

Climate Damage Functions for Productivity: Evidence from Enterprise Survey Microdata

Uba Matthew Ndubuisi

ubamathew2016@gmail.com

Ca' Foscari University of Venice

Research Article

Keywords: Climate change, Climate damage functions, Firm productivity, Firm-level microdata, Long-difference estimation

Posted Date: October 15th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11364256/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Climate Damage Functions for Productivity: Evidence from Enterprise Survey Microdata

Author(s): Matthew Ndubuisi Uba¹

Affiliation:

1. Department of Economics, Ca' Foscari University of Venice, Venice, Italy.

Corresponding Author(s): Matthew Ndubuisi Uba

Corresponding Author's Email: matthewndubuisi.uba@unive.it ubamathew2016@gmail.com

Abstract

This study estimates climate damage functions for productivity using firm-level microdata while incorporating climate extremes such as precipitation variability, flood exposure, and drought intensity. Motivated by recent methodological debate regarding spatial correlation and limited independent variation in aggregate climate–growth estimates, the analysis adopts a long-difference framework that isolates persistent climate effects rather than short-run shocks. Using productivity measures constructed from harmonized World Bank Enterprise Survey microdata covering 125 countries and linked to high-resolution ERA5 climate data, the results reveal a robust downward-sloping and convex temperature damage function, indicating that warming imposes increasingly large productivity growth losses in hotter baseline climates. While global-average effects are statistically weak, region-specific estimates uncover substantial heterogeneity. Extensions incorporating precipitation and climate extremes preserve the qualitative damage pattern and generally imply smaller projected losses, suggesting that part of the temperature effect may operate through additional climate channels. Leave-one-region-out tests confirm that the results are stable and not driven by any single region.

Keywords: Climate change; Climate damage functions; Firm productivity; Firm-level microdata; Long-difference estimation.

JEL Code: Q54, D22, O44, C23, Q56

1.0 Introduction

Understanding the economic consequences of climate change remains a central challenge for climate policy [20; 8], macroeconomic modelling [16; 1], and development planning [4; 13]. A large empirical literature suggests that rising temperatures reduce economic performance, particularly in lower-income regions [3; 15]. However, recent debates have highlighted methodological vulnerabilities in aggregate macro-climate econometric approaches, particularly the risk of overstated precision when economic units are strongly spatially correlated. Recent critiques of macro-climate growth models highlight that subdividing countries into many regions does not necessarily increase independent information when economic outcomes are strongly spatially correlated [2; 18; 7]. These concerns underscore the importance of complementary micro-level evidence for estimating climate damage

This paper therefore examines whether climate damage functions constructed from repeated cross-sectional firm-level microdata provide complementary evidence on climate-productivity relationships beyond those obtained from aggregate macroeconomic data.

To address this gap, I estimate climate damage functions using harmonized firm-level microdata from the World Bank Enterprise Surveys (WBES) covering 125 countries and multiple survey waves. Rather than using aggregate GDP, I construct value-added measures from firm-level observations using sales and intermediate inputs and subsequently aggregate these measures to country-region-year cells. Because the WBES consists of repeated cross-sectional surveys in which firms are randomly sampled

in each wave, aggregation provides a consistent basis for examining medium-run climate-productivity relationships across survey periods. Value added is particularly suitable for this purpose because it captures productivity-relevant net output more directly than gross sales and more closely reflects firms' contribution to economic production. Guided by growth theory, I estimate long-difference climate damage functions that relate annualised growth in log value added to changes in climate variables and their interactions with baseline climate conditions.

The results show a nonlinear and heterogeneous temperature-growth relationship that is robust across specifications. The estimated damage function is downward-sloping and convex, implying that warming imposes increasingly large productivity losses in hotter baseline climates. Although global-average effects are statistically weak, regional estimates reveal substantial heterogeneity, indicating that aggregate averages obscure meaningful differences in climate damage across regions. Robustness checks further show that these patterns are not driven by any single region.

This paper makes three contributions. First, it constructs climate damage functions using productivity measures derived from World Bank Enterprise Survey microdata covering 125 countries and multiple survey waves. Second, it estimates heterogeneous climate damage functions that explicitly incorporate baseline climate conditions, demonstrating that climate impacts vary substantially across climatic environments. Third, it combines a long-difference framework with multiple robustness exercises, including alternative climate specifications and leave-one-region-out estimation, to assess the stability of estimated climate-productivity relationships.

To examine this question empirically, the next section describes the firm-level and climate data, the construction of value added, and the long-difference framework used to estimate climate damage functions.

2.0 Method and Data

This section describes the data sources, variable construction, and empirical strategy used to estimate climate damage functions from firm-level microdata.

2.1 Data Source

Firm-level data for 125 countries are obtained from the World Bank Enterprise Surveys (WBES), with each country observed in at least two survey waves (Fig. 4). Detailed list of the countries observed by regions and the list of countries with their corresponding number of firm observations and survey wave-years can be found in Table S5-S6 respectively. The production indicators used in the analysis (Table 2) include annual sales for all products and services ($d2_i$), annual electricity expenditure ($n2b_i$), and annual expenditure on raw materials and intermediate inputs ($n2e_i$). Each firm was assigned a country identifier $c(i)$ and a region identifier $r(i)$. In the construction of operating cost and value added, Following existing WBES productivity studies, missing expenditure values were replaced with zero when non-response was interpreted as the absence of expenditure rather than missing reporting.

Indicator	Code	Survey Question
Sales	d2	In fiscal year, what were this establishment's total annual sales for all products and services?
Cost of Electricity	n2b	Total annual cost of electricity
Cost of Raw Material	n2e	Total annual cost of raw materials and intermediate goods used in production

Table 2: Productivity indicators

Regional classifications follow the WBES regional grouping as recorded in the dataset and used in the regressions through the categorical Region identification: East Asia and the Pacific (EAP), Europe and

Central Asia (ECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA), North and Central America (NCA), South Asia (SA), and Sub-Saharan Africa (SSA).

Climate exposure data consist of annual mean surface air temperature, precipitation, flood exposure proxied by number of days with precipitation exceeding 50mm, and drought exposure proxied by maximum number of consecutive dry days. These variables are retrieved from the World Bank Climate Change Knowledge Portal (WBCKKP), based on the ERA5 reanalysis product at 0.25-degree spatial resolution, covering the period 1950-2023. Flood observations with empty cells are assumed to represent zero days with precipitation exceeding 50 mm, and so was populated with 0.00001.

The climate dataset was originally assembled in 2024, when complete climate observations corresponding to the most recent survey years were not yet available. To maintain temporal alignment between climate exposures and survey observations, country-specific linear trends were used to generate climate values for 2024–2025. These extrapolated observations are used only for a small subset of survey waves and do not drive the identification of the estimated climate damage functions. For each country c , I estimated:

$$Climate_{c,t} = \alpha_c + \rho_c t + \varepsilon_{c,t}, t \leq 2023, \quad (1)$$

where α_c denotes a country-specific intercept, ρ_c long-run linear trend in the climate variable, and $\varepsilon_{c,t}$ is an error term. Predicted values for $t \in \{2024, 2025\}$ are then generated using the fitted coefficient from (1). The resulting climate series are merged into the firm-level data by country and survey year, so that each firm observation inherits the corresponding climate exposure $Climate_{c(i),t(i)}$. This extrapolation is used solely to align climate variables with the timing of firm surveys.



Figure 4: Distribution of survey waves across 125 observed countries

2.2 Construction of firm value added

I index firms, country, regions, and year by $i, c, r,$ and t respectively. The firm-level dataset from the WBES provides information on sales and intermediate input costs, which are used to construct operating costs and value added. Operating costs are defined as the sum of firm-reported intermediate input expenditures (2), firm value added is defined as the gross output minus operating cost (3). Observations with missing or non-positive value added are excluded to ensure consistency with production theory and numerical stability. I then construct log value added and trim extreme outliers resulting from reporting errors common in firm survey data. Log value added is defined in (4) and is winsorized by dropping observations below the 1st percentile and above the 99th percentile of its distribution (5).

$$CO_{icrt} = n2b_{icrt} + n2e_{icrt} . \quad (2)$$

$$VA_{icrt} = d2_{icrt} - CO_{icrt} . \quad (3)$$

$$\ln VA_{icrt} = \ln (VA_{icrt}). \quad (4)$$

$$\ln VA_{icrt} \in [q_{0.01}(\ln VA), q_{0.99}(\ln VA)]. \quad (5)$$

2.3 Empirical strategy

My empirical approach adapts the theoretical framework of Kalkuhl and Wenz [11], who show in a Ramsey-type growth model that climate affects economic outcomes through its impact on long-run growth rate of productivity, rather than solely through transitory weather shocks. In their framework, baseline climate conditions determine the slope of the baseline-growth-path productivity function, while short-run weather fluctuations generate temporary deviations.

Guided by this insight, I estimate a long-difference climate-growth equation that relates medium-term growth in firm performance to changes in variables interacted with long-run baseline climate exposure. Specifically, I model growth in log value added as a function of temperature and their interaction with baseline mean temperature, with extensions allowing precipitation, flood-days, and drought intensity to enter both directly and through interactions with their own baseline and baseline temperature.

The empirical analysis aggregates firm outcomes to country-region-period cells and exploits long differences between the first and last observed years for each cell. The aggregation procedure is motivated by the repeated cross-sectional nature of the WBES. Since firms are not generally observed in multiple survey waves, within-firm long-difference estimation is infeasible. Aggregation to country-region-year cells provides a consistent basis for tracking medium-run changes in average productivity while reducing sampling variability associated with repeated cross-sectional observations. This design isolates persistent climate-induced shifts in growth while avoiding limitations of annual panel regressions in short and uneven panels. As a result, the estimated coefficients can be interpreted as reduced-form evidence on the medium-run growth penalty associated with climate change, consistent with the climate-growth mechanism emphasized by Kalkuhl and Wenz [11].

Aggregation and long-difference construction: Firm-level outcomes are aggregated to country-region-year average to align with spatially matched climate data (T_{crt} , P_{crt} , F_{crt} , and D_{crt}) and to reduce firm-level measurement noise. After aggregation and long-difference construction, the estimation sample consists of 124 country-region cells. Aggregation to country-region cells ensures that firm outcomes are matched to climate exposures measured at comparable spatial resolution and reduces idiosyncratic firm-level noise. Let N_{crt} denote the number of firms in cell (c, r, t) . The aggregation procedure is given in (6). Climate variables measured at the same spatial and temporal resolution are then merged, where T denotes temperature, P precipitation, F extreme precipitation (flood-days exceeding 50mm), and D drought intensity measured as consecutive dry days.

$$\overline{\ln VA_{crt}} = \frac{1}{N_{crt}} \sum_{i \in (c, r, t)} \ln VA_{icrt}. \quad (6)$$

To implement the long-difference identification, I denote by $t_1(c, r)$ and $t_2(c, r)$ the first and last observed years for each country-region cell. The long-difference in average log value added is defined in (7). Because the spacing between t_1 and t_2 varies across cells, this difference is annualised in (8). Long-difference in climate variables are defined analogously in (9).

$$\Delta \overline{\ln VA_{cr}} = \overline{\ln VA_{cr,t_2}} - \overline{\ln VA_{cr,t_1}}. \quad (7)$$

$$g_{cr} = \frac{\Delta \overline{\ln VA_{cr}}}{t_2(c,r) - t_1(c,r)}. \quad (8)$$

$$\left\{ \begin{array}{l} \Delta T_{cr} = T_{cr,t_2} - T_{cr,t_1}, \\ \Delta P_{cr} = P_{cr,t_2} - P_{cr,t_1}, \\ \Delta F_{cr} = F_{cr,t_2} - F_{cr,t_1}, \\ \Delta D_{cr} = D_{cr,t_2} - D_{cr,t_1}. \end{array} \right\} \quad (9)$$

To capture heterogeneity by long-run climate exposure, I compute for each country-region cell the time-average climate baseline using all observed year available for that cell (10), where $\mathcal{T}_{cr}$ is the set of observed years for cell (c,r) and $n_{cr} = |\mathcal{T}_{cr}|$. For estimation and collinearity control, all long-difference climate variables and their baselines are mean-centred (11), and interaction terms are constructed from centred components in (12). Variance Inflation Factor (VIFs) are computed to diagnose collinearity. Higher VIFs for interaction terms are expected by construction and do not bias coefficient estimates, though they may inflate standard errors. Temperature anomalies are tested but excluded from preferred specifications because they are not separately identified from level changes in the short and uneven time series available at country-region level.

$$\left\{ \begin{array}{l} \bar{T}_{cr} = \frac{1}{n_{cr}} \sum_{t \in \mathcal{T}_{cr}} T_{crt}, \\ \bar{P}_{cr} = \frac{1}{n_{cr}} \sum_{t \in \mathcal{T}_{cr}} P_{crt}, \\ \bar{F}_{cr} = \frac{1}{n_{cr}} \sum_{t \in \mathcal{T}_{cr}} F_{crt}, \\ \bar{D}_{cr} = \frac{1}{n_{cr}} \sum_{t \in \mathcal{T}_{cr}} D_{crt}. \end{array} \right\} \quad (10)$$

$$\left\{ \begin{array}{l} \widetilde{\Delta T}_{cr} = \Delta T_{cr} - \mathbb{E}[\Delta T], \quad \widetilde{\bar{T}}_{cr} = \bar{T}_{cr} - \mathbb{E}[\bar{T}], \\ \widetilde{\Delta P}_{cr} = \Delta P_{cr} - \mathbb{E}[\Delta P], \quad \widetilde{\bar{P}}_{cr} = \bar{P}_{cr} - \mathbb{E}[\bar{P}], \\ \widetilde{\Delta F}_{cr} = \Delta F_{cr} - \mathbb{E}[\Delta F], \quad \widetilde{\bar{F}}_{cr} = \bar{F}_{cr} - \mathbb{E}[\bar{F}], \\ \widetilde{\Delta D}_{cr} = \Delta D_{cr} - \mathbb{E}[\Delta D], \quad \widetilde{\bar{D}}_{cr} = \bar{D}_{cr} - \mathbb{E}[\bar{D}]. \end{array} \right\} \quad (11)$$

$$\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr}, \quad \widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{P}}_{cr}, \quad \widetilde{\Delta F}_{cr} \times \widetilde{\widetilde{F}}_{cr}, \quad \widetilde{\Delta D}_{cr} \times \widetilde{\widetilde{D}}_{cr}. \quad (12)$$

2.4 Model specifications and robustness

The baseline long-difference climate damage specification (*Spec1*) relates to annualised growth in log value added to change in temperature and their interactions with baseline mean temperature and is defined in (13), with a version including region fixed effects (14) to absorb time-invariant regional heterogeneity. Specifications adding precipitation channels are given in (15) – (16). For robustness, I extend the baseline temperature-damage specification by adding climate extremes which include flood (day exceeding 50mm) and drought (consecutive dry days) as additional exposure channels, included both as long-difference terms and through interactions with their own long-run baseline and the long-run baseline temperature in (17) – (18).

All specifications are estimated by Ordinary Least Squares (OLS) on the long-difference sample. Because the unit of observation is the country-region cell, and shocks may be correlated within broader regions, inference is conducted using cluster-robust standard errors clustered at the region level (19). Clustering at the country level is not adopted because long-differencing removes time-invariant country components and the effective number of independent country clusters may be insufficient for reliable asymptotic inference. Also, it is important to note that EAP does not appear in the regression table because it is the omitted reference category in region fixed-effect specifications; its effect is absorbed into the intercept.

$$Spec1: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 \left(\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + u_{cr}. \quad (13)$$

$$Spec2: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 \left(\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \lambda_r + u_{cr}. \quad (14)$$

$$Spec3: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 \left(\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \pi_1 \widetilde{\Delta P}_{cr} + \pi_2 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{P}}_{cr} \right) + \pi_3 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + u_{cr}. \quad (15)$$

$$Spec4: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 \left(\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \pi_1 \widetilde{\Delta P}_{cr} + \pi_2 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{P}}_{cr} \right) + \pi_3 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \lambda_r + u_{cr}. \quad (16)$$

$$Spec5: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 \left(\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \pi_1 \widetilde{\Delta P}_{cr} + \pi_2 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{P}}_{cr} \right) + \pi_3 \left(\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \phi_1 \widetilde{\Delta F}_{cr} + \phi_2 \left(\widetilde{\Delta F}_{cr} \times \widetilde{\widetilde{F}}_{cr} \right) + \delta_2 \left(\widetilde{\Delta F}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + \delta_1 \widetilde{\Delta D}_{cr} + \delta_2 \left(\widetilde{\Delta D}_{cr} \times \widetilde{\widetilde{D}}_{cr} \right) + \delta_3 \left(\widetilde{\Delta D}_{cr} \times \widetilde{\widetilde{T}}_{cr} \right) + u_{cr}. \quad (17)$$

$$Spec6: g_{cr} = \alpha + \gamma_1 \widetilde{\Delta T}_{cr} + \gamma_2 (\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr}) + \pi_1 \widetilde{\Delta P}_{cr} + \pi_2 (\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{P}}_{cr}) + \quad (18)$$

$$\pi_3 (\widetilde{\Delta P}_{cr} \times \widetilde{\widetilde{T}}_{cr}) + \phi_1 \widetilde{\Delta F}_{cr} + \phi_2 (\widetilde{\Delta F}_{cr} \times \widetilde{\widetilde{F}}_{cr}) + \delta_2 (\widetilde{\Delta F}_{cr} \times \widetilde{\widetilde{T}}_{cr}) + \delta_1 \widetilde{\Delta D}_{cr} + \\ \delta_2 (\widetilde{\Delta D}_{cr} \times \widetilde{\widetilde{D}}_{cr}) + \delta_3 (\widetilde{\Delta D}_{cr} \times \widetilde{\widetilde{T}}_{cr}) + \lambda_r + u_{cr}.$$

$$\widehat{\text{Var}}(\hat{\theta}) \text{ clustered by } r. \quad (19)$$

For forward projections, I use the temperature-only Specification 1 – 2 because they provide a transparent reduced-form mapping from warming to productivity growth impacts. Mechanism specification including precipitation, flood and drought are not used for projections because doing so would require explicit joint scenarios for non-temperature climate variables. Let ΔT^{sc} denote the temperature increase under scenario sc relative to baseline. Holding non-temperature climate channels fixed at their centred value, the implied change in annualised growth is given by (20). Over a horizon H years from the baseline year 2025 to future year 2100, the cumulative effect on log value added is computed as in (21).

$$\Delta g_{cr}^{sc} = \gamma_1 \widetilde{\Delta T}^{sc} + \gamma_2 (\widetilde{\Delta T}^{sc} \times \widetilde{\widetilde{T}}_{cr}). \quad (20)$$

$$\Delta \ln VA_{cr}^{sc}(H) = \Delta g_{cr}^{sc} \cdot H. \quad (21)$$

Clustered standard errors: standard errors are clustered at the regional level throughout the analysis. This choice is motivated by the structure of the data and the possibility that observations within the same geographical region are exposed to common climatic, institutional, and macroeconomic conditions.

Leave-one-region-out (LORO) robustness: to test whether the estimated temperature-growth relationship is driven by any single WBES region, I re-estimate each specification six times, each time excluding one region r . Formally, for each r , I estimate the same long-difference OLS model on the subsample S_{-r} and compare $\hat{\gamma}_{1,-r}$ and $\hat{\gamma}_{2,-r}$ to full-sample counterparts.

Let the baseline long-difference model estimated on the full sample of country-region cells be given by (22), where g_{cr} is annualised long-difference growth in $\ln VA$, and X_{cr} contains the centred long-difference climate variables $\widetilde{\Delta T}_{cr}$ and their centred interactions $\widetilde{\Delta T}_{cr} \times \widetilde{\widetilde{T}}_{cr}$.

For each region $r \in R$, define a leave-one-out subsample in (23). Re-estimating the same specification on S_{-r} yields the parameter vector $\hat{\theta}_{-r}$ in (24). I then compare $\hat{\theta}_{-r}$ to the full-sample estimate $\hat{\theta}$ using the deviation measure in (25). inference is conducted using cluster-robust standard errors clustered at the region level and computed separately for each leave-one-out subsample in (26). If $\hat{\theta}_{-r}$ stays close

to $\hat{\theta}$ for all r , results are not driven by any single region, and large deviations indicate that a given region contributes disproportionately to parameter identification.

$$g_{cr} = \alpha + X'_{cr}\theta + u_{cr}. \quad (22)$$

$$S_{-r} = \{(c, r', \cdot) : r' \neq r\}. \quad (23)$$

$$\hat{\theta}_{-r} = \arg \min_{\theta} \sum_{(c, r') \in S_{-r}} (g_{cr'} - \alpha - X'_{cr'}\theta)^2. \quad (24)$$

$$\Delta\hat{\theta}_{-r} = \hat{\theta}_{-r} - \hat{\theta}. \quad (25)$$

$$\widehat{\text{Var}}(\hat{\theta}_{-r}) \text{ clustered by region.} \quad (26)$$

Having established the data construction, empirical strategy, and robustness design, the following section presents the estimated climate damage functions, scenario projections, and their implications for firm-level productivity under warming.

3.0 Results and Discussion

This study examines climate-productivity relationships using damage functions constructed from repeated cross-sectional WBES microdata linked to country-level climate exposures. The analysis focuses on medium-run productivity responses captured through annualised long-difference growth in aggregated log value added [7; 2; 18].

3.1 Descriptive patterns and motivation for the long-difference approach

The initial firm-level dataset consists of 232,152 observations from 125 countries distributed across eight geographical regions (Fig. S1; Fig. S2). After excluding observations with non-positive value added and applying winsorisation to log value added, the final firm-level sample contains 201,677 observations. Summary statistics for the firm-level and climate variables are reported in Table S1.

Contemporaneous relationships between log value added and the climate variables are generally weak (Table S2). Temperature, precipitation, and flood exposure show only very small positive correlations with log value added, while drought exposure is weakly negative. By contrast, precipitation and flood exposure are strongly positively correlated, which is expected because rainfall intensity is closely related to flood occurrence [19; 6]. These weak cross-sectional correlations reinforce the limits of short-run or purely contemporaneous approaches for identifying climate damages. Instead, they support the use of a long-difference framework that is better suited to capturing persistent climate-induced productivity changes, consistent with growth-based climate-productivity models [12; 11].

The long-difference transformation yields 124 country-region cells. Multicollinearity diagnostics reported in Table S3 indicate no serious instability in the regressors, although some interaction terms show elevated VIF values, as expected by construction. These values may widen standard errors but do not invalidate the estimated coefficients [19; 6].

3.2 Climate effects on productivity growth

The main regression results are reported in Table 1. At the global level, temperature effects are generally negative but statistically weak across specifications. Once regional heterogeneity is incorporated, however, a much clearer pattern emerges: climate effects on firm-level value added growth differ substantially across regions.

Across the regional specifications, negative and statistically significant temperature effects are concentrated in Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), Sub-Saharan Africa (SSA), and, in some specifications, Oceania and the Middle East and North Africa (MENA). By

contrast, North and Central America (NCA) and South Asia (SA) exhibit positive and statistically significant temperature effects in the regional models (Table 1). This contrast between weak global-average effects and pronounced regional responses is one of the central findings of the paper. It indicates that aggregate climate-productivity relationships conceal substantial heterogeneity and that a single global estimate cannot adequately represent climate damage dynamics across regions [23].

Precipitation, flood, and drought variables add useful information but do not overturn the core temperature result. Their coefficients are mostly small, and many are statistically weak, although the interaction between precipitation change and baseline temperature remains consistently negative and significant in the richer specifications (Table 1). Taken together, these results suggest that temperature remains the dominant reduced-form channel, while additional climate variables help illuminate mechanisms and mediation rather than fundamentally changing the estimated damage pattern.

3.3 Climate damage functions

The estimated climate damage functions are presented in Fig. 1. Across all six specifications, the implied relationship between baseline temperature and annualised growth in log value added is downward sloping and convex. This means that warming imposes increasingly large productivity growth losses in hotter baseline climates, which is consistent with the broader climate damages literature [3; 15]. The qualitative shape of the damage function remains stable when precipitation, flood, and drought variables are added and when regional fixed effects are included, indicating that the nonlinear temperature-growth relationship is not an artifact of omitted extreme-event variables.

Additional diagnostics reported in Fig. S3 reinforce this interpretation. Across specifications, predicted growth declines as temperature increases, and the fitted relationships remain close to the underlying observed data. The implied threshold at which warming turns productivity growth negative generally lies in the range of roughly 1°C to 2°C, depending on specification. This pattern suggests that even relatively modest warming can generate meaningful firm-level productivity losses [17], especially in hotter baseline climates. More comprehensive specifications also produce tighter confidence intervals, indicating improved precision around the damage thresholds.

These results provide direct support for the paper's main argument which highlights the value of heterogeneous damage functions constructed from firm-level microdata.

3.4 Scenario projections

Forward-looking projections based on the temperature-only specifications are shown in Fig. 2 and in the supplementary projections (Figs. S4–S5). These specifications are used because they provide the clearest reduced-form mapping from warming to productivity growth losses without requiring explicit assumptions about the joint future evolution of precipitation, floods, and droughts.

The projections show cumulative declines in log value added under all warming pathways at both global and regional levels (Fig. 2; Table S4). The overall message is robust: higher warming scenarios imply larger long-run productivity losses. At the same time, the richer specifications that include precipitation and climate extremes tend to imply smaller projected losses than the temperature-only models (Fig. 3; Table S4). This suggests that part of the temperature effect may operate through additional climate channels that mediate, rather than uniformly amplify, long-run damages [9].

This finding differs from Waidelich et al. [20], who report larger projected losses when climate variability and extremes are incorporated into the temperature dose-response function. One possible explanation is that, in the present firm-level setting, non-temperature climate variables capture adjustment and transmission mechanisms that partially redistribute the estimated temperature effect rather than intensify it mechanically. For this reason, the broader specifications are best interpreted as

mechanism-oriented extensions, whereas the temperature-only models remain the most transparent basis for scenario projection.

3.5 Leave-one-region-out robustness

The leave-one-region-out (LORO) analysis provides an important robustness check on identification. The results indicate that neither the linear temperature effect nor the interaction between temperature change and baseline temperature is driven by any single region. Although excluding ECA or SSA produces somewhat larger coefficient movements than excluding other regions, these shifts remain bounded and do not alter the qualitative conclusions. In particular, the nonlinear interaction term remains consistent with the interpretation that warming becomes more damaging in hotter baseline climates.

This matters directly for the broader methodological debate motivating the paper. In aggregate macro-climate studies, subdividing data spatially may create the appearance of precision without adding independent information when economic units move together [2; 18]. By contrast, the stability of the estimated damage function under LORO exercises suggests that the damage functions constructed from firm-level microdata are not an artifact of one influential regional cluster, but instead reflects structural patterns in the data. This strengthens confidence that the observed climate-productivity relationships reflect broad patterns within the data rather than the influence of a particular region.

3.6 Interpretation and implications

In general, the results point to four main conclusions.

First, short-run or contemporaneous correlations between climate and firm performance are weak, which helps explain why cross-sectional approaches may miss climate damages. The long-difference design is therefore important because it captures persistent productivity responses rather than transient shocks [12; 11].

Second, the estimated climate damage function is clearly nonlinear. The downward-sloping and convex pattern implies that warming generates increasingly large productivity growth losses in hotter baseline climates. This is a central result because it shows that damage estimation based on a single average temperature response is likely to be misleading.

Third, the regional results show that global averages obscure important heterogeneity. The strongest negative effects are concentrated in ECA, LAC, SSA, and in some specifications Oceania, while NCA and SA display positive estimated effects. This pattern suggests that baseline climate, institutional capacity, adaptation, and sectoral composition may all condition the productivity effects of warming. More broadly, it indicates that climate damages cannot be summarized adequately by a single global elasticity.

Fourth, the robustness checks show that these findings are not fragile. The stability of the damage function across specifications, diagnostics, and LORO exercises suggests that the core relationship is not driven by model overfitting or by one dominant regional block. In this respect, the paper contributes to recent methodological debate [2; 18] by showing that climate damage functions constructed from microdata-derived productivity measures recover stable and interpretable climate-damage patterns.

The results also have policy relevance. Because climate-related productivity risks are nonlinear and regionally heterogeneous, uniform climate stress assumptions may be inappropriate for financial risk assessment and long-horizon policy analysis. For regulators and financial institutions, this implies that climate risk evaluation, stress testing, and capital allocation frameworks should take baseline climate conditions and long-run productivity responses more seriously. The stability of the estimated firm-level damage functions also suggests that micro-level evidence can complement aggregate macroeconomic scenarios in climate-risk analysis. In addition, the smaller projected losses in specifications that include

precipitation and extremes point to the potential importance of adaptation and resilience investments, strengthening the case for expanding climate adaptation finance alongside mitigation efforts.

3.7 Limitations

The analysis has several limitations. First, although the underlying productivity measures are constructed from firm-level observations, the empirical analysis is conducted on aggregated country-region cells because the WBES consists of repeated cross-sectional surveys rather than a true longitudinal firm panel. Consequently, the estimated climate damage functions should be interpreted as regional productivity responses derived from firm-level microdata rather than as within-firm causal effects. Second, climate variables for the most recent survey years are extrapolated using country-specific trends to maintain temporal consistency with survey observations. Third, forward projections focus primarily on temperature-driven effects and do not explicitly model future changes in precipitation and climate extremes. Finally, because the WBES primarily covers formal firms, the estimated damage functions may understate climate impacts in economies where informal production is substantial.

Variable	Spec1	Spec2	Spec3	Spec4	Spec5	Spec6
Intercept	0.0162 (0.0138)	0.0485*** (0.0074)	0.0170 (0.0140)	0.0500*** (0.0107)	0.0171 (0.0094)	0.0563*** (0.0124)
$\Delta \bar{T}_{cr}$	-0.0023 (0.0231)	-0.0025 (0.0239)	-0.0035 (0.0219)	-0.0067 (0.0234)	0.0021 (0.0285)	-0.0003 (0.0308)
$\Delta \bar{T}_{cr} \times \bar{T}_{cr}$	-0.0016 (0.0024)	-0.0012 (0.0031)	-0.0023 (0.0026)	-0.0019 (0.0034)	-0.0015 (0.0031)	-0.0012 (0.0041)
$\Delta \bar{T}_{cr} (ECA)$		-0.0261*** (0.0023)		-0.0250*** (0.0047)		-0.0362** (0.0129)
$\Delta \bar{T}_{cr} (LAC)$		-0.0817*** (0.0089)		-0.0915*** (0.0131)		-0.0922*** (0.0155)
$\Delta \bar{T}_{cr} (MENA)$		-0.0052 (0.0090)		-0.0065 (0.0127)		-0.0237 (0.0230)
$\Delta \bar{T}_{cr} (NCA)$		0.0700*** (0.0088)		0.0848*** (0.0155)		0.1030*** (0.0217)
$\Delta \bar{T}_{cr} (Oceania)$		-0.0791*** (0.0076)		-0.0626*** (0.0090)		-0.0529 (0.0291)
$\Delta \bar{T}_{cr} (SA)$		0.0357** (0.0112)		0.0320** (0.0127)		0.0348* (0.0150)
$\Delta \bar{T}_{cr} (SSA)$		-0.0629*** (0.0077)		-0.0642*** (0.0101)		-0.0628*** (0.0096)
$\Delta \bar{P}_{cr}$			0.0000 (0.0000)	-0.0000 (0.0000)	0.0001 (0.0000)	0.0000 (0.0000)
$\Delta \bar{P}_{cr} \times \bar{P}_{cr}$			0.0000 (0.0000)	0.0000** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
$\Delta \bar{P}_{cr} \times \bar{T}_{cr}$			-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
$\Delta \bar{F}_{cr}$					-0.0207 (0.0331)	-0.0208 (0.0287)
$\Delta \bar{F}_{cr} \times \bar{F}_{cr}$					0.0034 (0.0074)	0.0066 (0.0070)

$\widetilde{\Delta F}_{cr} \times \widetilde{T}_{cr}$					0.0016	0.0003
					(0.0025)	(0.0031)
$\widetilde{\Delta D}_{cr}$					-0.0001	0.0001
					(0.0020)	(0.0025)
$\widetilde{\Delta D}_{cr} \times \widetilde{D}_{cr}$					-0.0000	-0.0000
					(0.0000)	(0.0000)
$\widetilde{\Delta D}_{cr} \times \widetilde{T}_{cr}$					-0.0004	-0.0003
					(0.0002)	(0.0003)
N	124	124	124	124	124	124
R-squared	0.001	0.056	0.019	0.078	0.037	0.096

Notes: Dependent variable is annualised growth in log value added. Cluster-robust standard errors (Region clusters) in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1. Long-difference climate–value added regressions

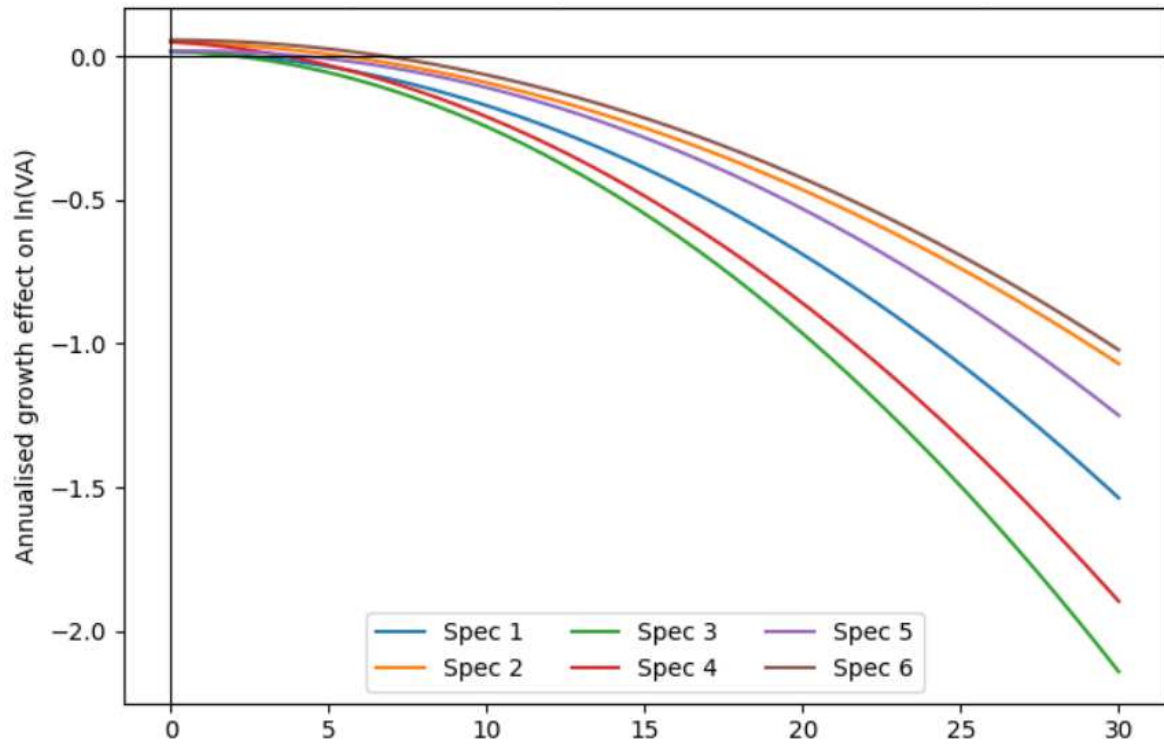


Figure 1: Estimated climate damage functions across specifications.

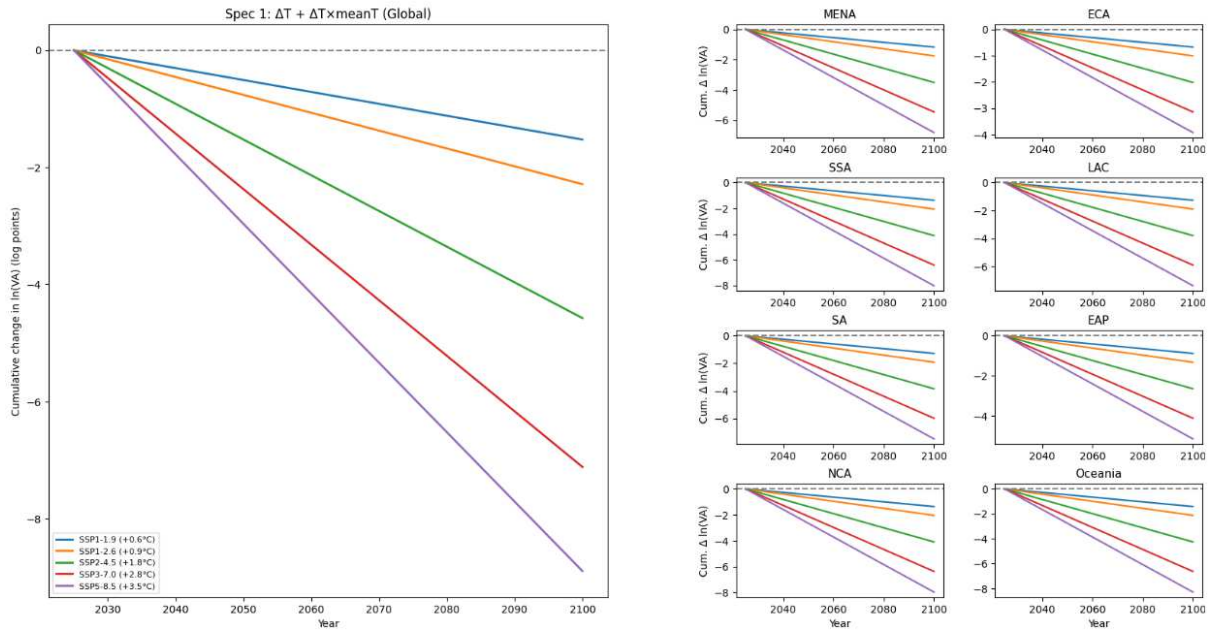


Figure 2: Warming scenarios projection for specification 1 (global) and 2 (regional).

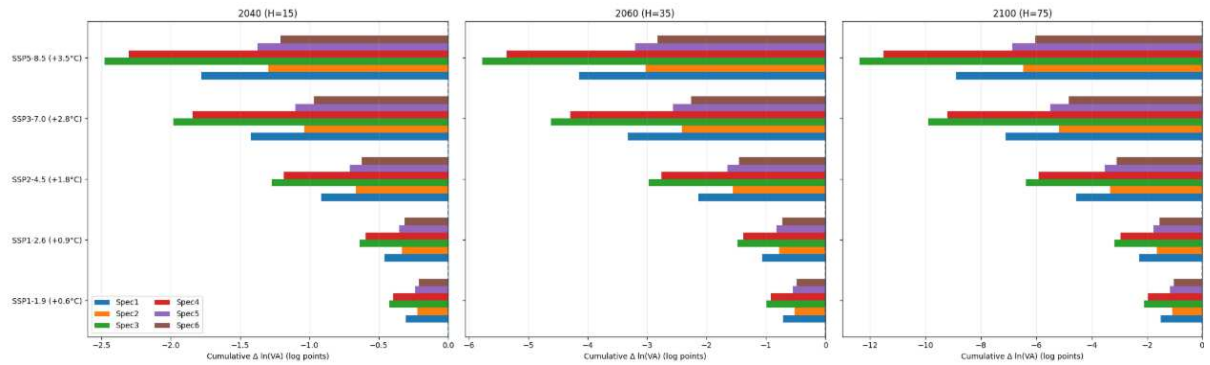


Figure 3: Comparative cumulative percentage loss in log value added across time horizon, warming scenarios and model specifications computed as $(\Delta g \times H)$, where Δg is the scenario-minus-baseline difference in annualised growth of $\ln(VA)$. Sample baseline temperature used is 19.15°C .

4.0 Conclusion

Using productivity measures constructed from World Bank Enterprise Survey microdata and a long-difference framework, this study estimates climate damage functions across 125 countries. The results indicate a nonlinear and heterogeneous relationship between climate change and productivity growth, with warming becoming increasingly damaging in hotter baseline climates. While the analysis does not eliminate all concerns regarding aggregation and spatial dependence, it provides complementary evidence that climate damages vary substantially across regions and climate conditions. These findings contribute to the growing literature on climate-economy interactions by highlighting the importance of heterogeneity in the estimation of climate damage functions.

Future work could extend this analysis by explicitly modelling firm-level adaptation and resilience investment, exploiting higher-resolution spatial climate data, and linking climate-induced economic losses to financial outcomes such as credit risk or investment behaviour. Integrating firm-level damage functions into macro-financial or integrated assessment models would further strengthen climate policy and financial stability analysis.

Acknowledgement

I thank the Enterprise Analysis Unit of the Development Economics Global Indicators Group of the World Bank for the data.

Author contributions

The author UMN is the sole contributor to this paper which includes writing the literatures in the manuscript, data extraction and preparation processes, methods applied in the climate damage function estimate, and result interpretation.

Informed consent

This article does not contain any studies with human participants performed by the author.

Competing interests

The author declares no competing interests.

Ethical statements

This article does not contain any studies with human participants performed by the author.

Funding Declaration

The author did not receive any funding for this research and publication from any agencies in the public, commercial, and not-for-profit sectors.

Data availability statement

The World Bank firm-level metadata used in this study can be assessed from:
<https://www.enterprisesurveys.org>

The climate data used in this study can be assessed from:
<https://climateknowledgeportal.worldbank.org/download-data>

The microdata analysed during the current study are available in the Zenodo repository with restricted access due to licensing conditions. Access can be requested from the corresponding author on reasonable request.

https://drive.google.com/drive/folders/1sTh4L4s389iD1pV_Dc-jxq_8ADG5N_Op?usp=sharing

The cleaned firm-level and climate dataset analysed during the current study are available in the Zenodo repository with restricted access due to licensing conditions. Access can be requested from the corresponding author on reasonable request.

https://drive.google.com/drive/folders/1ZP1tpZ3NP-oYkdMWy3TgC3R1icOsU5sQ?usp=drive_link

The python code used in data preparation and analysis during the current study are available in the Zenodo repository with restricted access due to licensing conditions. Access can be requested from the corresponding author on reasonable request.

https://drive.google.com/drive/folders/1Lz01mwJOR_duJjie_v565ItF0t6kySgc?usp=drive_link

References

1. Abalo Kodzovi Senu; Boehlert Brent; Bui Thanh; Burns Andrew; Castillo Diego; Chewpreecha Unnada; Haider Alexander; Hallegatte Stephane; Jooste Charl; McIsaac Florent; Ruberl Heather Jane; Smet Kim; Strzepek Ken (2025). The Macroeconomic Implications of Climate Change Impacts and Adaptation Options: A Modeling Approach (English). Policy Research Working Paper (WPS11133); Planet Washington, D.C.: World Bank Group. <http://documents.worldbank.org/curated/en/099722205282528064>
2. Bearpark, T., Hogan, D. & Hsiang, S. (2025). Data anomalies and the economic commitment of climate change. *Nature* 644, E7–E11 (2025). <https://doi.org/10.1038/s41586-025-09320-4>
3. IPCC (2023) Sections. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115. <https://doi.org/10.59327/IPCC/AR6-9789291691647>
4. Jing Wei, Tong Jiang, Philippine Ménager, Dong-Gill Kim, Wenjie Dong (2025). COP29: Progresses and challenges to global efforts on the climate crisis. *The Innovation*, Volume 6, Issue 1, 2025, 100748, ISSN 2666-6758. <https://doi.org/10.1016/j.xinn.2024.100748>
5. Khan, N., and M. Khan (2025). “Soft” Climate Change Exposure and Firm Performance Across Countries: Legitimacy Theory Perspective. *Business Strategy and the Environment* 34, no. 7: 8554–8570. <https://doi.org/10.1002/bse.70029>
6. Korbinian Breinl, David Lun, Hannes Müller-Thomy, Günter Blöschl (2021). Understanding the relationship between rainfall and flood probabilities through combined intensity-duration-frequency analysis. *Journal of Hydrology*, Volume 602, 2021, 126759, ISSN 0022-1694. <https://doi.org/10.1016/j.jhydrol.2021.126759>
7. Kotz, M., Levermann, A. & Wenz, L. (2024). RETRACTED ARTICLE: The economic commitment of climate change. *Nature* 628, 551–557 (2024). <https://doi.org/10.1038/s41586-024-07219-0>
8. Lars Peter Hansen (2022). Central banking challenges posed by uncertain climate change and natural disasters. *Journal of Monetary Economics*, Volume 125, 2022, Pages 1-15, ISSN 0304-3932. <https://doi.org/10.1016/j.jmoneco.2021.09.010>
9. Maria Pizzorni, Alberto Innocenti, Nicola Tollin (2024). Droughts and floods in a changing climate and implications for multi-hazard urban planning: A review. *City and Environment Interactions*, Volume 24, 2024, 100169, ISSN 2590-2520. <https://doi.org/10.1016/j.cacint.2024.100169>

10. Mandel, A., Battiston, S. & Monasterolo, I. (2025). Mapping global financial risks under climate change. *Nat. Clim. Chang.* 15, 329–334 (2025). <https://doi.org/10.1038/s41558-025-02244-x>
11. Matthias Kalkuhl, Leonie Wenz (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, Volume 103, 2020, 102360, ISSN 0095-0696. <https://doi.org/10.1016/j.jeem.2020.102360>
12. Naveen Kumar, Dibyendu Maiti (2024). Long-run macroeconomic impact of climate change on total factor productivity — Evidence from emerging economies, *Structural Change and Economic Dynamics*, Volume 68, 2024, Pages 204-223, ISSN 0954-349X. <https://doi.org/10.1016/j.strueco.2023.10.006>
13. Nesrin Ahmed Abbas Abuzied (2026). Economic impacts of extreme climate events: Policies and practices. *Environmental Development*, Volume 57, 2026, 101350, ISSN 2211-4645. <https://doi.org/10.1016/j.envdev.2025.101350>
14. NGFS (2024). Damage function, NGFS scenarios, and the economic commitment of climate change: An explanatory note. Network for Greening the Financial System (NGFS) Central Bank and Supervisions. Retrieved from: https://www.ngfs.net/system/files/import/ngfs/media/2024/11/05/ngfs_scenarios_explanatory_note_on_damage_functions.pdf
15. Philip Kofi Adom (2024). The socioeconomic impact of climate change in developing countries over the next decades: A literature survey. *Heliyon*, Volume 10, Issue 15, 2024, e35134, ISSN 2405-8440. <https://doi.org/10.1016/j.heliyon.2024.e35134>
16. Pritha Mitra, Mehdi Raissi, Bruno Versailles, Samuele Centorrino, Maksym Ivanyna, Koralai Kirabaeva, Emanuele Massetti, Mariza Montes de Oca Leon, Ha Nguyen, William Oman, Nooman Rebei, Filippos Tagklis, Alice Tianbo Zhang, Christoph Ungerer, Javier Uruñuela López, and Sha Yu (2025). Integrating Climate Change into Macroeconomic Analysis: A Review of Impact Channels, Data, Models, and Scenarios. *IMF Working Papers* 2025, 170 (2025), accessed 12/19/2025, <https://doi.org/10.5089/9798229021890.001>
17. Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, H. Khesghi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M.V. Vilarinho (2018). Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 93-174, doi:10.1017/9781009157940.004.

18. Schötz, C. (2025). Spatial correlation in economic analysis of climate change. *Nature* 644, E27–E30 (2025). <https://doi.org/10.1038/s41586-025-09206-5>
19. Tabari, H. (2020). Climate change impact on flood and extreme precipitation increases with water availability. *Sci Rep* 10, 13768 (2020). <https://doi.org/10.1038/s41598-020-70816-2>
20. Waidelich, P., Batibeniz, F., Rising, J. *et al.* (2024). Climate damage projections beyond annual temperature. *Nat. Clim. Chang.* **14**, 592–599 (2024). <https://doi.org/10.1038/s41558-024-01990-8>
21. World Bank (2022). Georgia - Country Economic Memorandum: Chapter 3 - Drivers of Firms' Productivity and Jobs Creation (English). Washington, D.C.: World Bank Group. <http://documents.worldbank.org/curated/en/099320506302229247>
22. Yongji Zhang, Lingxi Liu, Minghui Lan, Zhi Su, and Ke Wang (2024). Climate change and economic policy uncertainty: Evidence from major countries around the world. *Economic Analysis and Policy*, Volume 81, 2024, Pages 1045-1060, ISSN 0313-5926. <https://doi.org/10.1016/j.eap.2024.02.003>
23. Yuqing Cai (2025). How does climate change affect regional sustainable development? Empirical evidence from 186 countries around the world. *International Review of Economics & Finance*, Volume 99, 2025, 104047, ISSN 1059-0560. <https://doi.org/10.1016/j.iref.2025.104047>

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryInformationforClimateDamageFunction.pdf](#)