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LETTER

Reconsidering the macroeconomic damage of severe warming

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Abstract

Projections of macroeconomic damage from future climate change tend to suggest mild to moderate impacts. This can lead to welfare-optimal climate policies in integrated assessment models (IAMs) that recommend very slow emissions reductions over the coming decades, in sharp contrast with the ambitions of the Paris Agreement. These econometric models assume that weather impacting a single country is all that affects the economy of that country. We examine whether the addition of global weather conditions in the empirical modelling of economic growth affects the projections of the impact of climate change on global gross domestic product (GDP). In effect, we explore whether the interconnectedness of the global economy makes individual countries vulnerable to weather changes that impact other countries. Using three influential econometric models we add global weather to the regressions. We find that this leads to significant worsening of the projections of macroeconomic damage for given future emissions scenarios. Damage to world GDP in 2100 under SSP5-8.5, averaged across both econometric models and climate models increases from ∼11% under models without global weather to ∼40% if global weather is included. Further, we demonstrate that when the damage function used in a recent IAM is estimated from empirical models augmented with global weather conditions, they reduce the welfare-optimal amount of climate change from ∼2.7 °C to ∼1.7 °C which is consistent with the Paris Agreement targets. Our results highlight the need for econometric modelling and climate science's understanding of extreme events to be integrated much more consistently to ensure the costs of climate change are not underestimated.

1. Introduction

Global warming presents a serious risk to humans and the environment [1]. The impacts of global warming on human health [2], food security [3], labour productivity [4, 5], conflict [6, 7], mass migration [8, 9] and biodiversity [10] are reasonably well established. In contrast, there is low confidence in how global warming will impact the global macroeconomy [11]. The range of estimates varies widely but includes a projected impact of -23% to global gross domestic product (GDP) at 2100 under a high emissions future [12], a more modest -12% [13], and even more optimistic projections [14]. The global economic impact of climate change on GDP is not simply of academic interest; it can inform policy decisions on carbon pricing and allowable CO_2 emissions.

Previous attempts to estimate the impact of global warming on the global economy have employed diverse methods. For example, [12] argue that the *actual* temperature can have a direct and nonlinear impact on GDP growth rates, while [13] only allows *changes in temperature or rainfall* to temporarily affect growth. Regardless of this difference, both assume that local weather (that is, the weather impacting a single country) is all that is relevant to model how climate change will affect the economy of that country, and both use highly aggregated country-wide annual averages. Both project a scale of impacts in the remainder of this century that is likely to be dwarfed by technological progress implicitly hinting that the costs of even severe global warming to the economy are manageable.

In climate science, there is a recognition that averages (whether across space or through time) are not enough to capture the risks of global warming. Rather, it is the impact of global warming on the frequency, magnitude and duration of extreme events that is likely to have the greatest effect on systems [15]. This recognition is now influencing efforts to understand how global warming impacts the economy. For example, [16, 17] consider the extremes and variance of temperature and rainfall within a year across subnational regions in their modelling.

Here, we are concerned with the inclusion of global weather in models used to assess the impact of global warming on the global economy. The underlying assumption for the inclusion of global weather in economic modelling is that since international trade is fundamental to the supply chains of economic production, it is reasonable to expect that a country's future economic growth will be influenced by weather conditions everywhere in the world and not simply in that country itself. The question arises, how does incorporating global weather change impact existing models used to estimate economic losses?

The role of global weather in economic modelling was first proposed in [18] and explored in [19]. This paper extends earlier analyses by examining the projected impact of including global weather on three major econometric approaches used to assess the global impact of climate change on global GDP: [12, 13, 16]. We focus on these three empirical articles as they each make very different assumptions when estimating the relationship between the economy and weather, and are influential in academia, industry, and government. We therefore outline how the inclusion of global weather impacts projected losses, the distribution of losses across countries, the uncertainty of those losses, and how it changes optimal climate change policy.

2. Methods and data

2.1. Data

Historical weather data was taken from the CRU TS v4.07 dataset [20] which interpolates historical weather station data at a 0.5° longitude by 0.5° latitude spatial resolution from 1900 through to 2022. It contains monthly average mean temperature (in Celsius) and total monthly precipitation (in millimetres). Gridded observations were aggregated to country-level by taking an average that is weighted by estimated population (taken from [21]). They were then aggregated to annual variables by calculating the average monthly mean temperature and cumulative precipitation. The resulting dataset contains 169 countries observed on average over 50 years between 1962–2022.

CMIP6 projections for 22 climate models providing annual mean temperature and annual precipitation through to 2100 were taken from [16], who also provide the complete list of climate models used. Annual real GDP per capita was collected from [22], expressed in constant 2015 USD. The data and code used to generate the results of this article are available at: https://doi.org/10.5281/zenodo.14969241.

2.2. Methods

Following the methodologies of [12] ('Burke15'), [13] ('Kahn21'), and [16] ('Kotz24') we estimate historical regressions of economic growth using the data outlined above, both with and without global temperature included. For Burke15 this is:

$$g_{it} = \alpha_i + \boldsymbol{\beta}_1 \mathbf{T}_{it} + \boldsymbol{\beta}_2 \mathbf{T}_{it}^2 + \mathbb{1}(GW)\boldsymbol{\theta}\bar{\mathbf{T}}_t + \gamma_i t + \psi_i t^2 + \epsilon_{it} \quad (1)$$

where g_{it} is annual GDP per capita growth in percentage terms for country i at period t, $\mathbf{T}_{it}$ is a vector containing annual mean temperature and cumulative precipitation, and $\bar{\mathbf{T}}_t = N^{-1}\sum_{i=1}^{N}\mathbf{T}_{it}$ is globally averaged temperature and precipitation. Importantly, the indicator function $\mathbb{1}(\mathrm{GW})$ is 1 whenever the model is run with global weather and zero otherwise.

For Kahn21 it is:

$$g_{it} = \alpha_i + \sum_{\ell=1}^{L}\rho_\ell g_{i,t-\ell} + \sum_{\ell=0}^{L}\boldsymbol{\beta}_\ell \Delta\tilde{\mathbf{T}}_{i,t-\ell}^{+} + \sum_{\ell=0}^{L}\boldsymbol{\gamma}_\ell \Delta\tilde{\mathbf{T}}_{i,t-\ell}^{-} + \sum_{\ell=0}^{L}\mathbb{1}(\mathrm{GW})\left(\boldsymbol{\omega}_\ell \Delta\tilde{\bar{\mathbf{T}}}_{t-\ell}^{+} + \boldsymbol{\alpha}_\ell \Delta\tilde{\bar{\mathbf{T}}}_{t-\ell}^{-}\right) + \epsilon_{it} \quad (2)$$

where $\tilde{\bar{\mathbf{T}}}_t = \bar{\mathbf{T}}_t - M^{-1}\sum_{\ell=1}^{M}\bar{\mathbf{T}}_t$ and $\tilde{\mathbf{T}}_{it} = \mathbf{T}_{it} - M^{-1}\sum_{\ell=1}^{M}\mathbf{T}_{it-\ell}$, which is split into $\tilde{T}_{it}^{+}$ which contains positive deviations (while negative deviations are zeroed out) and $\tilde{T}_{it}^{-}$ which contains negative deviations (when implementing this model we set $L = 4$ and $M = 50$).

For Kotz24 it is:

$$g_{it} = \alpha_i + \sum_{\ell=0}^{L}\left(\beta_{1,\ell}\Delta\mathbf{T}_{i,t-\ell} + \beta_{2,\ell}\Delta\mathbf{T}_{i,t-\ell}\bar{\mathbf{T}}_i + \mathbb{1}(\mathrm{GW})\beta_{3,\ell}\Delta\bar{\mathbf{T}}_{t-\ell}\right) + \gamma_i t + \psi_i t^2 + \epsilon_{it} \quad (3)$$

where $\bar{\mathbf{T}}_i$ is the annual average temperature and precipitation for that country averaged over all years in the sample (consistent with the original article, we set $L = 8$ for temperature variables and $L = 4$ for rainfall when implementing this model). For full implementation details see supplementary material.

Next, we derive forecasts of future global GDP derived from estimated $\hat{g}_{it}$ using the three models above with and without the inclusion of global weather. To better capture uncertainty in both the econometric estimates and future weather, 2500 forecasts are produced that randomly pick from one of 22 CMIP6 models and also randomly resample the countries in the historical data with replacement to estimate the econometric model. Projected world GDP for specification s (meaning either the Burke15, Kahn21, or Kotz24 models), climate scenario c, country i, period t and replication r (each replication varies the climate model and resamples the historical data for estimation) is:

$$W\hat{GDP}_{\mathrm{scrt}} = \sum_{i=1}^{N} \hat{GDP}_{\mathrm{scri},t-1}\left(1+\hat{g}_{\mathrm{scrit}}\right) \quad (4)$$

where $\hat{g}_{\mathrm{scrit}}$ is the projected economic growth for country i, $\hat{GDP}_{\mathrm{scri},t-1}$ is the simulated level of GDP per capita of country i at period $t-1$. Forecasted damage to global GDP per capita from severe climate change is then calculated as the percentage deviation between the forecasts of world GDP under SSP5-8.5 against a baseline of forecasts under SSP1-2.6. Using SSP1-2.6 as the baseline is policy relevant as it assesses the economic costs of inaction relative to aggressive action on emissions reductions. It also avoids the need for a 'no further climate change' baseline which is arguably unrealistic.

Finally, we derive a revised damage function of economic loss as a function of degrees of warming as commonly implemented in integrated assessment models (IAMs). Here, $\mathrm{loss}_{sr} = \beta_2 W_{sr}^2 + \epsilon_{sr}$ where loss_{sr} is the degree of global economic loss (in percentage terms relative to the baseline) projected by specification s and replication r at a given period from (4). W_{sr} is the amount of warming from SSP5-8.5 relative to SSP1-2.6 that is associated with that forecasted loss. We then use the DICE 2023 IAM model from [23], reoptimised using this revised damage function.

3. Results

Figure 1 shows the projected percentage reduction in global GDP from a high emissions future (SSP5-8.5) relative to a lower emissions future (SSP1-2.6), for the three models outlined in section 2.2. Each economic model is run with and without global weather to determine its impact on the projections. Without the inclusion of global weather (blue line), all three models project more mild economic losses with a median loss at 2100 of −28% for the Burke15 model, −4% for the Kahn21 model, and −11% for the Kotz24 model. Projected losses from the latter two models are more optimistic than in the original articles, likely due to the variations in data and exact assumptions made.

Adding global weather systematically increases projected economic losses independent of the model used. This increase is dramatic in two of the three models. Median loss in the Kotz24 model increases to −40% by 2100, and to −86% in the Burke15 model. The forecasts also become more uncertain, in the Kotz24 and Khan21 models (demonstrated by the width of the shading), particularly towards the end of the century, owing to uncertainty regarding the magnitude of the effect that global weather has on economic growth. Nevertheless, even with the increase in uncertainty, the full range of projections lie outside the projected range of when global weather is not included. Supplementary material demonstrates that this effect of global weather is robust to subsample analysis, the inclusion of CO_2 concentrations as an independent variable, and also controlling for El Nino indices.

Median loss increases in the Kahn21 model with the inclusion of global weather, but still remains mild, increasing from −4% to −19%. This is unsurprising as the Kahn21 specification in (2) assumes any degree of climate change is fully adaptable. Both the Kahn21 and Kotz24 models only allow climate change to impact economic growth through deviations or changes in temperature and rainfall. This implies that any degree of climate change is fully adaptable in time, and only the transitions to new climates matter for economic growth.

By including further lags in the model, the Kotz24 model allows this adaptation to occur more slowly. Kahn21 additionally expresses weather relative to a norm (in this case, the norm is the average weather in the last M periods). As the climate worsens, the model allows this norm to change over time, but even under SSP5-8.5, deviations from this updating norm remain fairly small. This might explain why damages are smaller in the Kahn21 model relative to the Kotz24 model.

Figure 2 charts the median projected loss to GDP per capita from SSP5-8.5 (relative to SSP1-2.6) in 2100 by country, model specification, and whether global weather ('GW') was included in the specification. If global weather is excluded (left column), all model specifications suggest a small impact on GDP in most countries and in aggregate, with the relative effect of SSP5-8.5 ranging across countries from −82% (Mauritania) to +139% (Greenland) in the Burke15 model, −21% to +3% in the Kotz24 model, and −7% to −2% in the Kahn21 model. Some countries in the northern hemisphere, including Russia, Sweden, and Greenland are projected to benefit from warming.

The inclusion of global weather change has a moderate impact on the Kahn21 model, with median losses now ranging between −20% to −17% (figure 2, right column). The same inclusion leads to dramatic increases in projected GDP loss across countries in the Burke15 and Kotz24 models, reaching −97% to −43% in the Burke15 model and −56% to −11% in the Kotz24 model.

An important result shown in figure 2 is the implications on the global distribution of the costs

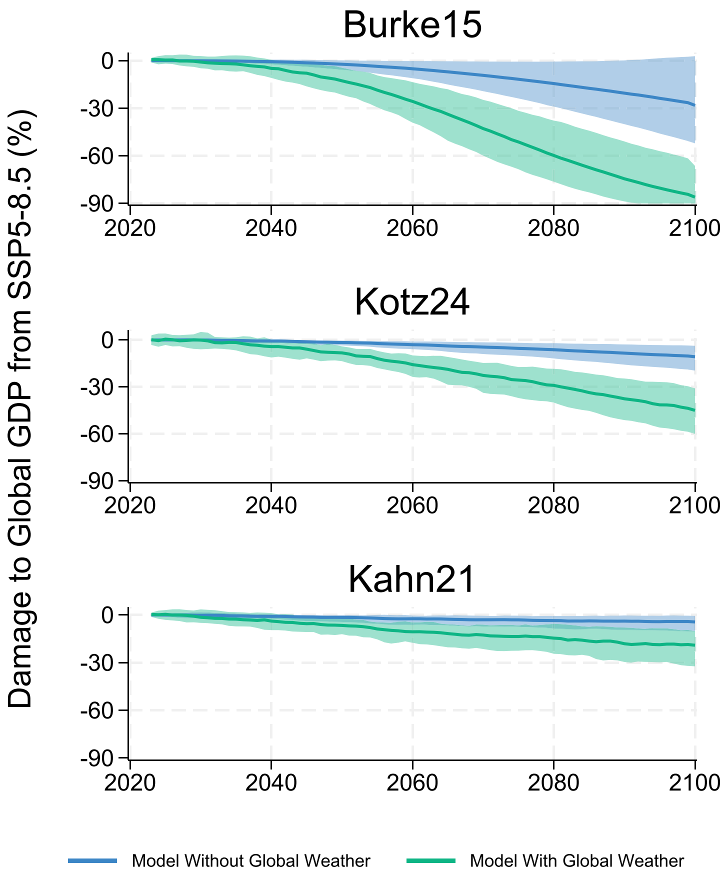

Figure 1. Projections of global economic loss from three models (both with and without the inclusion of global weather) from a high emissions scenario (SSP5-8.5) relative to a lower emissions scenario (SSP1-2.6) in percentage terms. Each solid line displays the median of 2500 forecasts, while the shading reflects the 95th and 5th percentile forecast.

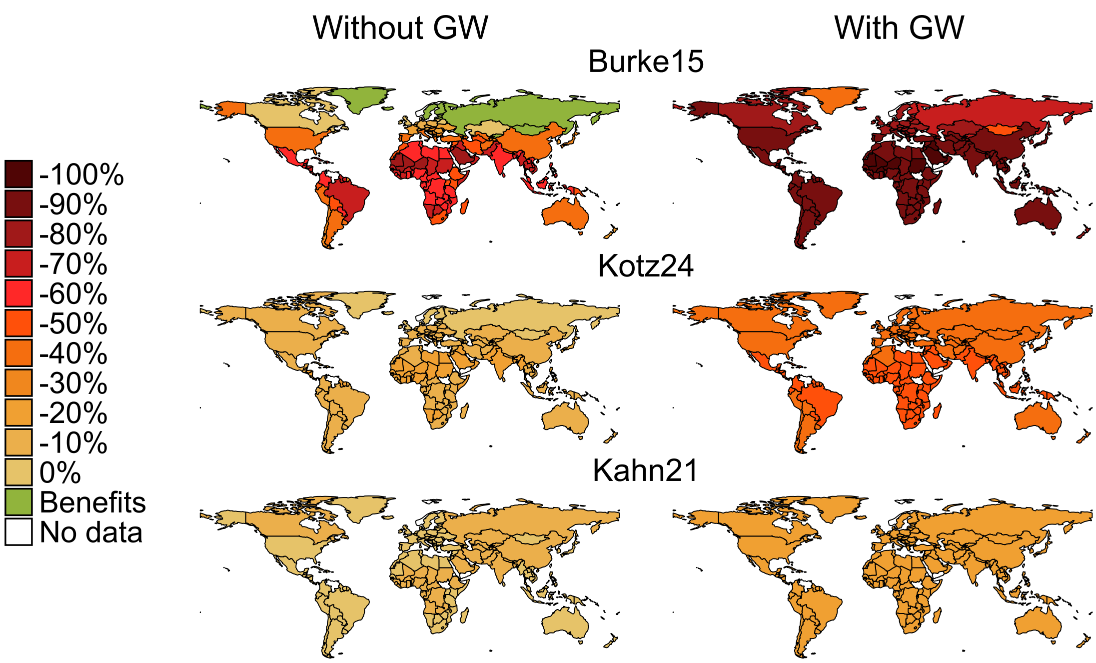

Figure 2. Median projected economic loss in 2100 by country, economic model, and whether global weather ('GW') was included. Loss is presented as percentage loss projected from SSP5-8.5 relative to a baseline of forecasted GDP per capita under SSP1-2.6.

of climate change. In [24] for example, the authors only find evidence that global warming will impact GDP in poorer countries. Adding global weather to the models leads to severe losses through much of the mid-latitudes of the northern hemisphere in two of the three models, particularly Europe, the US, China and India.

Nonetheless, there remains significant heterogeneity between countries in 2100 economic losses in both the Burke15 and Kotz24 models. This heterogeneity may increase with further modifications to the model specifications. Appendices B and D2 provide evidence that countries with a warmer climate may have more severe responses to global average temperature changes than cooler ones. A promising area of future research would be to extend these three models with global weather to allow for this type of heterogeneity in slope coefficients across countries, and explore how it impacts projections further.

4. Discussion

Figure 1 suggests that the current practice of including only local weather in modelling the macroeconomic impacts of climate change leads models to systematically underestimate the scale of the potential losses. Indeed, the magnitude of the losses in the Burke15 and Kotz24 models when global weather is included is arguably more consistent with the warnings from climate science of the dangers to our planet from SSP5-8.5.

4.1. Why does global weather matter so much in the empirical models?

We will briefly discuss several potential explanations for how global weather impacts economic growth separately from local weather. The first is simply that in a highly globalised world economy, shocks to economic growth in one country has spillover effects (alternatively called general equilibrium effects) on other countries. The second, proposed in [19], is that global weather is correlated with distributional aspects of local temperature that are important for determining extreme weather events. These are not captured by measuring annual average local temperature and cumulative precipitation. One candidate would be global climate phenomenon like El Nino, yet in appendix D1 we show that the results for global average temperature are robust to controlling for multiple El Nino indices.

We hypothesise that global weather may impact the ability of international trade to serve as a means for economies to insulate themselves from local weather shocks. In a stable climate during any given year, a number of countries will experience favourable weather conditions while a number of others will experience relatively poorer weather. If poor weather causes adverse outcomes such as crop failures or capital loss, that country can usually rely on good conditions in other countries to import the affected commodities at a competitive price. When globally averaged weather is particularly warm or dry in a given year, it increases the likelihood of more countries experiencing poor weather simultaneously and can have a large impact on the global supply chains of important commodities and cost-push inflation (for the case of agricultural commodities, see [25, 26] for a similar argument). Future climate change increases the risk that these conditions will occur (by raising global average temperature), and accordingly including global average temperature in the regression allows the model to incorporate this risk into future projections.

Clearly, one avenue for future research is to test these hypotheses and determine the precise mechanisms through which global weather impacts economic growth. If the impact of global weather on economic growth is driven by the role of trade and supply chains, we could expect that the impact is heterogeneous with the reliance of that country to trade and other features such as sectoral makeup of the economy. We note that climate science has developed a wide range of metrics to evaluate changes in the spatial and temporal characteristics of extreme events, including spatial and temporal compounding of extremes [27, 28]. Linking some of this understanding with economic growth modelling as well as behavioural modelling (see [29]) could provide deeper insights into how global warming impacts growth.

4.2. What are the implications of our results?

The policy implications of our results can be assessed by determining the impact it has on the welfare-optimal policy recommendations of IAMs (see [30] for a survey on the influence of these models on policy development). This can be done by recalculating the damage function, which is a simple mapping of global average temperature increase and global economic loss. We did this for the damage function used in the DICE 2023 model (see [23]) to match the projected economic losses outlined in figure 1 for all three models including global weather. We then solved the DICE 2023 model based on this revised damage function, and the welfare-optimal climate policy results are presented in figure 3.

First, the top-left panel shows the original DICE 2023 damage function and the revised one, which begins to diverge after only one degree of warming. The top-right panel shows the optimal amount of climate change. The standard DICE 2023 model finds an optimal amount of warming of 2.7 degrees by the end of this century, which is close to where warming is estimated to reach under current policies (see e.g. [31]). Using the revised damage function reduces this to roughly 1.7 degrees and plateaus after 2060.

The bottom-left panel in figure 3 shows the optimal global CO_2 emissions. Only the revised

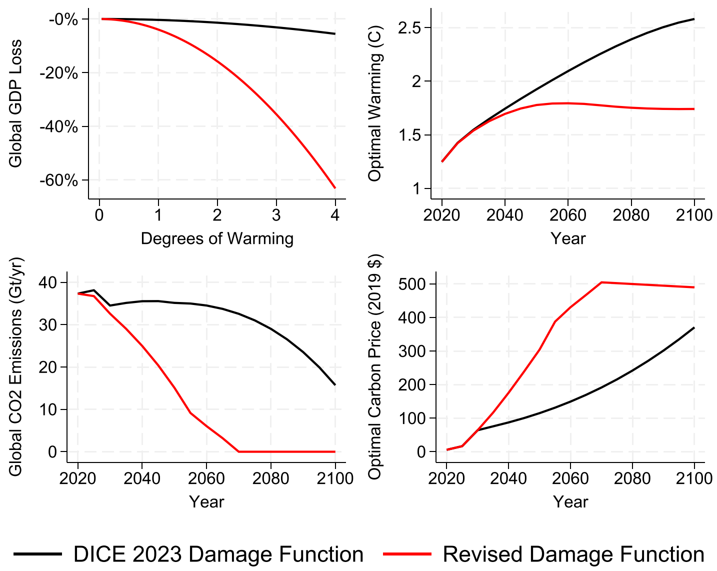

Figure 3. Welfare optimal climate policy in DICE 2023 using either the standard damage function outlined in [23] or the revised damage function recalculated to fit the projections of economic loss presented in figure 1 of this article.

damage function shows a trajectory of emissions that is close to what is currently recommended by the IPCC [1]. Finally, the bottom-right panel shows the welfare optimal carbon price. The revised damage function features a much higher optimal carbon price after 2030. In short, the policy recommendations that emerge from DICE 2023 are vastly different when using a damage function calibrated from models that include global weather, and become much closer to the policy action commonly advocated within climate science (e.g. see [10]).

The projected economic losses in figure 1 also highlight the level of uncertainty associated with the impacts of future warming. The range of forecasts across the three models are relatively similar for SSP5-8.5 (relative to SSP1-2.6) when global weather is ignored in the model, whereas the uncertainty increases between models when global weather is included (compare the blue ranges with the green ranges across the three models in figure 1). Arguably, by excluding global weather, current modelling leads to a false sense of overconfidence in the range of potential impacts from even extreme warming. This is particularly reflected in the fact that IAMs often do not allow for uncertainty in the damage function (see e.g. [32] for further discussion of uncertainty in IAMs).

Finally, our results have implications for future efforts to assess the potential impact of climate change on GDP. The very strong effect that global weather has in all three empirical models encourages future research to determine whether: (i) the effect of local weather is sensitive to external conditions, (ii) global weather is correlated with distributional aspects of local temperature that are important for determining extreme weather events, (iii) global weather has a direct impact on local GDP through spillovers and other economic mechanisms, and (iv) countries respond to global weather shocks differently (due to e.g. different climates, differing reliance of trade and global supply chains, and different sectoral structure). We believe that economics and climate science need to come much closer together to jointly examine how local and external historical weather impact on economies, and how climate models might be used to inform forecasts using economic models.

4.3. Limitations

Our results are based on the very high emissions future SSP5-8.5 relative to a counterfactual of SSP1-2.6. In appendix D3 we outline the results for SSP5-8.5 against a 'no further climate change' scenario, and find that the conclusions in this paper are robust to this choice of baseline. Using SSP5-8.5 enables us to be more consistent with the original papers of the three empirical models used in this article. Under less severe warming scenarios, the gap in projected losses without and with global weather will shrink. It is worthwhile to note that damage functions used in IAMs, as in the top-left panel of figure 3, focus on damage as a function of degree of warming and hence should not be sensitive to emission scenario choice. Inevitably, forecasts of what will actually occur in the coming century should consider the probability of a particular emission scenario, along with its potential effects on economic growth.

One fundamental limitation of empirical forecasts of future climate change is the reliance on historical relationships with weather data to forecast climate scenarios that lie outside human experience. This necessarily involves extrapolating the shape of the functional form of weather and economic growth beyond the range of the sample data, and that relies on linearity of the function to be valid which is almost certainly untrue in our case. Economies may adapt to climate change over time, suggesting a smaller sensitivity to future climate change, but the unprecedented levels of heat (coupled with tipping points) might cause a higher sensitivity to extreme warming than what is extrapolated from historical data.

The importance of this limitation is heightened in a model that includes global weather, as there is more historical variation in local weather around the world and over time than there is in global weather over time. For instance, global average temperature in our historical sample has a mean of 18.41 degrees and a standard deviation of 0.43. The SSP5-8.5 projections of global average temperature at 2100 has a mean of 24.6 across all 22 CMIP6 models used in this article, which is 14 standard deviations away from the historical mean.

A final limitation is that this article incorporates global weather into empirical models in a very simple way, to keep the specification as close to the existing models as possible and increase comparability. We are not arguing that our modifications lead to perfect specifications, and further improvements could certainly be made. In future work, weighting the averages by distance and/or historical trade activity could be useful. Additionally, capturing more distributional aspects of weather within a year has been shown to increase the explanatory power of these models (e.g. [16, 17]), and the same is likely to be true when entering global weather into the specification. Future research is needed to understand the precise mechanisms through which global weather matters for local economies, and how to use more disaggregated weather information to further enrich these models and gain additional insight into the risks of future warming.

5. Conclusion

The future effects of climate change on the global economy is arguably one of the most pressing and unsolved questions in economics. We provide evidence that one of the assumptions that underlie most of the current models used to answer this question, that climate change will impact a particular country's economy only through changes to local weather conditions, causes an underestimation of the potential impacts. Uncertainty remains large across the three model specifications tested, but in each case the scale of projected economic losses from including global weather is considerable.

The implications of these results for climate change policy are significant. The increase in projected damage is sufficient to cause the welfare-optimal amount of climate change estimated by the DICE 2023 IAM to decrease from around 2.7 °C to 1.7 °C. In addition, the welfare-optimal speed of decarbonisation is greatly increased. The results also have implications for future work, demonstrating the sensitivity of previous projections of economic damages and the need to determine the precise mechanisms through which global weather conditions affect economic growth independently from local weather shocks.

Data availability statement

The data that support the findings of this study is openly available at the following URL: https://doi.org/10.5281/zenodo.14969241 [33].

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