THE
QUARTERLY JOURNAL
OF ECONOMICS

Vol. 141 2026 Issue 2

THE MACROECONOMIC IMPACT OF CLIMATE CHANGE: GLOBAL VERSUS LOCAL TEMPERATURE*

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This article estimates that the macroeconomic damages from climate change are an order of magnitude larger than previously thought. Exploiting natural global temperature variability, we find that 1ºC warming reduces world GDP by over 20% in the long run. Global temperature correlates strongly with extreme climatic events, unlike country-level temperature used in previous work, explaining our larger estimate. We use this evidence to estimate damage functions in a neoclassical growth model. Business-as-usual warming implies a present welfare loss of more than 30%, and a social cost of carbon in excess of $1,200 per ton. These impacts suggest that unilateral decarbonization policy is cost-effective for large countries such as the United States. *JEL codes:* E01, E23, F18, O44, Q54, Q56.

I. INTRODUCTION

Climate change is frequently described as one of the defining economic challenges of our time. This view, however, stands in

* We thank Marios Angeletos, Helene Benveniste, Marshall Burke, Gabriel Chodorow-Reich, Simon Dietz, Stephane Hallegatte, Jim Hamilton, Xavier Jaravel, Ben Jones, Pete Klenow, Eben Lazarus, Pooya Molavi, Ishan Nath, Ben Olken, Esteban Rossi-Hansberg, Toan Phan, Jón Steinsson, Jeffrey Shrader, Jim Stock, Chris Wolf, the referees, editors Robert Barro and Larry Katz, and numerous participants at conferences and seminars for helpful comments and suggestions. We thank Krzysztof Lisiecki, Lilian Hartmann, Ramya Raghavan, and Cathy Wang for outstanding research assistance. Adrien Bilal gratefully acknowledges support from the Chae Family Economics Research Fund at Harvard University.

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The Quarterly Journal of Economics (2026), 889–944. https://doi.org/10.1093/qje/qjag011.
Advance Access publication on February 19, 2026.

sharp contrast to empirical estimates of its impact on economic activity: they imply that a permanent 1°C rise in temperature reduces world output by 1%–3%. Under conventional discounting and background economic growth, these effects seem modest. Why, then, does climate change loom so large in economic debate? Do existing estimates not account for the full impact of climate change, or are its true economic consequences indeed limited?

In this article, we show that the macroeconomic effects of climate change are an order of magnitude larger than previously documented. We rely on time-series local projections to estimate the effect of global temperature on gross domestic product (GDP). This approach exploits natural variability in global mean temperature—the source of variation closest to climate change—which we show to be a stronger predictor of damaging extreme climatic events than country-level temperature. Our estimates imply that a permanent 1°C rise in global temperature lowers world GDP by over 20%. We use our reduced-form results to estimate structural damage functions in a neoclassical growth model. Climate change of 2°C by 2100 leads to a present-value welfare loss of more than 30% and a social cost of carbon (SCC) in excess of $1,200 per ton of carbon dioxide.

In the first part of the article, we develop our time-series approach. We assemble two climate-economy data sets whose strengths complement each other. The first data set builds on the Barro-Ursúa measures of economic activity, complemented with global mean temperature information from the U.S. National Oceanic and Atmospheric Administration (NOAA). This data set spans 43 countries over 160 years, from 1860 to 2019. We refer to it as the BU sample.

The second data set draws on the Penn World Tables, providing economic data on GDP, consumption, investment, and productivity. It spans a broader set of 173 countries over a shorter period, from 1960 to 2019. To measure climate conditions, we construct global and country-level temperatures from high-resolution gridded land and ocean surface air data from Berkeley Earth. We further incorporate reanalysis-based indicators of extreme weather—capturing heat, drought, wind speed, and precipitation at a granular level—from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). We refer to this data set as the PWT sample.

Identifying the effect of temperature on GDP per capita is complicated by their jointly trending behavior. We thus construct global and local (country-level) temperature shocks: innovations to the temperature process that are orthogonal to their long-run trends and persist for two years using the approach in Hamilton (2018). Our choice of period is motivated by the geoscience literature. Natural climate variability is driven by multiple phenomena. External causes such as solar cycles and volcanic eruptions lead to medium- and short-run fluctuations in the Earth's mean temperature. Internal climate variability—interactions in the climatic system itself—lead to irregular fluctuations in temperature and weather extremes. For instance, the El Niño cycle varies unpredictably between two and seven years.

We map out the dynamic causal effects of our global temperature shocks on world GDP per capita using local projections. In the broader PWT sample, a global temperature shock scaled to 1ºC leads to a gradual decline in world GDP per capita that peaks at 14% after 6 years with a 95% confidence interval of (6%, 22%), and is statistically significant at the 5% level in years 2–8. In the longer BU sample, the same temperature shock leads to a peak effect at 18% after 5 years with a 95% confidence interval of (6%, 30%), and is statistically significant at the 5% level in years 0–6. In both cases, effects do not fully mean revert even after 10 years. Our results remain unchanged for alternative de-trending approaches, such as one-step ahead-forecast errors, a one-sided Hodrick-Prescott filter, or taking simple first differences.

Importantly, the temperature shocks have a partially persistent effect on the level of temperature, that remains near 0.5ºC for multiple years after the shock. As in an instrumental variable approach, the fundamental determinant of output is the temperature level, while the temperature shock simply extracts quasi-experimental variation. Hence, the 14%–18% effects 6 years after the initial shock reflect the accumulated effects of persistently elevated global temperature itself but are less than the implied effect of a permanent 1ºC increase in the level of temperature.

We convert these estimates identified from partially transitory global temperature shocks to the effect of a permanent increase in global temperature by taking the ratio of the cumulative impulse responses of GDP per capita and global temperature. Our reduced-form estimates imply that a permanent 1ºC rise in global temperature leads to a 22%–34% reduction in world GDP per capita in the PWT and BU samples, respectively.

Although climate change occurs in a sequence of small increments, this conversion relies on the same conditions that underpin existing estimates of temperature impacts: the relationship between temperature and GDP holds beyond the range of temperature shocks observed in sample, and it holds for expected permanent temperature changes in addition to medium-run unexpected temperature changes. We partly address these limitations with our structural model, which accounts for long-run expectations and adaptation through capital adjustment.

The causal interpretation of our headline results is subject to three identification concerns. We address them in a series of robustness exercises. First, we account for omitted variable bias: global temperature shocks may coincide with the global economic and financial cycle. We control for rich measures of world economic performance: indicators for global economic recessions, global macro-financial variables (past world and country real GDP, commodity prices, and interest rates), and regional economic trends. Our results remain unaffected by the specific set of controls and are not driven by any particularly influential years, indicating that temperature shocks are largely unrelated to economic shocks.

Second, we account for reverse causality: as output declines after a temperature shock, energy consumption and greenhouse gas emissions fall, lowering temperatures and increasing output going forward. Qualitatively, reverse causality thus leads us to underestimate the true effect of a global temperature shock. Quantitatively, it is likely negligible because short-run fluctuations in emissions imply small temperature variations. We confirm these arguments by explicitly adjusting for the impact of past greenhouse gas and aerosol emissions with a climate model and find virtually identical results.

Third, we verify that our estimates are stable across time periods and causes of temperature variation. Our main analysis reveals similar estimates in the shorter PWT sample (1960–2019) and in the longer BU sample (1860–2019). We find comparable estimates in shorter time periods (1860–1928, 1940–2019, 1980–2019, 1960–2007) as well as when we exclude El Niño and volcanic eruptions from our identifying variation. Collectively, our robustness exercises suggest that our specification captures the causal effect of global temperature on economic activity.

Our estimated impact of temperature shocks on world GDP contrasts with existing estimates. Comparable approaches to ours in Nordhaus (1992), Dell, Jones, and Olken (2012), Moore and Diaz (2015), Burke, Hsiang, and Miguel (2015), and Nath, Ramey, and Klenow (2024) imply that a permanent 1°C rise in temperature reduces GDP by at most 3%. Why do we find effects that are an order of magnitude larger?

We focus on a different source of variation. Changes in global mean temperature capture the comprehensive impact of climate change. By contrast, previous work exploits changes in country-level, local temperature. When we estimate the impact of local temperature on country-level GDP with the same empirical specification, we find similarly modest and imprecise effects to previous studies: 1% per 1ºC temperature shock, implying a 3% decline following a permanent 1ºC rise in temperature. These effects are not significant at the 5% level. Econometrically, panel analyses using local temperature net out common impacts of global temperature through time fixed effects. Instead, we focus on these common effects.

Why, then, does global temperature depress economic activity more than local temperature? We argue that global temperature is fundamentally different from local temperature. The geoscience literature shows that droughts, extreme wind, and precipitation are outcomes of the global climate that depend on ocean temperatures and atmospheric humidity throughout the world, rather than outcomes of local temperature realizations (Seneviratne et al. 2016; Wartenburger et al. 2017; Seneviratne et al. 2021; Domeisen et al. 2023).

In line with this view, we find that ocean temperature, rather than land temperature, is responsible for the majority of the effects of global temperature on economic activity. In addition, global temperature shocks predict a pronounced and persistent rise in the frequency of four extreme climatic events that cause economic damage: extreme temperature, droughts, extreme wind, and extreme precipitation. By contrast, local temperature shocks only predict a weak rise in these extremes.

Quantitatively, including these four extreme events accounts for half of the estimated impact of global temperature. We reach this conclusion by estimating the effect of extreme events on GDP, which we combine with the dynamic correlation between global temperature shocks and extreme events to construct a counterfactual impact of global temperature on GDP. Of course, our aggregation exercise is unlikely to account for the full effect of global temperature on GDP: we would need to specify and measure the universe of channels whereby global temperature affects the economy. Using global temperature directly bypasses this challenge. By contrast, we do not find evidence that economic spillovers through international trade alone can quantitatively account for the gap between local and global temperature impacts.

How and where do the worldwide GDP effects of global temperature materialize? We document that capital, investment, and productivity all decline after a global temperature shock. Warm and low-income countries appear to be more strongly affected than cold and high-income countries, although these comparisons are somewhat noisy. Overall, however, global temperature has more uniformly detrimental effects than local temperature.

In the second part of the article, we develop a simple neoclassical growth model to translate our medium-run reduced-form estimates into long-run output and welfare effects. Consistent with Nordhaus (1992), we remain purposefully parsimonious and let global temperature affect aggregate productivity.

We estimate productivity shocks that correspond to a global temperature shock by matching the estimated impulse response function of output. This mapping has a closed-form expression that guarantees identification. In doing so, we account for the internal persistence of global mean temperature in response to temperature shocks. We remain conservative and impose persistent level effects rather than growth effects. The estimated damage function implies that a one-time transitory 1ºC rise in global mean temperature leads to a 4% peak productivity decline when targeting the PWT estimates. The estimated model also matches the untargeted impulse response of capital to a temperature shock.

Our main counterfactual is a gradual increase in global mean temperature that starts in 2024 and reaches 3ºC above preindustrial levels by 2100, so 2ºC above 2024 temperatures, with a 2% rate of time preference. Climate change implies a 53% GDP per capita decline by 2100, or 26% per 1ºC. The long-run adjustment of capital amplifies the effect of global temperature on GDP by one-fifth relative to the reduced-form estimates. This amplification mechanism is muted in the reduced-form estimates based on smaller and more transitory temperature changes. Capital and consumption drop by 51% and 53%, respectively, leading to a 35% welfare loss in permanent-consumption equivalent in 2024. Of course, these counterfactuals represent losses relative to a baseline trend in economic activity between 2024 and 2100, not absolute losses relative to 2024. These counterfactuals also reflect estimation uncertainty. For instance, the 95% confidence interval for 2100 output losses ranges from 29% to 77%. Even at the lower end of the confidence interval, our baseline counterfactuals are comparable to the economic losses caused by the 1929 Great Depression, but experienced permanently.

If the economic effects of global temperature are substantial, why were they not noticed after nearly 1ºC of global warming since 1960? Because climate change occurs in small increments, its effects are hidden behind background economic variability. We show that since 1960, climate change caused a gradual reduction in the annual world growth rate that reaches one-third of baseline by 2019. Because climate change is also permanent, its effects keep accumulating over time. According to our counterfactual, world GDP per capita would be more than 20% higher today had no warming occurred between 1960 and 2019.

We characterize the SCC using the global temperature response to a carbon dioxide (CO_2) pulse from Dietz et al. (2021b) and Folini et al. (2025). We obtain an SCC in excess of $1,200 per ton. This value is six times larger than the high end of existing estimates ($185 per ton, Rennert et al. 2022). The 95% confidence interval for the SCC ranges from $399 per ton to $2,015 per ton. While this range is nontrivial, its lower bound is multiple times larger than conventional SCC values. Our focus on global temperature shocks accounts for this difference. When we reestimate our model based on the impact of local temperature shocks as in previous research, the welfare cost of our climate change scenario is 5% and the SCC is $149 per ton. Neither of these values is statistically significant at the 5% level.

How sensitive are these results to specification choices? Targeting the empirical estimates in the BU sample implies a 61% GDP per capita loss by 2100 and an SCC in excess of $1,500. Any plausible discount rate and warming scenario results in welfare losses in excess of 15% and an SCC above $370 per ton. Discount rates close to 1% imply an SCC exceeding $2,500 per ton. Scenarios with 2100 warming 5ºC above preindustrial levels lead to welfare losses larger than 50%. Varying the climate sensitivity by a factor of 2 implies an SCC between $600 and $2,400 per ton.

We conclude by delineating the consequences of our results for decarbonization policy, which we explore further in a companion paper (Bilal and Känzig 2025). Decarbonization interventions cost $80 per ton of CO_2 abated on average (Bistline, Mehrotra, and Wolfram 2023). A conventional SCC value of $149 per ton based on local temperature implies that these policies are cost-effective only if governments internalize benefits to the entire world, as captured by the SCC. However, a government that only internalizes domestic benefits values decarbonization using a domestic cost of carbon (DCC). The DCC is always lower than the SCC because damages to a single country are lower than at a global scale. Under conventional estimates, the DCC of the United States is below policy costs, making unilateral emissions reduction prohibitively expensive. Under our estimates based on global temperature, the DCC of the United States exceeds policy costs. In that case, unilateral decarbonization policy is cost-effective for a large economy such as the United States.

Our article contributes to an influential literature measuring economic damages from climate change surveyed in Burke et al. (2023) and Moore et al. (2024). The conventional panel approach estimates the effect of small, short-run local temperature shocks (Dell, Jones, and Olken 2012, 2014; Burke, Hsiang, and Miguel 2015; Moore and Diaz 2015; Newell, Prest, and Sexton 2021; Kahn et al. 2021; Barrage and Nordhaus 2024). Across all these studies, estimates consistently imply that a permanent 1ºC rise in temperature leads to a 1%–3% reduction in GDP. Our article takes a fundamentally different approach: we directly exploit time-series variation in a more comprehensive metric of climate change—global mean temperature.

Local temperature estimates can lead to larger long-run economic effects if one assumes growth effects—that short-run economic effects persist forever (Dell, Jones, and Olken 2012; Moore and Diaz 2015; Burke, Hsiang, and Miguel 2015). Our treatment of persistence builds on Nath, Ramey, and Klenow (2024), who show how to distinguish empirically between the polar assumptions of growth effects and level effects for local temperature. Our local temperature estimates are quantitatively consistent with theirs—a 2%–3% GDP loss per permanent 1ºC increase—which we use as our benchmark.

Few studies have explored time-series variation in temperature (Bansal and Ochoa 2011; Berg, Curtis, and Mark 2024; Neal, Newell, and Pitman 2025). They emphasize either contemporaneous effects, GDP dispersion, or spillover effects. All of them focus on average land temperature rather than global temperature inclusive of oceans. By contrast, we show that global ocean temperature—rather than land temperature—is the main driver of aggregate effects, that their delayed peak outweighs contemporaneous effects, and that extreme events rather than spillovers help bridge the gap between global and local temperature impacts.

This article relates to the literature studying the economic impact of natural disasters such as storms, heatwaves, or El

Niño (Barro 2006, 2009; Deschênes and Greenstone 2011; Hsiang, Meng, and Cane 2011; Deryugina 2013; Hsiang and Jina 2014; Callahan and Mankin 2023; Dingel, Meng, and Hsiang 2023; Tran and Wilson 2023). We evaluate the effect of global temperature directly and provide new evidence on the relationship between global temperature and a wide range of extreme climatic events.

This top-down approach connects to the literature using integrated assessment models surveyed in Nordhaus (2013). Our counterfactuals suggest that these models often found limited costs of climate change because they were calibrated to local temperature, not due to incomplete economic foundations (Nordhaus 2013; Stern, Stiglitz, and Taylor 2022).

More recently, bottom-up models featuring rich regional heterogeneity, migration (Desmet et al. 2021; Cruz and Rossi-Hansberg 2024), and capital investment (Krusell and Smith 2022; Bilal and Rossi-Hansberg 2023) match micro-level estimates and aggregate using the model. Our top-down global-temperature approach holistically captures damages without having to quantify each channel, but remains necessarily limited in assessing distributional and adaptation effects.

In fact, both our global-temperature and the conventional local-temperature approaches capture adaptation only imperfectly, as both rely on moderate short-run variation. Although assessing the role of adaptation is beyond the scope of this article, the stability of our estimates across time periods suggests that it does not play a major role (Burke et al. 2024). Should there be an unprecedented uptake in adaptation in the future, our numbers would still represent an upper bound on damages absent adaptation and society's willingness to pay for it.

The rest of the article is organized as follows. Section II describes the data and estimates the macroeconomic effects of global temperature shocks in the time series. Section III confirms the effect of global temperature in the panel of countries and discusses identification concerns. Section IV compares the effects of global and local temperature. Section V introduces our dynamic model and describes our structural estimation approach. Section VI evaluates the welfare implications of climate change. Section VII concludes.

II. Global Temperature and Economic Growth

We aim to estimate the effects of climate change on economic activity. Climate change is a transformation in a wide range of weather patterns, ocean currents, and atmospheric conditions relative to preindustrial times. The Intergovernmental Panel for Climate Change (IPCC) summarizes this complex phenomenon with a single, scalar measure: global mean temperature. Therefore, we use global mean temperature as our main metric of a changing climate and investigate how it affects the economy.

II.A. Climate-Economy Data

To study the effects of temperature on the economy, we assemble two complementary data sets. We use global aggregates from these data sets in this section and country-level outcomes in Section III.

Our first data set is based on the Barro and Ursúa (2008) macroeconomic data, which provides GDP and population figures for 43 countries from 1860 to 2007. We extend this data using the World Bank Development Indicators, yielding coverage from 1860 through 2019. We obtain a consistent, direct measure of global mean temperature over this long time frame from NOAA. This data set is the BU sample.[1]

Our second data set builds on the Penn World Tables (Feenstra, Inklaar, and Timmer 2015). We obtain information on GDP, population, consumption, investment, and productivity for 173 countries from 1960 to 2019. This data set is the PWT sample. We also rely on the World Bank Development Indicators as an alternative over this time frame.

We complement the PWT data set with richer climate and weather information given its more recent time coverage. We obtain temperature data from the Berkeley Earth Surface Temperature Database (Rohde and Hausfather 2020). It provides temperature anomaly data at a spatial resolution of $1^{\circ} \times 1^{\circ}$ of latitude and longitude. Based on this gridded data, we construct population- and area-weighted temperature measures at the country level. We also construct area-weighted measures of global temperature, which includes land and ocean surface air temperature. Reassuringly, our measure correlates virtually perfectly with the direct measure from NOAA.

1. We thank Robert Barro for kindly sharing the GDP and population data underlying the GDP per capita indices.

FIGURE I

Global Average Temperature and Output Since 1860

Panel A: Evolution of global average temperature from NOAA since 1860. Panel B: Evolution of world real GDP per capita (in 2017 US$) computed based on PWT (1960–2019, dashed blue) and BU (1860–2019, solid green) data.

In addition, we incorporate indicators of extreme weather events—covering heat, drought, wind, and precipitation—from ISIMIP's observed climate data set (Lange et al. 2023). This source provides global daily reanalysis data on temperature, wind speed, and precipitation from 1901 to 2019 at a 0.5º × 0.5º resolution, with higher-quality measurements in the second half of the twentieth century. We construct exposure indices by recording, for each country and year, the fraction of days in which observed weather exceeds (or falls below) fixed percentiles of the 1950–1980 daily weather distribution. We further detail data sources and construction in Online Appendix A.

Together, the BU and PWT data sets allow us to leverage the strengths of each in our analysis. The BU data set provides a long time frame of 160 years, and the PWT data set offers broader country coverage in a more recent period when climatic information is more accurately measured.

II.B. Global Temperature Shocks

Figure I displays the evolution of global average temperature and world real GDP per capita since 1860 in our data set. In the early stages of the industrial period, global mean temperature remains relatively stable near 14ºC. However, from the 1920s onward, global average temperature begins to steadily rise. At the same time, we observe relatively stable economic growth over the entire sample, in both the PWT and BU samples.

The trending behavior of the two series in Figure I complicates the identification of the economic effects of temperature increases. A simple regression of global GDP per capita on temperature will yield a spurious correlation between the two variables

(Granger and Newbold 1974). In our case, reverse causality is an additional challenge. Economic growth is associated with higher greenhouse gas emissions, which eventually translate into higher temperature over long horizons. Therefore, we do not focus on the level of temperature as the treatment in our projections but on so-called temperature shocks. We define such shocks as possibly persistent deviations from the long-run trend in global mean temperature.

What drives these variations in temperature around the trend? The geoscience literature indicates two types of causes. First, external causes such as solar cycles and volcanic eruptions lead to short-run fluctuations in the Earth's mean temperature. Solar cycles have a typical period of 10 years and can warm the Earth by as much as 0.1ºC (National Oceanic and Atmospheric Administration 2009). Volcanic eruptions have shorter-lived cooling effects of up to two years due to sulfuric aerosols that increase albedo (National Oceanic and Atmospheric Administration 2005). Second, internal climate variability—interactions in the climatic system that lead to irregularly recurring events—also affects temperatures. For instance, the El Niño–La Niña cycle varies unpredictably between two and seven years and substantially affects global mean temperatures and weather extremes (Kaufmann, Kauppi, and Stock 2006; National Oceanic and Atmospheric Administration 2024).

How do we isolate the trend and transient components of temperature? To estimate the effects of temperature on future economic outcomes, it is critical to preserve the causality of the data in a time-series sense: we cannot rely on future values of temperature to identify the trend in the current period. In addition, the physical properties of natural climate variability suggest allowing for somewhat persistent deviations from trend.

An approach that satisfies our needs along both these dimensions is the method proposed by Hamilton (2018) and used in Nath, Ramey, and Klenow (2024) for local temperature. We regress global mean temperature on its lags as of period $t-h$ and construct the temperature shock as the corresponding innovation:

$$\widehat{T_t^{\text{shock}}} = T_t - (\widehat{\alpha} + \widehat{\beta}_1 T_{t-h} + \ldots + \widehat{\beta}_{p+1} T_{t-h-p}), \tag{1}$$

where $\widehat{\beta}_i$ denotes the coefficient estimates of the regression of temperature on its lag $j = h+i-1$ and $\widehat{\alpha}$ is the estimated intercept. This exercise amounts to isolating shocks that persist typically for h periods. Selecting the horizon h is of course an important

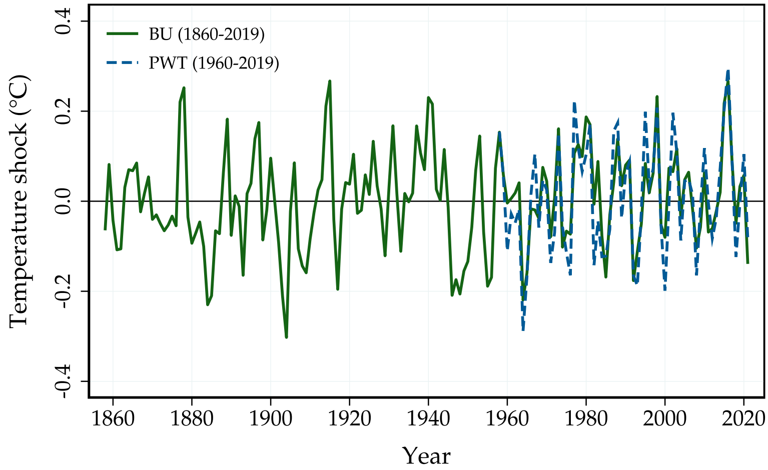

FIGURE II

Global Temperature Shocks

Global temperature shocks computed using the Hamilton (2018) filter. PWT: $h = 2$, $p = 2$, 1960–2019, dashed line. BU: $h = 2$, $p = 6$, 1860–2019, solid line.

choice. Motivated by the fact that the climatic events that we consider can last for up to several years, we select a horizon of $h = 2$. We set the number of lags to $p = 2$ in the PWT sample. In the BU sample, we use $p = 6$ to capture the more pronounced curvature in the temperature series over a longer horizon. As we show in Section III.B, varying these values leaves our results essentially unchanged.

Figure II shows the resulting global temperature shocks over our sample of interest. As expected, the temperature shocks fluctuate around zero with an almost equal number of positive and negative shocks. The largest temperature shocks in our sample are near 0.3ºC. Online Appendix Figure B.1 indicates that the series is also weakly autocorrelated, because we allow for relatively persistent deviations from the long-run temperature trend. In our empirical specification, we therefore control for lagged temperature shocks as well. Otherwise, serial correlation may bias the estimated effects.

II.C. The Effect of Temperature Shocks in the Time Series

The economic effects of temperature shocks may take time to materialize. Therefore, we focus on the dynamic effects of temperature shocks up to 10 years after the initial shock. We evaluate directly these medium-run effects of temperature without extrapolating short-term temperature impacts.

We estimate the dynamic causal effects to global temperature shocks using local projections as in Jordà (2005). This approach involves estimating the following series of regressions, one for each horizon $h = 0, \dots, 10$:

$$y_{t+h} - y_{t-1} = \alpha_h + \theta_h T_t^{\text{shock}} + \mathbf{x}_t' \boldsymbol{\beta}_h + \varepsilon_{t+h}, \tag{2}$$

where y_t is the outcome variable of interest, T_t^{shock} is the temperature shock, and θ_h is the dynamic causal effect of interest at horizon h. We refer to the latter as the impulse response function. $\mathbf{x}_t$ is a vector of controls, and ε_t is a potentially serially correlated error term. Our main outcome variable of interest is (log) world real GDP per capita. Because we use the cumulative growth rate as the dependent variable, we estimate a possibly persistent level effect. The estimation sample is 1960–2019 for the PWT data and 1860–2019 for the BU data.[2]

We use local projections in our main analysis because they tend to be robust at longer horizons (Montiel Olea et al. 2024). Compared to vector autoregressions (VARs) or distributed lag models, local projections directly estimate the effects of interest rather than extrapolating from the first few autocovariances and allow for more flexible controls. Yet we obtain similar results under alternative estimation models in Online Appendix B.3.

To account for the serial correlation in GDP growth and temperature shocks, we include lags of real GDP growth per capita and the global temperature shock. To net out the global business cycle more comprehensively, we control for large economic shocks, such as the post–World War recessions, the large oil shocks in the 1970s, or the Great Recession, using one common dummy variable for all recessions.[3] For the shorter sample starting in 1960,

2. Leveraging that temperature data is available for a longer period than GDP data, we estimate temperature shocks based on this longer sample (1950–2022 for PWT and 1850–2022 for BU) to mitigate the influence from observations at the beginning and the end of the sample.

3. Our definition of global recession dates follows the World Bank (Kose, Sugawara, and Terrones 2020). Specifically, we focus on the following episodes: 1873–1877, 1893–1897, 1918–1921, 1921–1939, 1945–1947, 1973–1975, 1979–1983, 1990–1992, 2007–2009, and 2011–2012. To allow for potential persistent effects of recessions, we also include lags of the global recession indicator variable.

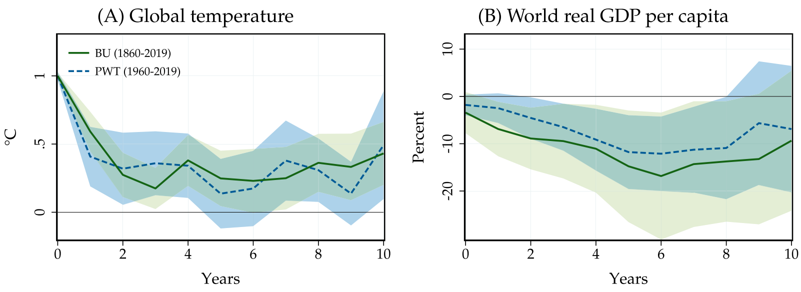

FIGURE III

The Effect of Global Temperature Shocks on Temperature and World Output

Impulse responses of global mean temperature and world real GDP per capita to a global temperature shock, estimated based on specification (2). Controls: lags of the dependent variable, temperature shock, world real GDP growth, current and lagged recession dummies, and a linear time trend. The lag length differs by sample (two lags in PWT; four lags in BU). Lines: point estimate in PWT (dashed) and BU sample (solid). Shaded areas: 95% confidence bands for PWT (darker) and BU sample (lighter).

we include two lags of our controls; for the longer sample, we include four lags. We also include a linear time trend to account more flexibly for trending behavior. Inference uses heteroskedasticity- and autocorrelation-consistent (HAC) standard errors that account for potential serial correlation in the local projection error terms.[4]

Figure III shows the impulse responses of global temperature and world real GDP per capita to a global temperature shock scaled to 1°C. The lines denote point estimates and the shaded areas are 95% confidence bands. By construction, global temperature increases by 1°C on impact in Panel A. The effect of a global temperature shock on global temperature turns out to be highly persistent in the PWT and BU samples: after 10 years global temperature is still elevated by nearly 0.5°C.

The persistent rise in global temperature leads to meaningful economic effects. Panel B shows that on impact, world GDP falls by 2%–3% in the PWT and BU data sets, respectively.

4. Our main specification does not account for estimation uncertainty in the global temperature shock. However, we alternatively conduct inference using bootstrapping techniques or jointly estimate the effect of temperature on GDP per capita with longer lag lengths. Both approaches take estimation uncertainty into account and yield very similar inference. See Online Appendices B.2 and B.3 for more details.

However, the effect builds up over time. After 6 years, world GDP per capita falls by 12%–16%, with effects that persist up to 8 to 10 years after the initial shock. Our estimates are comparable up to statistical precision in the PWT and BU data sets, indicating that focusing on the more recent period with broader country coverage or on a longer time span with fewer, higher-income countries leads to similar results. The effect is statistically significant at the 5% level from years 2 to 8 in both samples. The magnitude of our estimates scaled to a 1ºC temperature shock is similar to growth effects that typically occur after severe financial crises (Cerra and Saxena 2008; Reinhart and Rogoff 2009).

The gradual decline in world GDP reflects not only the direct impact of the initial temperature shock but also the subsequent effects of persistently elevated temperature that accumulate over time. As in an instrumental variable approach, the fundamental determinant of output is the temperature level, while the temperature shock is simply an identification device. Hence, the 12%–16% impacts six years after the initial shock exceed the effect of a one-time, fully transitory 1ºC increase in temperature, but are less than the effect of a permanent 1ºC increase.

To assess the role of persistence, we first construct a counterfactual path of output that would correspond to a fully transitory global temperature change with a linear combination of the output and temperature impulse response functions (Sims 1986). Online Appendix Figure B.5 shows that the accumulated effects of persistently elevated temperature account for a substantial part of the peak effect: the new peak then just exceeds 5% instead and occurs five years after the shock.

Next, we infer what the impact of a permanent 1ºC rise in global temperature would be. We follow standard practice and calculate the ratio of the cumulative impulse response of output per capita to the cumulative impulse response of temperature, which corresponds to a special case of the method in Sims (1986). We find that a permanent 1ºC rise in global temperature leads to a 20% long-run reduction in world GDP per capita in the PWT data set and 29% in the BU data set.

Although climate change occurs in a sequence of small increments, scaling our estimates to a 1ºC increase relies on two conditions. Importantly, the same conditions also underpin existing estimates based on local temperature variation. The first condition is that the relationship between temperature and GDP per capita holds beyond the range of temperature shocks observed in sample. A 1°C global temperature shock is a large shock that does not occur directly in our historical sample: we observe smaller shocks of 0.1°C–0.2°C in practice. In effect, we abstract from potential nonlinearities.

Among the relatively small shocks we observe, we do not find much evidence for nonlinearities. Online Appendix Figure B.6 reports comparable effects of small, larger, or only positive shocks. In principle, a changing climate might affect economic activity as long it differs from preindustrial conditions irrespectively of the sign of global temperature changes. Our results instead suggest that both the sign and magnitude of global temperature changes are relevant as long as global temperature accurately summarizes climate change: positive shocks lower GDP while negative shocks raise GDP.

These results do not imply that nonlinearities do not matter for larger changes that have not yet materialized. However, in the presence of potential future tipping points, one may expect larger effects than predicted by our linear estimates (Dietz et al. 2021a). If costly adaptation to global temperature effects becomes more prevalent in the future than it has historically, then realized effects may be lower than our estimates.

The second condition making our scaling consistent is that the estimated relationship between GDP per capita and global temperature holds for expected permanent temperature changes. We assess whether allowing capital investment to respond to expectations of long-run changes affects our counterfactuals with our structural model in Sections V and VI.

III. Global Temperature Shocks in the Panel of Countries

So far we have evaluated the impact of global temperature shocks directly on world GDP per capita. We now aim to achieve three distinct goals. Our first goal here is to use a country-level econometric specification that is more directly comparable to previous work. Our second goal is to further corroborate our results when controlling for a wider set of variables and varying the time span of our analysis. Our third goal in Section IV is to contrast the effect of global temperature with existing work that has focused on country-level temperature.

III.A. Global Temperature Shocks in the Panel

To estimate the dynamic causal effects of temperature shocks in the panel, we employ the panel local projections approach in Jordà, Schularick, and Taylor (2020). In this section we still estimate the effect of global temperature shocks, now averaged across 173 countries in the PWT data set and across 43 countries in the BU data set. Specifically, we estimate the following series of panel regressions for horizons $h = 0, \ldots, 10$:

$$(3) \qquad y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \theta_h T_t^{\text{shock}} + \mathbf{x}_t' \boldsymbol{\beta}_h + \mathbf{x}_{i,t}' \boldsymbol{\gamma}_h + \varepsilon_{i,t+h},$$

where $y_{i,t}$ is the outcome variable of interest for country i in year t, T_t^{shock} is the global temperature shock, and θ_h is the dynamic causal effect of interest at horizon h. $\mathbf{x}_t$ is a vector of global controls, $\mathbf{x}_{i,t}$ is a vector of country-specific controls, and $\varepsilon_{i,t}$ is an error term.

The panel specification (3) is closer to the standard panel estimators used to study the effects of local temperature shocks (e.g. Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015; Nath, Ramey, and Klenow 2024). Of course, the identifying variation in global temperature shocks T_t^{shock} remains common across all countries, and thus we cannot include year fixed effects. Therefore, we include global controls as in the aggregate time-series specification (2). For the same reason, the error term is potentially serially and cross-sectionally correlated. Inference thus relies on Driscoll and Kraay (1998) standard errors that are robust to cross-sectional and serial dependence.

To assess whether our results hold across a wide range of specifications, we include a richer set of control variables. Specifically, we now additionally control for lags of world commodity prices and the U.S. Treasury yield.[5] In addition, we flexibly absorb lags of country-level GDP per capita and region-specific linear trends. Our main outcome variable of interest is country-level log real GDP per capita. The PWT sample is an unbalanced panel spanning 1960–2019, and the BU sample is an unbalanced panel spanning 1860–2019.

Figure IV displays the impulse responses to a global temperature shock, estimated in the panel of countries. Consistent with our aggregate time-series evidence, global temperature shocks

5. For the PWT sample, we use the WTI crude price and the 1-year Treasury yield; for the BU sample, we use an energy price index including coal and oil and the 10-year Treasury yield.

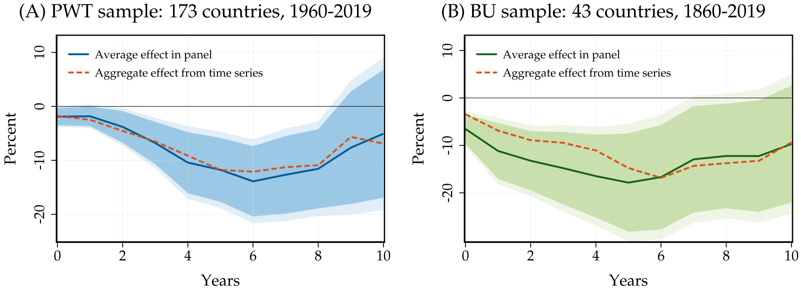

FIGURE IV

The Effect of Global Temperature Shocks: Panel Versus Time Series

Impulse responses of real GDP per capita to a global temperature shock estimated in the panel using specification (3). Controls: Lags of the dependent variable, temperature shock, world real GDP growth, commodity price inflation, U.S. Treasury yield, current and lagged recession dummies, and subregion specific time trends. The lag length differs by sample (two lags in PWT; four lags in BU). Panel A: PWT sample (173 countries, 1960–2019). Panel B: BU sample (43 countries, 1860–2019). Lines: baseline estimates from the panel specification (solid) against time-series response from specification (2) (dashed). Dark and light shaded areas: baseline 90% and 95% confidence bands.

lead to a significant fall in real GDP per capita. In the broader PWT sample, a global temperature shock scaled to 1°C leads to a gradual decline in world GDP that peaks at 14% after six years with a 95% confidence interval of (6%, 22%), and is statistically significant at the 5% level in years 2–8. In the longer BU sample, the same temperature shock leads to a peak effect at 18% after five years with a 95% confidence interval of (6%, 30%), and is statistically significant at the 5% level in years 0–6. We then use the same approach as in Section II.C to convert our estimates into the effect of a permanent increase in temperature. We obtain that a permanent 1°C rise in global temperature leads to a 22%–34% reduction in long-run GDP per capita.

Although our dependent variable is disaggregated at the country level, the time-series nature of our identifying variation in global temperature requires care in interpreting our results. We demonstrate that our main estimate is robust to accounting for a range of identification concerns.

III.B. Sensitivity to Specification Choices

We explore whether variants of our baseline econometric specification lead to similar or different results.[6]

1. Omitted Variable Bias. In small samples, global temperature innovations may happen to be correlated with the global economic cycle over time. For instance, if a severe El Niño event increases global temperature at the same time that a global recession occurs for unrelated reasons, we may mistakenly attribute adverse economic effects to climatic variations.

To account for this possibility, we already include a rich set of controls of the world economic performance in our main specification in equation (3). In Figure V, Panels A and B, we show that our results hold regardless of the particular set of macroeconomic and country-level controls, separately for the PWT and BU data sets. We consider multiple specifications based on more parsimonious sets of controls: a specification that does not include oil prices and the Treasury yield, a specification that also excludes the global recession dates, and a specification that omits the region-specific trends. We also consider an expanded specification where we control for more lags of all our global controls (four lags in the PWT sample and eight lags in the BU sample).

The point estimates are similar across specifications, suggesting that global temperature shocks and economic shocks are largely unrelated in our sample. However, the additional controls help reduce sampling uncertainty and lead to more precise estimates. If anything, omitting to control for worldwide recessions appears to lead to smaller rather than larger effects.

We confirm that spuriously correlated economic shocks are unlikely to drive our results by examining how each year in the sample affects our estimates. For all years t, Figure V, Panels C and D plot the change in GDP six years later at $t + 6$—the peak effect in the PWT sample—against the temperature shocks at time t after residualizing both from our set of controls and averaging across countries. The negative relationship turns out to be robust and is not driven by a specific set of outliers. Online Appendix Figure B.8 displays a systematic jackknife exercise in which we

6. For completeness, we also reproduce these variants in the time-series specification of Section II.C in Online Appendix Figure B.7. We find similar results.

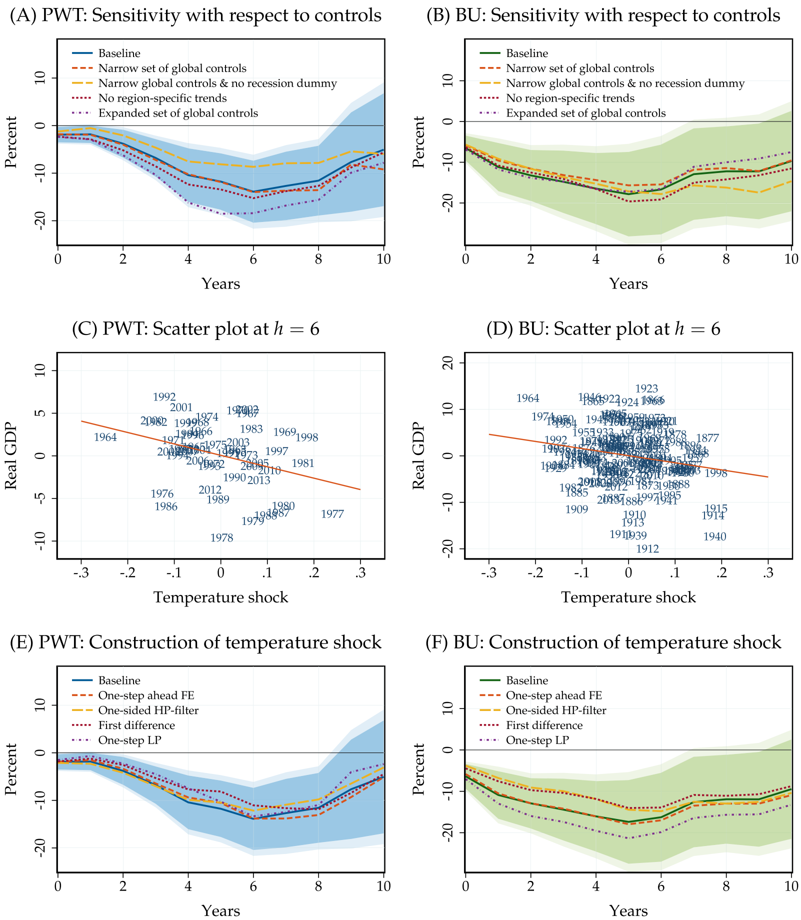

FIGURE V

Sensitivity of the Effect of Global Temperature Shocks I

Impulse responses of real GDP per capita to a global temperature shock, estimated from specification (3). Left column: PWT data set (173 countries, 1960–2019. Right column: BU data set (43 countries, 1860–2019). Top row: sensitivity to controls included: Narrow set of global controls includes only world real GDP growth (omitting commodity price inflation and the treasury yield); expanded set includes four lags of global controls in PWT and eight lags in BU. Middle row: scatter plot of temperature shocks against the cumulative change in real GDP per capita six years after the initial shock, both after residualizing our set of controls and averaging across countries. Bottom row: sensitivity to the construction of temperature shock: baseline with $h = 2$; one-step ahead forecast error $h = 1$ (with confidence bands in Online Appendix Figure B.13); one-sided HP filter; first difference; one-step LP estimation with global temperature level. Lines: point estimate. Dark and light shaded areas: baseline 90% and 95% confidence bands.

censor one year at a time and find that our estimates are not driven by specific years.[7] Overall, these results indicate that our estimates are unlikely to be driven by economic shocks spuriously correlated to temperature shocks.[8]

2. Definition of Temperature Shock. We show that our results hold across a variety of definitions of temperature shocks. In our baseline specification, we measure temperature shocks using the Hamilton (2018) filter with a horizon $h = 2$. In Figure V, Panels E and F, we show that constructing temperature shocks as one-step-ahead forecast errors $h = 1$ following previous work (see Bansal and Ochoa 2011; Nath, Ramey, and Klenow 2024), using a one-sided HP filter, or based on simple first differences produces similar results.

Figure V, Panels E and F also show that our results are virtually unchanged when we directly estimate the effects of temperature on world GDP per capita without highlighting the identifying variation through global temperature shocks. In that case, instead of estimating temperature shocks in a first step using a filter and then projecting world real GDP on temperature shocks in a second step, we directly project world real GDP per capita on temperature levels, including sufficiently many lags of temperature. Both approaches are numerically equivalent when we construct the shocks as one-step-ahead forecast errors with the same controls. We provide more details in Online Appendix B.3.

III.C. Reverse Causality and Sample Stability

We explore whether accounting for reverse causality or changing the underlying time period affects our estimates.

7. The year 1940 appears as a potentially exceptional observation in the BU sample. It corresponds to the post–World War II contraction six years later. Yet our jackknife exercise in Online Appendix Figure B.8 reveals that dropping this observation does not change our estimates materially. Our results in the BU sample are not particularly sensitive to any individual observation due to the larger number of data points. In addition, we show that our estimates remain similar in several subsamples in Section III.C.

8. In Online Appendix C.3, we further establish that unobserved global shocks are not driving our results by exploiting an intermediate level of spatial aggregation of temperature shocks. This specification allows us to control for time fixed effects; reassuringly, the results are broadly comparable.

1. Reverse Causality. Changes in economic activity may affect short-run variations in temperature: a decline in economic activity lowers emissions and temperature, hence increasing output going forward, and potentially biasing our estimates.

There are two reasons reverse causality due to greenhouse gases is unlikely to substantially affect our interpretation. First, this reverse causality concern typically leads us to underestimate the effect of temperature on economic output. As temperature rises and economic activity initially declines, the resulting fall in greenhouse gas emissions implies lower future temperatures and higher future output. Thus, true damages would be larger than our estimates.

Second, annual fluctuations in emissions imply negligible temperature variations relative to the typical temperature shocks that we exploit. For instance, typical year-to-year fluctuations in CO_2 emissions are of the order of two gigatons. After accounting for oceanic and biosphere absorption, these annual fluctuations translate into one gigaton of atmospheric CO_2. This magnitude corresponds to 0.1 part per million (ppm) in atmospheric CO_2 concentration. Current CO_2 atmospheric concentration is just above 400 ppm. Given a climate sensitivity of 1.5, year-to-year fluctuations in emissions thus imply year-to-year fluctuations in temperature of approximately 0.005ºC—an order of magnitude below natural climate variability which is of the order of 0.1ºC.

Aerosol emissions can also lead to reverse causality, for instance due to sulfur dioxide (SO_2). Aerosols have the opposite effect of greenhouse gases and reduce global temperature by reflecting incoming sunlight. Aerosols are shorter-lived than greenhouse gases in the atmosphere, which may amplify or dampen reverse causality concerns relative to greenhouse gases depending on the horizon of interest.

Two exercises confirm that reverse causality is unlikely to affect our results. First, we test whether our temperature shocks are forecastable by past macro-financial variables with a series of Granger-causality tests in Online Appendix Table B.1. We find no evidence that global temperature shocks are forecastable, consistent with the substantial lag and small sensitivity between emissions and temperature changes.

Second, we explicitly account for the feedback between output and temperature through emissions. We consider the two

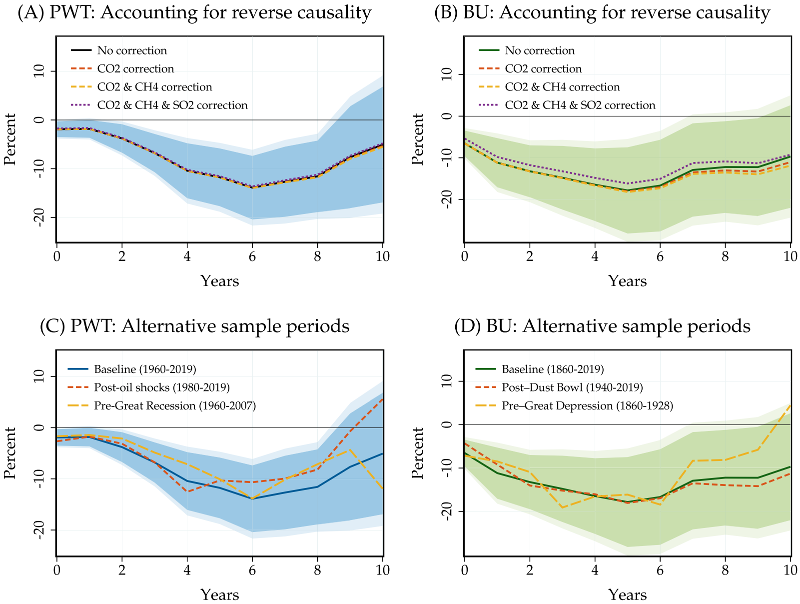

FIGURE VI

Sensitivity of the Effect of Global Temperature Shocks II

Impulse responses of real GDP per capita to a global temperature shock, estimated from specification (3). Left column: PWT data set (173 countries, 1960–2019). Right column: BU data set (43 countries, 1860–2019). Top row: GDP per capita response after adjusting for reverse causality due to the temperature feedback of carbon dioxide (CO_2), methane (CH_4), and sulfur dioxide (SO_2). Bottom row: results for alternative subsamples; PWT: 1980–2019 and 1960–2007; BU: 1940–2019 and 1860–1928. Lines: point estimate. Dark and light shaded areas: baseline 90% and 95% confidence bands.

most important greenhouse gases: CO_2 and methane (CH_4). We also include the main source of aerosol emissions: SO_2. We use standard estimates of the emissions-to-GDP elasticity and leading estimates of the dynamic sensitivity of temperature to an emissions impulse to construct our adjustment. Figure VI, Panels A and B confirm that explicitly adjusting for reverse causality has no meaningful effect on our results. We provide more details in Online Appendix B.8.

2. Sample Period. Figure VI, Panels C and D evaluate whether our results depend on the sample period. We obtain similar results in the PWT data set in two subsamples (1960–2007 and 1980–2019). Macroeconomic controls such as global recessions, global oil prices, and the U.S. Treasury yields are important to ensure subsample stability in the PWT data: the smaller the subsample, the more likely that global temperature shocks happen to be spuriously correlated with unrelated economic shocks. Our results also continue to hold in subsamples of the BU data set (1860–1928, 1940–2019) up to statistical precision. Given the continued rise of global temperature over the course of the twentieth century, the stability of our estimates across time periods suggests a lack of adaptation to temperature shocks, at least historically.

III.D. Additional Exercises

We conduct an additional set of robustness exercises in Online Appendix B.9, whose conclusions we summarize here.

1. External Validity. We show that our results do not depend on specific sources of global temperature variation. Online Appendix Figure B.9 reevaluates our results after netting out temperature variation generated by El Niño by controlling for an oceanic El Niño index in our main specification. The responses are close to our baseline estimates. Similarly, controlling for volcanic eruptions yields virtually unchanged results. These exercises indicate that our main results capture a broad effect of global temperature on economic activity that is not specific to particular sources of temperature variation.

2. Weighting. Online Appendix Figure B.10 shows that our results in the panel are unaffected when weighting observations by country GDP. This consistency is not surprising given that we already show in Figure IV that our time series and panel results are similar.

3. Pre-trends. We investigate whether our results may be due to differential pre-trends. Although Online Appendix Table B.1 already suggests that Granger causality is unlikely to be a concern, we do not detect any statistically significant nor economically meaningful pre-trend in the years before the shock in Online Appendix Figure B.10.

4. Data Choices. We show that our results are robust with respect to a range of alternative data choices. Online Appendix Figure B.11 and B.12 reveal similar results with GDP data from the World Development Indicators, with temperature data from NOAA and NASA, when restricting the analysis to the countries studied in Dell, Jones, and Olken (2012) and Burke, Hsiang, and Miguel (2015), and with different numbers of lags included in our local projections. Overall, our robustness exercises confirm the persistently negative effect of global temperature shocks on real GDP per capita.

IV. Global Versus Local Temperature

IV.A. Local Temperature and Economic Activity

How do the effects of global temperature shocks compare with those of local temperature shocks? Conventional estimates that do not assume growth effects imply that a permanent 1ºC rise in local temperature reduces GDP by 1%–3% (Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015; Moore and Diaz 2015; Kahn et al. 2021; Nath, Ramey, and Klenow 2024). To ensure that our findings are not driven by differences in econometric specifications or data choices, we reproduce the effects of local temperature shocks in our empirical framework. We focus on the shorter PWT data set, as most studies of local temperature rely on the more recent sample beginning in the 1960s. We measure local temperature shocks using the Hamilton (2018) filter, similarly to Nath, Ramey, and Klenow (2024), as we do in Section II.B for global temperature but now based on population-weighted country-level temperature data.

Local and global temperature shocks turn out to be only weakly correlated. Often, global shocks do not correspond to local shocks and they frequently move in different directions. Online Appendix Figure C.1 shows two illustrative examples of local temperature shocks, for the United States and South Africa.

To estimate the responses to local shocks, we rely on our panel specification (3), with the critical difference that the temperature shock is a country-specific temperature shock $T_{i,t}^{\text{shock}}$. In this first specification, we do not include time fixed effects to maximize comparability with specification (3). However, we also consider two alternative specifications:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \theta_h^{\text{global}} T_t^{\text{shock}} + \theta_h^{\text{local}} T_{i,t}^{\text{shock}} + \mathbf{x}_t' \boldsymbol{\beta}_h + \mathbf{x}_{i,t}' \boldsymbol{\gamma}_h + \varepsilon_{i,t+h}, \tag{4a}$$

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \delta_{t,h} + \theta_h T_{i,t}^{\text{shock}} + \mathbf{x}_{i,t}' \boldsymbol{\gamma}_h + \varepsilon_{i,t+h}. \tag{4b}$$

In specification (4a), we estimate the effects of global and local temperature shocks jointly. This provides a straightforward way to assess whether the two responses are statistically different from each other. Specification (4b) includes time fixed effects, which allows us to flexibly control for any unobserved common shocks. In that case, the time fixed effects absorb the global temperature shocks and any other global controls.

Figure VII, Panel A shows the estimated impulse responses to a local temperature shock of 1°C, together with the responses to a global temperature shock from Section III.A. Local temperature shocks lead to a fall in real GDP, even though the response is not statistically significant at the 5% level. On impact, the effect stands at −0.5% and reaches −1% after four years. These point estimates and associated uncertainty are similar to previous findings in Dell, Jones, and Olken (2012), Burke, Hsiang, and Miguel (2015), Moore and Diaz (2015), Kahn et al. (2021), and Nath, Ramey, and Klenow (2024) when aggregated across all countries and accounting for the empirical degree of persistence, and of course mask a substantial degree of underlying heterogeneity. Controlling for time fixed effects does not make much of a difference. If at all, the inclusion of time fixed effects attenuates the effects of local temperature somewhat.

The comparison reveals that global temperature shocks have more pronounced effects on economic activity than local temperature shocks. The estimated effects of global temperature shocks are an order of magnitude larger than those of local temperature shocks, based on the same empirical model and the same sample period. This difference is not only economically but also statistically significant. Panel B reveals that the responses of GDP to global and local temperature shocks over our horizon of inter-

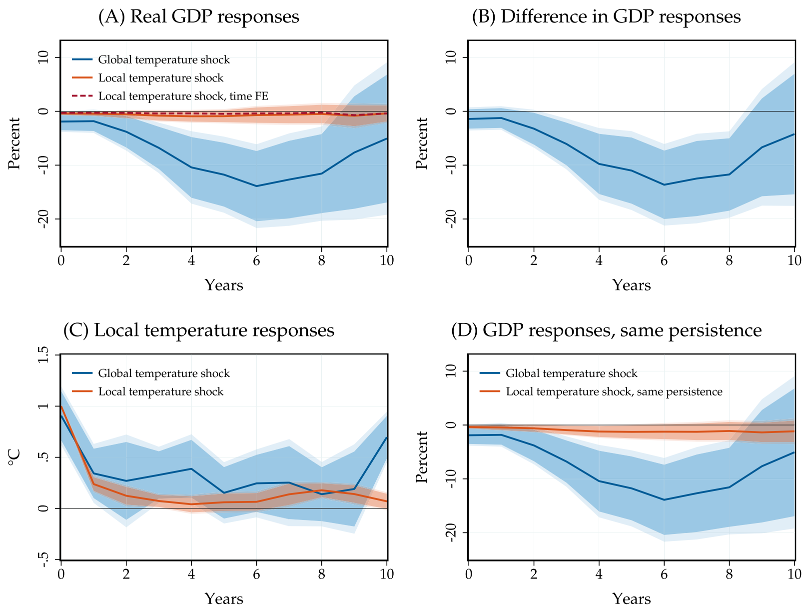

FIGURE VII

The Effect of Global Versus Local Temperature Shocks

Impulse responses of GDP per capita, estimated in the PWT data set over the period 1960–2019. Panel A: Solid lines: GDP responses to global and local temperature shocks based on specification (3); dashed red: GDP response to local temperature shock from the model with time fixed effects, specification (4b). Panel B: Difference between GDP responses to global and local temperature shocks based on joint model (4a). Panel C: Local temperature response to temperature shocks. Panel D: GDP responses imposing the persistence of the global temperature response on local temperature. Dark and light shaded areas: 90% and 95% confidence bands.

est based on specification (4a) are statistically different at the 5% level in years 3–8.[9]

One possible explanation for the differential effect of global and local temperature shocks is statistical: global temperature shocks may lead to a more pronounced increase in local temperature. Figure VII, Panel C shows the response of local temperature to a local and a global temperature shock, respectively. On impact, both local and global temperature shocks lead to an in-

9. Estimating the effect of both shocks simultaneously does not change the univariate impulse responses materially, reflecting that different variation identifies the impact of global and local temperature shocks. See Online Appendix C.2 for details.

crease in local temperature near 1ºC. Yet the increase in local temperature is somewhat more persistent after a global temperature shock.[10]

To account for this difference in persistence, we construct a counterfactual local temperature shock, imposing the same internal persistence as for the global shock, again using the method in Sims (1986). Figure VII, Panel D shows that the difference in persistence cannot account for the differential effect of global and local temperature shocks. Imposing the same persistence increases the impacts of local temperature somewhat, but the cumulative effects of global temperature shocks are still an order of magnitude larger.

Alternatively, we convert our local temperature estimates into the counterfactual impact of a permanent 1ºC rise in local temperature. As in Section II, we calculate the ratio of the cumulative impulse response of output per capita to the cumulative impulse response of local temperature. We find that a permanent 1ºC rise in local temperature leads to a 3% reduction in long-run world GDP, almost exactly as in Nath, Ramey, and Klenow (2024). However, this effect is not statistically distinguishable from zero at the 5% level in our sample.

Our analysis thus indicates that the key difference lies in the nature of the shock, rather than in the set of global controls, time fixed effects, or persistence of temperature to the shock. Climatic variation within a country or even smaller geographic units may help alleviate identification concerns but misses any global effects of climate change—itself a global phenomenon. By contrast, our approach purposefully studies these common effects by focusing on climatic variation at the global level.

IV.B. Reconciling the Effects of Global and Local Temperature

Why does global temperature cause larger economic losses than local temperature? We start with our main hypothesis: global temperature shocks are inherently different from local temperature shocks and capture potentially damaging climatic implications that local temperature does not. Then we discuss alternative explanations based on economic spillovers.

10. Our unweighted regression implies that the time 0 effect of global temperature is close to 1ºC. When area-weighted, the global temperature time 0 impact is larger than 1ºC, as land warms more than oceans on average. See Online Appendix Figure C.7.

We first investigate whether global temperature predicts meaningful shifts in climatic phenomena. We ask how temperature shocks correlate with the likelihood of extreme weather events: extreme temperature, drought, extreme precipitation, and extreme wind speed. As detailed in Section II.A and Online Appendix A, we define an exposure index for each event as follows. We start by constructing average temperature, precipitation, and wind speed for each country and day. Next we count the fraction of days in each year and country for which this country weather average exceeds or falls below a given threshold. This exposure index can thus be interpreted as a probability. We use the panel local projection specification (3) and denote by θ_h^X the impact of a 1ºC temperature shock on the exposure index of event X at horizon h. Figure VIII displays our results.

Local temperature shocks lead to an increase in the share of extreme heat and drought days. However, global temperature shocks lead to a noticeably larger increase in these extremes. Our extreme heat and drought indices have a baseline probability of 0.05 and 0.25 in 1950–1980, respectively. Thus, a 1ºC global temperature shock correlates with a fivefold rise in the frequency of extreme heat and a 15% increase of the frequency of droughts—an order of magnitude more than for local temperature shocks. The contrast is even starker for extreme precipitation and extreme wind speed: global temperature shocks predict a large increase in their frequency, while local temperature shocks have no significant effect. We construct extreme precipitation and wind indices to have a baseline probability of 0.01 in 1950–1980. Thus, a 1ºC global temperature shock correlates with an increase in the frequency of extreme precipitation by over 50% and extreme wind by nearly 40%.

These findings are consistent with the geoscience literature: wind speed and precipitation are outcomes of the global climate—through oceanic warming and atmospheric humidity—rather than outcomes of local temperature distributions (Seneviratne et al. 2016; Wartenburger et al. 2017; Seneviratne et al. 2021; Domeisen et al. 2023). Given that extreme climatic events are known to cause economic damage (Deschênes and Greenstone 2011; Hsiang and Jina 2014; Bilal and Rossi-Hansberg 2023), the differential correlation of global versus local temperature shocks on extreme climatic events may rationalize the larger economic effects of global temperature shocks.

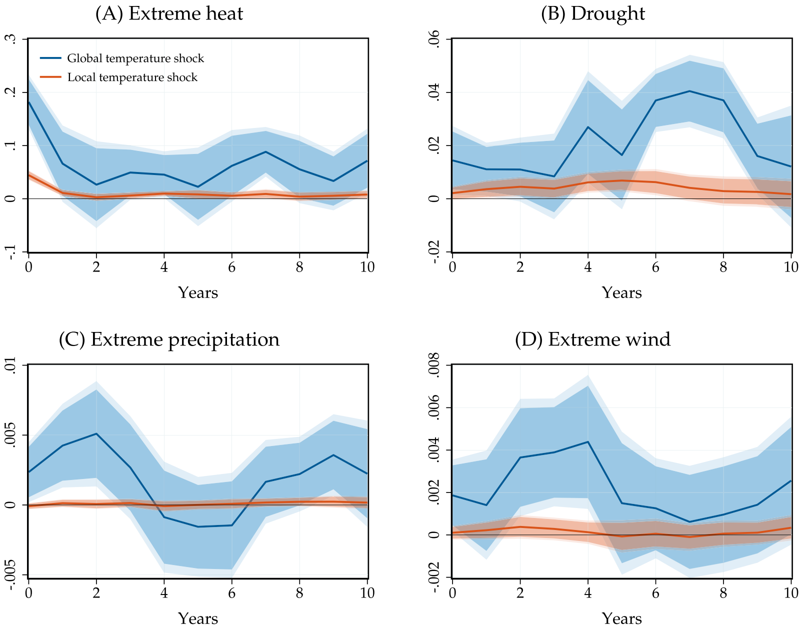

FIGURE VIII

Extreme Weather Events and Temperature

Impulse responses θ_h^X of extreme temperature, drought, extreme precipitation, and extreme wind exposures to global and local temperature shocks, estimated based on specification (3) with the expanded set of global controls in the PWT sample, 1960–2019. Extreme weather exposure indices record the share of days in a given year and country where country-level average daily temperature, precipitation, or wind speed are above or below a threshold. We define thresholds using the daily weather distribution in 1950–1980. Temperature: above 95th percentile. Drought: below the 25th percentile. Precipitation: above the 99th percentile. Wind: above the 99th percentile. Though not necessary for our results, we smooth the precipitation and wind measures with a backward-looking (current and previous two years) moving average to remove their inherent noise. Solid lines: point estimate. Dark and light shaded areas: 90% and 95% confidence bands.

To gauge the quantitative importance of this channel, we start by estimating the effect of local extreme events in a panel local projection specification, detailed in Online Appendix C.4. We estimate these effects jointly to account for the potential correlation between extreme events. We denote by ϕ_h^X the impact of extreme event X's exposure index on GDP at horizon h. Online Appendix Figure C.4 reveals that these events are associated with economic damages. A fivefold rise in extreme heat exposure at the country level lowers GDP by 2% at peak. A 15% rise in drought

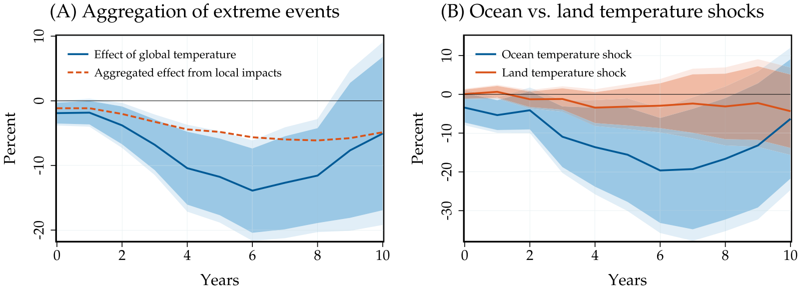

FIGURE IX

The Role of Ocean Temperature and Extreme Events

Panel A: Aggregated effect on GDP based on local temperature and extreme events impacts Θ_h (dashed red) together with the impulse responses to a global temperature shock based on our baseline empirical model (3) in the PWT sample, 1960–2019. Panel B: Impulse responses of GDP to an ocean temperature and a land temperature shock, estimated jointly in a specification otherwise identical to (3). Dark and light shaded areas: 90% and 95% confidence bands.

exposure lowers GDP by 1.5%. A 50% increase in extreme precipitation lowers GDP by 0.5%, and a 40% increase in wind exposure lowers output by 0.4%.

Next we aggregate the local effects of extreme events. We interact the increase in extreme-event exposure following a global temperature shock θ_h^X from Figure VIII with the GDP loss associated with these extreme events from Online Appendix Figure C.4. To do so, we adjust the estimates ϕ_h^X to correspond to a one-time fully transitory rise in exposure again using the method in Sims (1986). This persistence adjustment transforms the initial estimates ϕ_h^X into new estimates ψ_h^X. In practice, this adjustment has minor consequences because extreme events have low unconditional internal persistence. We aggregate these effects according to $\Theta_h = \sum_X \sum_{t=0}^{h} \theta_t^X \psi_{h-t}^X$, where the sum over X includes the four extreme events and local temperature. Thus, the aggregate impact Θ_h now factors in the persistent response of extreme events to a global temperature shock $\{\theta_h^X\}_h$.

Figure IX, Panel A displays our results. The rise in local temperature and extremes leads to a meaningfully larger economic effect than for local temperature alone. The peak effect on GDP is in excess of 6%, and the cumulative impact represents over half of the cumulative effect of a global temperature shock. This result indicates that global temperature has a larger impact on economic activity than local temperature largely because the physical nature of the shock is different: it captures the broader implications of warming and in particular the rise in damaging extreme events.

We confirm our transmission channel of global temperature shocks through extreme events by considering ocean and land temperature. Since oceanic warming is critical for the formation of some of our extreme events, we expect it to account for a large part of our global temperature impacts. We jointly estimate the impact of ocean and land temperature shocks on GDP in Figure IX, Panel B. The impact of ocean temperature on GDP aligns with the overall effect of global temperature—if anything, it is larger—suggesting that ocean temperatures are key to understand the impact of warming on economic activity. The impact of land temperature is smaller than ocean temperature, but more pronounced than the effect of local temperature, suggesting that spatially correlated changes in local temperature may comove with more extreme events than idiosyncratic temperature fluctuations. Yet these comparisons are noisy and should be interpreted with caution.

Our results highlight that it is critical to consider climatic outcomes beyond local temperature in panel approaches, but also illustrate the challenges associated with such bottom-up aggregation exercises. Capturing all relevant local effects individually is challenging: researchers need to know ex ante which variables to consider, be able to measure them consistently throughout the world, and accurately estimate their degree of internal persistence. Even then, Figure IX, Panel A suggests that this bottom-up aggregation approach still underestimates the full effect of global temperature even with four measures of extreme events. A key advantage of our time-series approach is that it directly encompasses all relevant local effects that are predictable by global temperature.

A prominent alternative explanation to rationalize the gap between local and global temperature impacts is that local temperature is the true determinant of damages but compounds through economic spillovers that are netted out in the panel specification. We empirically test this possibility using bilateral trade data in Online Appendix C.5. Consistent with our geophysical interpretation, we find that although trade spillovers do appear to matter marginally, they fall short of accounting for a sizable fraction of the gap between local and global temperature estimates.

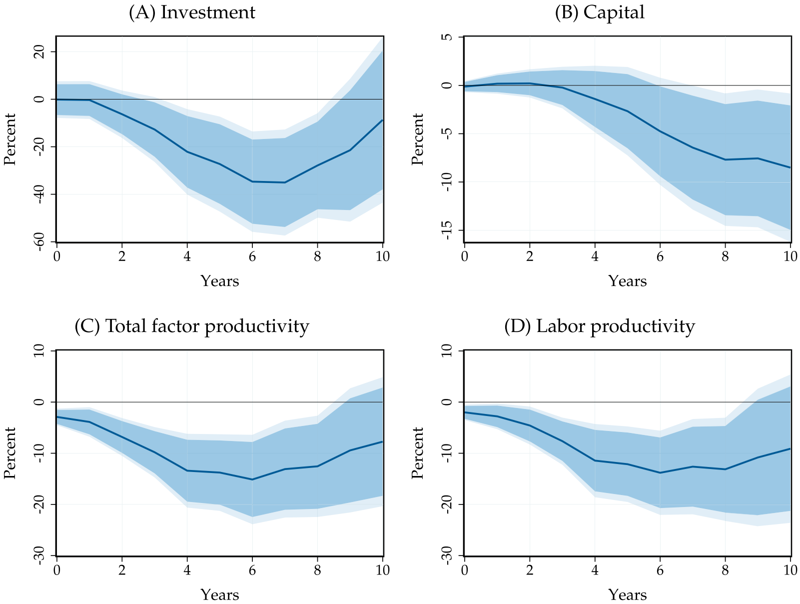

FIGURE X

Transmission of Global Temperature Shocks

Impulse responses of investment per capita, the capital stock per capita, total factor productivity, and labor productivity to a global temperature shock, estimated based on specification (3) in the PWT sample, 1960–2019. Labor productivity: output over employment. Total factor productivity: Penn World Tables. Solid line: point estimate. Dark and light shaded areas: 90% and 95% confidence bands.

IV.C. Margins of GDP and Regional Effects

We have documented that global temperature shocks lower world GDP, but how and where does GDP respond most?

We evaluate the effects of global temperature shocks on capital, investment, and productivity in our PWT panel in Figure X. Global temperature shocks lead to a significant fall in investment and in the capital stock. Consistent with Hsiang and Jina (2014), we find that disasters associated with global warming do not stimulate growth. Instead, national income, productive capital, and investment all dwindle. Total factor productivity (TFP) as estimated in the Penn World Tables and labor productivity fall significantly after global temperature shocks. The effects strengthen from -2% on impact to over -10% after four years.

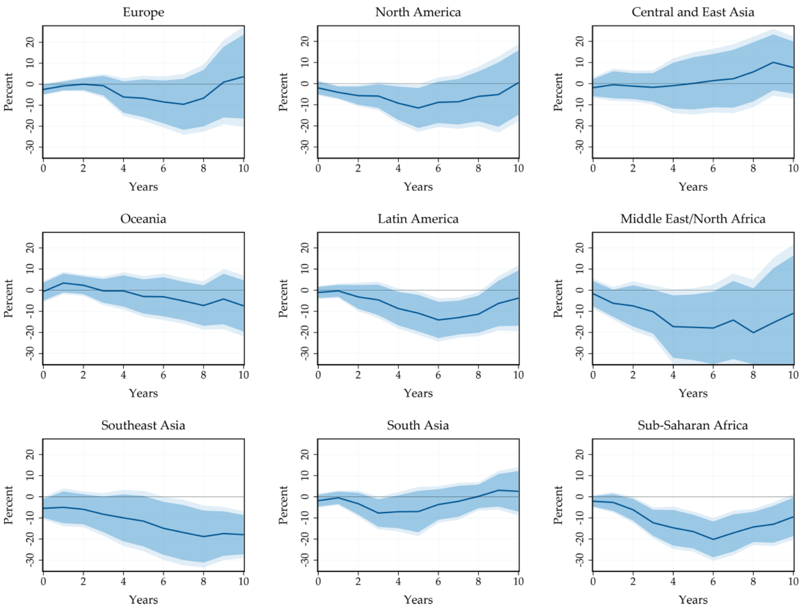

FIGURE XI

Regional Impacts of Global Temperature Shocks

Impulse responses of GDP per capita to global temperature shocks for different regions across the world based on specification (3) in the PWT sample, 1960–2019, conditioning on the different regions. Solid lines: point estimate. Dark and light shaded areas: 90% and 95% confidence bands. Impulse responses of local temperature to global temperature shocks by region in Online Appendix Figure C.10.

In addition to unpacking the margins of GDP, we analyze how the impact of global temperature varies across different regions. Are warmer or lower-income countries more affected? Figure XI displays the effect of global temperature shocks on nine regions of the world. Almost all regions experience GDP losses. We estimate the strongest negative effects—close to −20% at peak—in hot regions such as Southeast Asia and Sub-Saharan Africa. Contrary to local temperature, global temperature leads to adverse economic effects even in higher-income, colder regions. The peak effect in North America and in Europe is near −10%, albeit not very precisely estimated.

We corroborate that our estimates are not driven by particularly affected regions by reestimating our world specification from Section III after excluding Sub-Saharan Africa from the sample.

Online Appendix Figure B.12 reveals that the average world effects remain largely unchanged.

We evaluate whether the impact of global temperature shocks systematically varies by country baseline temperature and income level in Online Appendix Figure C.9. Although somewhat imprecisely estimated, we find suggestive evidence that warm and low-income countries display stronger adverse effects of global temperature shocks, while cold and high-income countries are less sensitive to global temperature shocks. This result is qualitatively consistent with previous evidence on local temperature (Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015). Quantitatively, however, global temperature shocks have larger and more uniformly detrimental effects than local temperature shocks.

So far we established the reduced-form impact of global temperature shocks on economic activity at the world and country level in the medium run. We turn to our structural model to convert these estimates into long-run effects and calculate welfare losses and the SCC.

V. A Model of Climate Change Across the World

Our framework closely follows the standard neoclassical growth model. As such, it mirrors the backbone of the dynamic integrated climate economy (DICE) model introduced by Nordhaus (1992) and developed in Barrage and Nordhaus (2024). Our key innovation is to use our reduced-form estimates of the effect of global temperature shocks to structurally estimate damage functions in the model.

V.A. Model Description

1. Setup. Time is continuous and runs forever. There is a unit continuum of infinitely lived identical households who populate the world economy. Households have constant relative risk aversion flow preferences: $U(C) = \frac{C^{1-\gamma}-1}{1-\gamma}$. Labor supply is exogenous and set to $L_t = 1$. The pure rate of time preference of households is ρ.

Firms produce according to a Cobb-Douglas production function in capital K_t and labor L_t with time-dependent TFP Z_t: $Y_t = Z_t K_t^{\alpha} L_t^{1-\alpha}$. They hire labor and rent capital from households in competitive factor markets. Capital depreciates at rate δ, which is constant over time and covered by firms. The path of productivity Z_t is perfectly foreseen.

Households earn wages w_t, hold capital K_t, and rent it out to firms for production. The net interest rate is r_t. Firms make zero profits given constant returns to scale, so we omit profits in the budget constraint of the household, which writes: $C_t + \dot{K}_t = w_t + r_t K_t$. Households are endowed with an initial capital stock K_0.

A competitive equilibrium of our economy is a collection of sequences $\{C_t, K_t, r_t, w_t\}_{t=0}^{\infty}$ such that households optimize given prices $\{r_t, w_t\}_{t=0}^{\infty}$:

$$\max_{\{C_t, K_t\}_t} \int_0^{\infty} e^{-\rho t} U(C_t) dt \quad \text{subject to} \quad C_t + \dot{K}_t = w_t + r_t K_t \quad \text{given } K_0;$$

firms optimize given prices $\{r_t, w_t\}_t$: $\max_{K_t^D, L_t^D} Z_t (K_t^D)^{\alpha} (L_t^D)^{1-\alpha} - (r_t + \delta) K_t^D - w_t L_t^D$; and factor markets clear: $K_t = K_t^D$ and $1 = L_t^D$.

2. Climate Change. We model climate change as changes in TFP Z_t over time, relative to its baseline value Z_0. This representation follows existing work (Nordhaus 1992; Nordhaus and Yang 1996; Moore and Diaz 2015; Kahn et al. 2021) and parsimoniously but comprehensively captures the combined effects of the rich set of weather extremes described in Section IV.B on world economic activity. We leave a richer representation based on natural disasters at the country level for future work (Barro 2006, 2009).

We take the path of global mean temperature T_t relative to a reference level T_0 as given, and denote by $\widehat{T}_t \equiv T_t - T_0$ the path of excess temperature. Global mean temperature affects TFP through the structural damage function $\{\zeta_s\}_{s \geqslant 0}$:

$$Z_t = Z_0 \exp\left(\int_0^t \zeta_s \widehat{T}_{t-s} ds \right). \tag{5}$$

The structural damage function ζ_s governs the persistence of the effect of transitory global temperature shocks on TFP. When ζ_s is a Dirac mass point at $s = 0$, global temperature shocks have purely transitory level effects. When ζ_s is a positive function that asymptotes to zero, global temperature shocks have persistent level effects. When ζ_s is a positive function that asymptotes to a positive value, global temperature shocks have growth effects.

When temperature $T_t \equiv \overline{T}$ is constant, the economy converges to its steady state with the corresponding value of TFP $\overline{Z} = Z_0 \exp((\overline{T} - T_0) \int_0^{\infty} \zeta_s ds)$.

This expression highlights that the cumulative damage function $\int_0^\infty \zeta_s ds$ determines the long-run impact of global temperature changes. In that case, ζ_s needs to be integrable to obtain a well-defined steady state. Hence, under growth effects, there is no well-defined steady state and the economy asymptotes to zero for any amount of permanent warming. Yet in Figure III we do not find statistically significant evidence supporting growth effects.

We do not model the feedback between the economy and emissions and associated externalities because we focus on climate damages. Thus, the competitive equilibrium is efficient as is standard in the neoclassical growth model.

3. Social Cost of Carbon. In our framework, we define the SCC as the one-time dollar amount $\mathcal{C}$ that households would pay at time 0 that would make them indifferent between a world with an additional ton of CO_2 emitted at time 0, and a world starting in steady state, without emissions but having paid $\mathcal{C}$.

Given that we do not model emissions directly, we must map a one-time CO_2 pulse into a temperature path to calculate the SCC. We follow Folini et al. (2025) and use the temperature response of global mean temperature to a CO_2 pulse from Dietz et al. (2021b), itself based on Joos et al. (2013).

We denote by $\{\widehat{T}_t^{\text{SCC}}\}_{t\geqslant 0}$ the path of excess warming implied by a one-time pulse of one ton of CO_2 emitted at time 0. The median response in Dietz et al. (2021b) indicates that after a one gigaton pulse of carbon, temperature rises steadily and eventually stabilizes at 0.002°C after 15 years.[11] Our welfare numbers do not depend on the temperature response to a CO_2 pulse but instead on a particular warming scenario.

We construct a productivity path $\{Z_t^{\text{SCC}}\}_{t\geqslant 0}$ according to equation (5) in which we use the temperature path $\{\widehat{T}_t^{\text{SCC}}\}_{t\geqslant 0}$ rather than a global warming scenario. The model delivers a path of value functions $\{V_t^{\text{SCC}}(K)\}_{t\geqslant 0}$, equilibrium capital stocks $\{K_t^{\text{SCC}}\}_{t\geqslant 0}$ with initial condition $K_0^{\text{SCC}} = K^{ss}$, leading to a path of realized values $\{V_t^{\text{SCC}}(K_t^{\text{SCC}})\}_{t\geqslant 0}$, in response to this CO_2 pulse-induced warming. Our definition requires that the SCC $\mathcal{C}$ be given implicitly by:

$$V^{ss}(K^{ss} - \mathcal{C}) = V_0^{\text{SCC}}(K^{ss}), \tag{6}$$

where *ss* superscripts denote initial steady-state quantities.

11. For brevity, we refer to the "best fit CMIP5 ensemble" response in Dietz et al. (2021b) as the "median response."

To gain intuition, consider the case when the SCC is not too large. Then, a first-order perturbation implies that the SCC satisfies $\mathcal{C} = \int_0^\infty e^{-\rho t} u'(C^{ss})(C^{ss} - C_t^{\text{SCC}})dt = \frac{1}{\rho}\frac{C^{ss} - \overline{C}^{\text{SCC}}}{C^{ss}}$, where $\frac{C^{ss} - \overline{C}^{\text{SCC}}}{C^{ss}}$ is the consumption-equivalent welfare loss from the warming implied by the CO_2 pulse. These identities highlight that the SCC is equal to the present stock valuation of flow consumption-equivalent welfare losses from the warming induced by the CO_2 pulse. Although these conditions are useful to gain intuition, in our quantification we always use the nonlinear definition (6) that accounts for a time-varying marginal rate of substitution.

V.B. Estimation Strategy

Our next step is to estimate the structural damage function ζ_s. To do so, we match the reduced-form impulse response functions of output to global temperature shocks from Figure VII, Panel A. We proceed in two steps.

In the first step, we calibrate our model based on standard values from the literature, with the exception of our damage function. We set risk aversion to $\gamma = 1$. The capital share is $\alpha = 0.33$. The annual capital depreciation rate is $\delta = 0.08$. Our choice of annual pure rate of time preference $\rho = 0.02$ follows Rennert et al. (2022) and is consistent with a 2% annual interest rate in steady state. Of course, the equilibrium path of consumption in the model determines the effective consumption-based discount rate. We assess the robustness of our results with respect to the rate of time preference in Section VI.D.[12]

In the second step, we invert our model to estimate the sequence of TFP that corresponds to a temperature shock. We leverage that the actual temperature shocks that arise during our sample are small as in Online Appendix Figure C.1 and therefore imply output and capital fluctuations of the order of 1%. Therefore, we can use a first-order perturbation of the model around the initial steady state for estimation. For any sequence of excess temperature $\widehat{T}_t$, we denote by $\widehat{z}_t$ the resulting log deviation in TFP,

12. This framework immediately accommodates balanced productivity growth. Provided we adjust the the rate of time preference and the baseline capital depreciation rate, standard rescaling arguments ensure that allocations and welfare would be identical in counterfactuals when the baseline economy is in steady state or on a balanced growth path. See Weitzman (1998), Stern (2007), Nordhaus (2007), Dasgupta (2008), and Kelleher and Wagner (2019) for additional discussion of the discount rate.

and by $\widehat{y_t}$ the log deviation in output along the transition. We emphasize that we use log-linearization for estimation only, not for counterfactuals.

PROPOSITION 1 (MODEL INVERSION). There exists $\mathcal{K}_{t,s}$ given in Online Appendix D.3, that only depends on steady-state objects and is independent from $\{\zeta_s\}_{s\geqslant 0}$, such that, to a first order in $\{\widehat{T_t}\}_{t\geqslant 0}$:

$$\widehat{y_t} = \widehat{z_t} + \alpha \int_0^{\infty} \mathcal{K}_{t,s}\widehat{z_s}ds.$$

PROOF. See Online Appendix D.3.

Proposition 1 delivers an identification result. Given observed output response $\widehat{y_t}$, we can recover the underlying sequence of productivity shocks $\widehat{z_t}$. The first component in Proposition 1 corresponds to the direct effect of productivity on output. The second component corresponds to the equilibrium response of capital. It is an integral over all times because investment is forward-looking and capital accumulates slowly over time.

The main content of Proposition 1 lies in this second component. By log-linearizing equilibrium conditions and solving explicitly for the equilibrium sequence of capital, we relate capital deviations to the sequence of productivity shocks through the sequence-space Jacobian $\mathcal{K}_{t,s}$ (Auclert et al. 2021; Bilal and Goyal 2023). In the context of the neoclassical growth model, this Jacobian admits a closed-form expression as a function of parameters and steady-state objects. When $\mathrm{Id} - \alpha\mathcal{K}$ is invertible—where Id denotes the identity map, for instance when α is small enough—productivity shocks are identified. Proposition 1 allows us to obtain the sequence of TFP $\widehat{z_t}$ that correspond to any sequence of temperature shocks $\widehat{T_t}$.

We use Proposition 1 to estimate ζ_s. We consider the response of output to an observed temperature shock in Figure III, Panel B, that corresponds to the underlying temperature path $\widehat{T_t}$ in Figure III, Panel A. Proposition 1 delivers the corresponding sequence of productivity shocks $\widehat{z_t}$. We then identify ζ_t as the innovations to these sequences as per equation (5).

This approach is consistent with households having rational expectations about future temperature shocks: after a temperature shock, households expect temperature to remain persistently elevated as in Figure III, Panel A. One advantage of this approach is that we identify damage functions from empirical impulse responses to a shock that is itself persistent. Thus, counterfactuals that focus on a permanent increase in temperature build on moments identified from responses to a persistent shock—though not a fully permanent shock—rather than a purely transitory shock.

In practice, we face two additional challenges. We address them by imposing a smooth functional form for our structural damage function. We constrain ζ_s to be of the form $A\left(e^{-Bs} - e^{-Cs}\right)$.

The first challenge that our constrained estimation addresses is that we can only estimate the impulse response functions $\widehat{y_t}$ up to a finite horizon. By contrast, Proposition 1 requires the entire impulse response function. We cannot simply set the output impulse response to 0 from year 11 onward, as this may imply a large underlying capital windfall gain or loss for the economy. By constraining the shape of the structural damage functions, we use our 11 data points to estimate the three damage function parameters.

The second challenge is to discipline the long-run effects of temperature shocks. By constraining the structural damage functions, we ensure that the effects of transitory temperature changes vanish in the very long run. If we estimated the structural damage functions entirely unconstrained and with a longer horizon, temperature shocks could potentially have longer-ranging but extremely imprecisely estimated effects. Therefore, our approach is conservative in that it limits the long-run effect of a one-time transitory temperature shock.

Hence, instead of exactly inverting the model, we estimate A, B, and C for ζ_s using nonlinear least squares to minimize the squared deviations from the equation in Proposition 1 for the first 10 years only.

V.C. Estimation Results

Figure XII shows our estimation results. We target PWT impulse response functions in the main analysis to maximize comparability to existing work that evaluates the effect of local temperature. We show that if anything, the impact of global temperature is larger when using the BU impulse response functions in Section VI.D.

Panel A reproduces the underlying temperature path from Figure III. Panel B reveals that the estimated model closely fits the empirical response of output given its limited degrees of

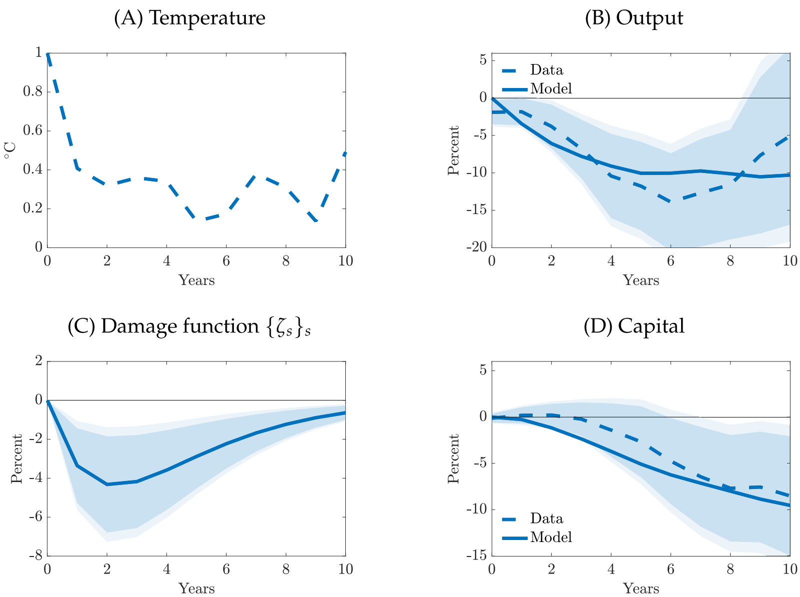

FIGURE XII

Output, Capital, and Productivity Global Temperature Shocks

Estimation results from matching the model impulse response to the empirical response of output to global temperature shocks in the PWT data. Panel A: Underlying temperature path. Panel B: Output responses to this internally persistent temperature path. Panel C: Implied productivity shocks; confidence intervals based on the delta method as detailed in Online Appendix D.4. Panel D: Nontargeted capital responses to the internally persistent temperature path. Dashed lines: data. Solid lines: model fit. Dark and light shaded areas: 90% and 95% confidence bands.

freedom. Of course, the model fit relies on our constrained functional form: if we did not constrain the damage function, the fit would be one-to-one.

Panel C depicts the estimated structural damage function ζ_s. It coincides with the productivity responses to a one-time transitory global temperature shock of 1°C. It implies a short-run productivity loss of 4% that takes place two years after the temperature shock. Despite the corresponding temperature shock being transitory, the effect on productivity decays only slowly and persists for up to 10 years. We compute confidence bands with the delta method as detailed in Online Appendix D.4. The damage function is statistically significant at the 5% level and reflects the confidence bands around our empirical output response.[13]

We test whether the estimated model also delivers empirically plausible implications for capital. In the estimation, we have not used any information about the empirical impulse response of capital to a global temperature shock. Panel D compares the prediction of our estimated model to the data from Figure X. Despite being nontargeted, the response of capital in the model is close to its empirical counterpart.

How do the productivity effects of global temperature shocks compare with those associated with local temperature shocks? Given that the empirical responses for local temperature shocks are closer to zero as shown in Figure VII, such shocks likely also imply smaller damages. To answer this question quantitatively, we repeat our estimation but targeting the impulse response of output to local temperature shocks.

Online Appendix Figure D.1 displays the productivity effects of local temperature shocks. The damage function peaks at 0.5%, is not statistically different from zero at the 5% level, and the implied cumulative productivity effect is more than eight times smaller than under global temperature shocks. We conclude that climate damages associated with global temperature shocks are larger than those implied by local temperature shocks.

VI. The Macroeconomic Impact of Climate Change

VI.A. Representing Climate Change

To evaluate the consequences of climate change, we specify a path for global mean temperature. The baseline year $t = 0$ corresponds to 2024. The world subsequently warms by 3ºC above preindustrial levels by 2100, after which temperature asymptotes to 3.3ºC. This scenario is broadly consistent with IPCC business-as-usual scenarios that imply 3ºC–4ºC of warming by 2100 (Hausfather and Peters 2020; Lee et al. 2023). Given that the world has warmed by approximately 1ºC since preindustrial

13. Although our focus is on global climate damages, we study the implied regional damage functions associated with our global temperature shocks in Online Appendices C.7 and D.5. Online Appendix Figure D.2 displays regional damage functions. Online Appendix Figure D.3 depicts counterfactual paths of GDP per capita for each region.

times, this scenario implies 2ºC of additional warming since $t = 0$ (2024) by year $t = 76$ (2100).

We construct two counterfactuals to highlight the role of global temperature. In the first counterfactual, we use the structural damage function estimated under global temperature shocks ζ_s^{global} in Figure XII, Panel C to construct productivity changes using equation (5) together with excess temperature $\widehat{T}_t$. In the second counterfactual, we use the structural damage function estimated under local temperature shocks ζ_s^{local} in Online Appendix Figure D.1(C), using again equation (5) with the same excess temperature path $\widehat{T}_t$.

Our counterfactuals compare allocations and welfare in an economy that warms according to $\widehat{T}_t$, to allocations and welfare in an economy that remains in steady state under $\widehat{T}_t \equiv 0$. Welfare losses from climate change are defined as an equivalent percent decline in steady-state consumption. The SCC, which we report in 2024 international dollars, is defined in equation (6) and is independent from the global warming scenario because it relies on the temperature response to a CO_2 pulse $\{\widehat{T}_t^{\text{SCC}}\}_{t\geqslant 0}$. Conversely, the welfare calculations are independent from $\{\widehat{T}_t^{\text{SCC}}\}_{t\geqslant 0}$. To solve for counterfactuals, we use standard global numerical methods to obtain the global solution—we only use log-linearization for estimation.

These counterfactuals assess the impact of gradually rising temperatures by multiple degrees using damage functions estimated under temperature shocks of smaller magnitude. In our framework, households can adjust to large anticipated temperature changes by shifting their consumption and investment behavior. Nevertheless, the parsimonious nature of our framework necessarily abstracts from other possible changes in behavior.

VI.B. Economic Activity, Welfare, and the Social Cost of Carbon

Figure XIII presents our main results. Panel A depicts the path of global mean temperature. Panel B reveals that output drops rapidly as global temperature rises, relative to a world that is not warming. In 2050, output declines by 28%. In 2100, output is 53% below what it would have been without climate change. This decline reflects accumulated productivity losses that reach 40%. These effects are statistically significant at the 5% level.

Panel C highlights the adverse impact of lower productivity on capital accumulation. Initially, investment rises as house-

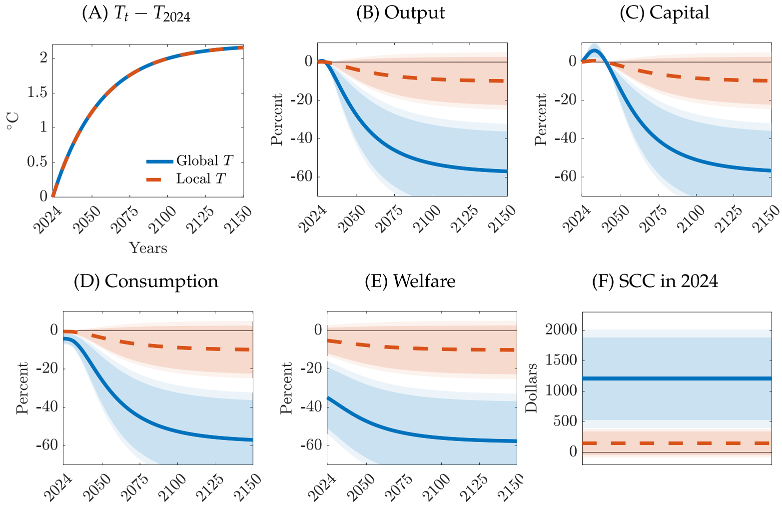

FIGURE XIII

Transitional Dynamics Under Climate Change

Transitional dynamics of the estimated model under the scenario in Panel A. Solid blue lines: the model estimated under global temperature. Shaded blue: 90% and 95% confidence intervals. Dashed red lines: the model estimated under local temperature. Shaded red: 90% and 95% confidence intervals. Confidence intervals are based on the delta method as detailed in Online Appendix D.4. Damage functions are estimated in PWT data.

holds anticipate lower income going forward and therefore save, following standard permanent income logic. Capital starts decumulating rapidly thereafter under the pressure of lower output. By 2100, capital is 51% below what it would have been without climate change.

Panel D indicates that consumption drops, eventually reaching a 53% loss by 2100. This decline in consumption translates into substantial welfare losses. Panel E shows that the 2024 welfare effect of climate change amounts to a 35% loss in consumption equivalent percent. This welfare loss exceeds the initial consumption impact as households discount but value future declines in consumption as well. As temperature keeps rising, welfare continues to decline and reaches a 56% loss. All these values are statistically significant at the 5% level.

Our results point to significant economic costs of climate change. They are comparable to the U.S. Great Depression of 1929 but are experienced permanently. They also correspond to approximately 10 times the losses from moving from today's trade relations to complete autarky (Arkolakis, Costinot, and Rodríguez-Clare 2012). Of course, the cost of climate change is relative to a benchmark economy without climate change in which background economic growth may still take place.

Panel F uses our structural damage function to construct the SCC. We obtain an SCC of $1,207 per ton. This value is more than six times larger than the $185 per ton value in Rennert et al. (2022). The 95% confidence interval for the SCC ranges from $399 per ton to $2,015 per ton. Despite nontrivial uncertainty, even the lower bound of that confidence interval is several times larger than conventional SCC estimates.

Our focus on global temperature shocks is the main driver of these conclusions. Under the local temperature damage function, Figure XIII shows that climate change implies a 9% long-run output decline, a 5% present value welfare cost, and an SCC of $149 per ton. None of these effects are statistically significant at the 5% or 10% levels. These values and the associated uncertainty are consistent with results in Nordhaus (1992); Dell, Jones, and Olken (2012); Burke, Hsiang, and Miguel (2015); Rennert et al. (2022); Barrage and Nordhaus (2024); and Nath, Ramey, and Klenow (2024). We conclude that global temperature effects are both larger and more precisely estimated than local temperature effects.

VI.C. Growth Accounting

If the economic effects of global temperature are so large, why were they not noticed after nearly 1ºC of global warming since 1960? We answer this question by analyzing the historical impact of climate change. We start the economy in 1960 and consider the realized path of warming until 2019, after which we impose constant temperature. We construct counterfactual changes in output relative to a baseline economy that remains in steady state. We add these changes directly to the data.

Figure XIV displays the results. Panel A reveals that climate change is responsible for moderate but persistent reductions in the world's annual growth rate. In the 1960s, there is little warming and thus little effect on economic growth. Between 1980 and 2019, potential growth without climate change deviates more systematically from realized growth with climate change. These results highlight that historical warming occurs in small

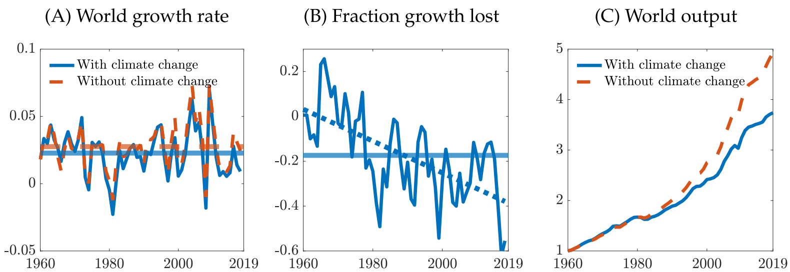

FIGURE XIV

Growth Accounting with Climate Change

The impact of past climate change on world GDP. Panel A: World output growth rate with (solid blue) and without (dashed red) climate change. Horizontal lines: sample averages. Panel B: Fraction of growth rate lost to climate change (annual growth loss out of 1960–2019 mean). Horizontal line: sample average. Dashed line: linear regression fit. Panel C: World output with (solid blue) and without (dashed orange) climate change, normalized to one in 1960. The damage function is estimated under global temperature in PWT data.

increments. Warming shocks thus have moderate economic year-to-year effects in comparison to other economic shocks. The analyses in Sections II and III detects these effects that are otherwise hidden behind background economic variation.

Panels B and C show that the annual growth effects of climate change eventually accumulate because climate change is a permanent shift, despite having an initially moderate effect on growth. Panel B indicates that climate change reduces the world growth rate by as much as a third of baseline growth in the twenty-first century. Panel C shows that this growth slowdown implies that world GDP per capita would be 25% higher today had no warming occurred between 1960 and 2019. Even though in this counterfactual we hold temperature constant at its 2019 level in all subsequent years, economic losses continue to accumulate after 2019. These delayed impacts are due to the lagged productivity effects embedded in our estimated damage functions $\{\zeta_s\}_s$ and to the internal transitional dynamics of the neoclassical growth model. By 2040, output is 32% below its potential due to climate change: one quarter of the economic losses caused by past warming are yet to materialize.

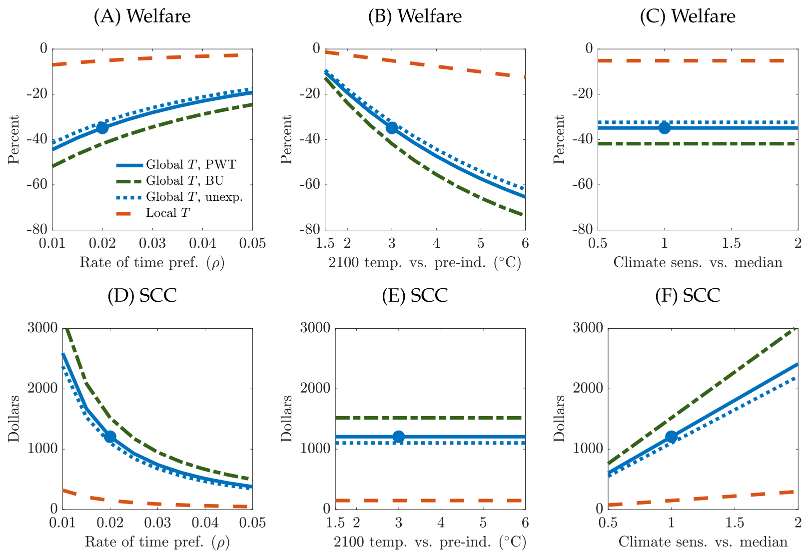

FIGURE XV

Welfare and the Social Cost of Carbon Under Alternative Choices

Sensitivity of welfare costs and the social cost of carbon in 2024 with respect to the rate of time preference (ρ), 2100 global mean temperature relative to preindustrial levels, the climate sensitivity, estimation sample, and treatment of expectations. Solid blue lines: the model estimated using global temperature shocks under baseline expectations and PWT data. Dashed-dotted green lines: the model estimated using global temperature shocks under baseline expectations and BU data. Dotted blue lines: the model estimated using global temperature shocks with temperature shock surprises and PWT data. Dashed red lines: the model estimated using local temperature shocks under baseline expectations and PWT data.

VI.D. Sensitivity

Given the magnitude of our results, we investigate which parameters may be particularly important for them. Figure XV displays how our results depend on five key choices: the rate of time preference ρ, 2100 global mean temperature, the estimation sample, the climate sensitivity, and our treatment of expectations.

Panel A shows 2024 welfare losses as a function of the rate of time preference ρ, and Panel D shows the corresponding SCC. As expected, a higher rate of time preference lowers welfare losses and the SCC: households then discount more damages that are far in the future. Our baseline rate of time preference $\rho = 0.02$ is consistent with Rennert et al. (2022) and with the secular decline in interest rates. However, welfare losses still exceed 20% at rates of time preference above 0.04. The corresponding SCC remains three times as large as the high end of previous estimates and still seven times larger than the SCC based on local temperature under the same rate of time preference. By contrast, as we approach very low discount rates consistent with Stern (2007), welfare losses exceed 40% and the SCC rises above $2,500 per ton. Welfare losses are less sensitive to the discount rate than the SCC because these losses represent an annualized flow of losses, while the SCC is a discounted stock valuation.

Panels B and E show welfare losses and the SCC when we vary 2100 temperature relative to preindustrial levels. Welfare losses under 15% materialize only at very low warming scenarios of 1.5ºC since preindustrial levels by 2100. The IPCC evaluates that the world is on track for 3ºC to 4ºC above preindustrial levels under business as usual: global mean temperatures already largely exceed 1ºC since preindustrial levels, and in 2023 reached 1.45ºC since preindustrial levels. By contrast, scenarios under which global mean temperatures reach 6ºC since preindustrial levels in 2100 lead to present value welfare losses of 60%. In Panel D, the 2024 SCC is independent from the warming scenario because it only depends on the temperature response to a CO_2 pulse given our definition.

Panels C and F display how the climate sensitivity affect our conclusions. The climate sensitivity governs how carbon emissions map into current and future warming. Consequently, welfare losses to a given warming scenario in Panel C are independent from the climate sensitivity. However, as shown in Panel F, the SCC is not. Our main analysis uses the median climate sensitivity from Dietz et al. (2021b) and Ricke and Caldeira (2014). When we halve or double the climate sensitivity—corresponding to the range across climate models from Dietz et al. (2021b)—the SCC varies from $600 to $2,400 per ton.

Figure XV also depicts how these results shift when we estimate damage functions using the BU data instead of the PWT data. As we estimate larger GDP effects in the BU sample, we obtain larger damage functions and more pronounced counterfactuals. Welfare losses rise to 42%, 2100 GDP losses grow to 61% and the SCC increases to over $1,500 per ton.

Finally, we show how our conclusions change when we treat household expectations differently. In our main estimation, we assume that households have rational expectations about the temperature path after a temperature shock. An alternative is to assume that households are surprised every period by persistently elevated temperatures following a temperature shock. Under this assumption, we linearly combine our estimated impulse response functions to obtain the output responses to a one-time transitory temperature shock. We target these responses to a transitory shock to estimate structural damage functions, instead of estimating damage functions first as in our baseline. We provide more details in Online Appendix D.5. The dotted lines in Figure XV display our results under this alternative treatment of expectations. The results are very close to our baseline, highlighting that our baseline treatment of expectations is not driving our results. Collectively, these sensitivity exercises indicate that significant climate damages occur over a wide range of specification choices.

VII. Conclusion

We show that the effect of climate change on economic activity is likely an order of magnitude larger than previously thought. We leverage natural climate variability in global mean temperature to obtain time-series estimates that are informative of the overall effect of global warming. Of course, identification is more challenging in the time series because of global confounders at high and low frequencies. Although no set of sensitivity analyses is ever entirely exhaustive, our estimates remain stable across a wide range of specifications that vary the set of controls, sample periods, and source of global temperature fluctuations and adjust for reverse causality. Collectively, these exercises suggest that our specification captures the causal effect of global temperature on economic activity.

Quantitatively, we find that a permanent 1ºC rise in global temperature causes global GDP to persistently decline by over 20%. These effects are due to ocean temperatures and an associated surge in extreme climatic events. By contrast, local temperature shocks used in the conventional panel literature lead to a minimal rise in extreme events and smaller economic effects. Together, our results imply an SCC in excess of $1,200 per ton, a welfare loss of more than 30%, and a GDP per capita loss in excess of 50% by the end of the century under a moderate warming scenario.

Our results also have salient consequences for decarbonization policy, which we discuss further in a companion paper (Bilal and Känzig 2025). Most decarbonization interventions cost

\$80 per ton of CO_2 abated on average (Bistline, Mehrotra, and Wolfram 2023). Consider a conventional SCC value based on local temperature variation of \$149 per ton. In that case, decarbonization policies are cost-effective only if governments internalize benefits to the entire world, as captured by the SCC.

However, a government that only internalizes domestic benefits evaluates decarbonization policies with a DCC, which is always lower than the SCC because losses to a given country are lower than for the world. Under conventional estimates based on local temperature variation, the DCC of the United States is below policy costs. Unilateral emissions reduction are then prohibitively expensive. By contrast, under our estimates based on global temperature variation, the DCC of the United States exceeds policy costs. Unilateral decarbonization policy then becomes cost-effective for large economies such as the United States.

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

The data and code underlying this article are available in Bilal and Känzig (2026), in the Harvard Dataverse, https://doi.org/10.7910/DVN/O4AUDQ.

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