0.150)	(0.145)
Interacted with					
Poor dummy	-0.742**	-0.698**	-0.669**	-0.658**	-0.642**
	(0.318)	(0.302)	(0.288)	(0.280)	(0.272)
Tropical dummy	-0.335	-0.300	-0.262	-0.201	-0.182
	(0.432)	(0.409)	(0.387)	(0.375)	(0.363)
Tropical spillover temperature	-7.224**	-7.208**	-7.013**	-6.816**	-6.620**
	(3.406)	(3.270)	(3.128)	(3.062)	(3.005)
Interacted with					
Poor dummy	4.138	3.823	3.656	3.716	3.603
	(2.703)	(2.577)	(2.438)	(2.370)	(2.309)
Tropical dummy	3.042	3.280	3.275	2.990	2.920
	(3.563)	(3.417)	(3.264)	(3.192)	(3.131)
Non-tropical spillover temperature	-0.173	-0.119	-0.0880	-0.0522	-0.0213
	(0.282)	(0.259)	(0.245)	(0.237)	(0.230)
Interacted with					
Poor dummy	-0.566	-0.587	-0.577	-0.565	-0.546
	(0.476)	(0.452)	(0.431)	(0.420)	(0.409)
Tropical dummy	0.645	0.576	0.493	0.440	0.381
	(0.483)	(0.458)	(0.437)	(0.427)	(0.415)
Min. GVA growth rate (pp)	-23.13	-18.08	-14.47	-12.76	-11.50
Min GVA growth rate (pp)	22.68	17.38	14.32	12.90	11.75
Observations Capped	82	164	246	328	410

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S17: Robustness checks: Spillover weights

	(1) Baseline 3yr-SMA	(2) Current year	(3) One year lag	(4) 2 year SMA	(5) 4 year SMA	(6) 5 year SMA
Direct temperature	0.217	0.211	0.208	0.200	0.211	0.210
	(0.183)	(0.183)	(0.183)	(0.183)	(0.184)	(0.184)
Interacted with						
Poor dummy	-0.742**	-0.725**	-0.738**	-0.738**	-0.731**	-0.738**
	(0.318)	(0.318)	(0.319)	(0.318)	(0.318)	(0.318)
Tropical dummy	-0.335	-0.315	-0.354	-0.342	-0.336	-0.300
	(0.432)	(0.431)	(0.439)	(0.433)	(0.431)	(0.431)
Tropical spillover temperature	-7.224**	-6.736**	-5.739*	-6.879**	-7.664**	-7.705**
	(3.406)	(3.212)	(3.340)	(3.359)	(3.456)	(3.462)
Interacted with						
Poor dummy	4.138	3.114	2.919	3.894	4.223	4.519*
	(2.703)	(2.636)	(2.774)	(2.697)	(2.709)	(2.722)
Tropical dummy	3.042	3.134	2.702	3.074	3.357	2.940
	(3.563)	(3.375)	(3.511)	(3.531)	(3.591)	(3.585)
Non-tropical spillover temperature	-0.173	-0.172	-0.182	-0.125	-0.148	-0.144
	(0.282)	(0.281)	(0.281)	(0.281)	(0.282)	(0.282)
Interacted with						
Poor dummy	-0.566	-0.398	-0.395	-0.524	-0.590	-0.605
	(0.476)	(0.481)	(0.480)	(0.478)	(0.474)	(0.473)
Tropical dummy	0.645	0.476	0.456	0.543	0.694	0.721
	(0.483)	(0.491)	(0.487)	(0.487)	(0.480)	(0.477)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S18: Robustness checks: Lag order

	(1) Baseline - lag 3	(2) Order - lag 2	(3) Order - lag 4	(4) Order - lag 5
Direct temperature	0.217	0.221	0.213	0.180
	(0.183)	(0.182)	(0.185)	(0.186)
Interacted with				
Poor dummy	-0.742**	-0.733**	-0.749**	-0.800**
	(0.318)	(0.320)	(0.318)	(0.319)
Tropical dummy	-0.335	-0.395	-0.0980	-0.0587
	(0.432)	(0.439)	(0.427)	(0.429)
Tropical spillover temperature	-7.224**	-8.321**	-7.490**	-7.029**
	(3.406)	(3.473)	(3.355)	(3.353)
Interacted with				
Poor dummy	4.138	4.252	5.021*	5.042*
	(2.703)	(2.720)	(2.618)	(2.620)
Tropical dummy	3.042	4.328	1.876	1.394
	(3.563)	(3.629)	(3.514)	(3.512)
Non-tropical spillover temperature	-0.173	-0.101	-0.180	-0.0941
	(0.282)	(0.278)	(0.281)	(0.284)
Interacted with				
Poor dummy	-0.566	-0.661	-0.581	-0.616
	(0.476)	(0.472)	(0.476)	(0.478)
Tropical dummy	0.645	0.886*	0.646	0.633
	(0.483)	(0.478)	(0.484)	(0.485)
Observations	7560	7728	7392	7224

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

Table S19: Robustness checks: Others

	(1) Baseline	(2) Clustering K-median	(3) Errors Country	(4) Non-linear Temp	(5) Endo. var. Channel	(6) Endo. var. Growth rate	(7) Country Trend
Direct temperature	0.217	0.217	0.213	0.225	0.201	0.214	0.206
	(0.183)	(0.183)	(0.256)	(0.183)	(0.180)	(0.183)	(0.183)
Interacted with							
Poor dummy	-0.742**	-0.755**	-0.741**	-0.755**	-0.700**	-0.746**	-0.734**
	(0.318)	(0.316)	(0.377)	(0.319)	(0.319)	(0.318)	(0.322)
Tropical dummy	-0.335	-0.313	-0.334	-0.314	-0.334	-0.297	-0.322
	(0.432)	(0.434)	(0.444)	(0.433)	0.429	(0.431)	(0.437)
Direct temperature (Sq.)				0.211			
				(0.146)			
Interacted with							
Poor dummy				0.163			
				(0.480)			
Tropical dummy				-0.991			
				(0.732)			
Tropical spillover temperature	-7.224**	-7.147**	-7.349**	-7.490**	-7.067**	-6.832**	-7.404**
	(3.406)	(3.151)	(2.865)	(3.415)	(3.369)	(3.384)	(3.350)
Interacted with							
Poor dummy	4.138	4.346	4.188	4.409	4.227	4.209	4.128
	(2.703)	(2.659)	(2.743)	(2.706)	(2.685)	(2.701)	(2.669)
Tropical dummy	3.042	2.793	3.115	2.822	2.788	2.586	3.200
	(3.563)	(3.187)	(3.061)	(3.596)	(3.530)	(3.545)	(3.505)
Non-tropical spillover temperature	-0.173	-0.182	-0.155	-0.201	-0.122	-0.150	-0.157
	(0.282)	(0.282)	(0.372)	(0.279)	(0.277)	(0.281)	(0.282)
Interacted with							
Poor dummy	-0.566	-0.575	-0.569	-0.570	-0.535	-0.594	-0.516
	(0.476)	(0.474)	(0.483)	(0.476)	(0.474)	(0.476)	(0.477)
Tropical dummy	0.645	0.680	0.648	0.710	0.568	0.643	0.623
	(0.483)	(0.482)	(0.479)	(0.484)	(0.482)	(0.482)	(0.488)

All models include direct and spillover precipitation shock, economy fixed effects, regional trend and the *autarky dummy* as control variables, with robust errors and endogenous variables as per capita GVA growth rate and per capita GVA growth rate from agriculture sector.
Per capita GVA growth rate from non-agriculture sector is computed by subtracting the estimates of that of agriculture sector from per capita GVA growth rate. Temperature is measured in degrees Celcius, and growth rates are percentage points (pp). The impact of one standard deviation shock on each group is computed using a linear combination hypothesis (χ^2- Wald test statistic)–Refer to the online methods for details.
We consider three lags as they pass the serial correlation test for GMM estimation for consistency. There are 7,560 country-year observations. Significance level: *** p < 1%, ** p < 5%, * p < 10%.

References:

1. Ayinde, O.E., Muchie, M., & Olatunji, G.B. (2011). Effect of climate change on agricultural productivity in Nigeria: a co-integration model approach. *Journal of Human Ecology, 35*, 189-194, https://doi.org/10.1080/09709274.2011.11906406
2. Birthal, P.S., Hazrana, J., & Negi, D.S. (2021, 11). Impacts of climatic hazards on agricultural growth in India. *Climate and Development, 13*, 895-908, https://doi.org/10.1080/17565529.2020.1867045
3. Guiteras, R. (2009). *The impact of climate change on Indian agriculture*, Manuscript, Department of Economics, University of Maryland, College Park, Maryland
4. Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy, 129*, 1797-1827, https://doi.org/10.1086/713733
5. Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., & Zhang, L. (2009, 5). The impact of climate change on China's agriculture. *Agricultural Economics, 40*, 323-337, https://doi.org/10.1111/j.1574-0862.2009.00379.x
6. Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018, 3). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management, 88*, 1-17, https://doi.org/10.1016/j.jeem.2017.11.001
7. Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review, 97*, 354-385, https://doi.org/10.1257/aer.97.1.354
8. Donadelli, M., Jüppner, M., Riedel, M., & Schlag, C. (2017, 9). Temperature shocks and welfare costs. *Journal of Economic Dynamics and Control, 82*, 331-355, https://doi.org/10.1016/j.jedc.2017.07.003
9. Gallic, E., & Vermandel, G. (2020, 5). Weather shocks. *European Economic Review, 124*, 103409, https://doi.org/10.1016/j.euroecorev.2020.103409
10. Schlenker, W., & Roberts, M.J. (2009, 9). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences, 106*, 15594-15598, https://doi.org/10.1073/pnas.0906865106
11. Abidoye, B.O., & Odusola, A.F. (2015, 3). Climate change and economic growth in Africa: An econometric analysis. *Journal of African Economies, 24*, 277-301, https://doi.org/10.1093/jae/eju033
12. Barrios, S., Ouattara, B., & Strobl, E. (2008, 8). The impact of climatic change on agricultural production: Is it different for Africa? *Food Policy, 33*, 287-298, https://doi.org/10.1016/j.foodpol.2008.01.003
13. Kotir, J.H. (2011, 6). Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability, 13*, 587-605, https://doi.org/10.1007/s10668-010-9278-0
14. Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture, 13*, 660-665, https://doi.org/10.1016/S2095-3119(13)60701-7
15. Aaheim, A., Amundsen, H., Dokken, T., & Wei, T. (2012, 10). Impacts and adaptation to climate change in European economies. *Global Environmental Change, 22*, 959-968, https://doi.org/10.1016/j.gloenvcha.2012.06.005
16. Jones, B.F., & Olken, B.A. (2010, 5). Climate shocks and exports. *American Economic Review, 100*, 454-459, https://doi.org/10.1257/aer.100.2.454

17. Dallmann, I. (2019). Weather variations and international trade. *Environmental and Resource Economics, 72*, 155-206, https://doi.org/10.1007/s10640-018-0268-2
18. Li, C., Xiang, X., & Gu, H. (2015, 10). Climate shocks and international trade: Evidence from China. *Economics Letters, 135*, 55-57, https://doi.org/10.1016/j.econlet.2015.07.032
19. Karlsson, J. (2021, 10). Temperature and exports: Evidence from the United States. *Environmental and Resource Economics, 80*, 311-337, https://doi.org/10.1007/s10640-021-00587-5
20. Acemoglu, D., Carvalho, V.M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica, 80*, 1977-2016, https://doi.org/10.3982/ECTA9623
21. Carvalho, V.M., Nirei, M., Saito, Y.U., & Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east Japan earthquake. *The Quarterly Journal of Economics, 136(2)*, 1255–1321, https://doi.org/10.1093/qje/qjaa044
22. Hallegatte, S. (2012). *Modeling the roles of heterogeneity, substitution, and inventories in the assessment of natural disaster economic costs*, World Bank Policy Research Working Paper 6047.
23. Koks, E., Thissen, M., Alfieri, L., De Moel, H., Feyen, L., Jongman, B., & Aerts, J. (2019). The macroeconomic impacts of future river flooding in Europe. *Environmental Research Letters, 14(8)*, 084042, https://doi.org/10.1088/1748-9326/ab3306
24. Willner, S.N., Otto, C., & Levermann, A. (2018). Global economic response to river floods. *Nature Climate Change, 8(7)*, 594–598, https://doi.org/10.1038/s41558-018-0173-2
25. Ahmadi, M., Casoli, C., Manera, M., & Valenti, D. (2022). *Modelling the effects of climate change on economic growth: a bayesian structural global vector autoregressive approach*, FEEM Working Paper 46
26. Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., & Wood, E.F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data, 5*, 180214, https://doi.org/10.1038/sdata.2018.214
27. Rencher, A.C. (2002). *Methods of multivariate analysis.* J. Wiley.
28. Im, K.S., Pesaran, M.H., & Shin, Y. (2003, 7). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*, 53-74, https://doi.org/10.1016/S0304-4076(03)00092-7
29. Burke, M., Hsiang, S.M., & Miguel, E. (2015, 11). Global non-linear effect of temperature on economic production. *Nature, 527*, 235-239, https://doi.org/10.1038/nature15725