The Importance of External Weather Effects in Projecting the Macroeconomic Impacts of Climate Change

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Summary The potential impact of severe climate change on the world economy is uncertain and important. Previous econometric models predict mild aggregate damages and that some countries will be unaffected. This article demonstrates that these predictions depend on the assumption that economies are unaffected by weather shocks in other countries, which causes a mischaracterisation of global weather shocks. Generalising existing models leads them to predict catastrophic damages, where all countries are affected to different degrees. This has fundamental implications for damage functions used in Integrated Assessment Models, and explains the contrast between how economics and physical sciences characterise severe climate change.
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1. INTRODUCTION

Scientists have uncovered potential impacts of future climate change on our planet that are both numerous and severe (recently surveyed in Pörtner et al. 2022 and Hoegh-Guldberg et al. 2019). Given the magnitude of the problem, and the imminence of its arrival, discerning the potential impacts of future climate change on the economy is arguably of first order importance. Perhaps surprisingly, most economic studies that model macroeconomic impacts predict a mild aggregate effect from climate change (see Tol 2009 and Kahn et al. 2021). They also predict that some countries will be completely unaffected or even benefit from future climate change.

Why does this contrast exist between the characterisations of severe climate change in the physical sciences and economics? The key contribution of this article is to demonstrate that these two results from the economics literature rely on an assumption inherent in prior models that a country's economic growth is only affected by weather shocks in their own country. This has led to econometric models identified from local or regional weather shocks in the historical data being inappropriately used to predict the impact of future global shocks. Even simple modifications to existing models to relax this assumption lead to vastly more pessimistic predictions of the economic damage of climate change.

Modelling the impact of future climate change on the economy is a complicated task: it involves a long time horizon to 2100, there are myriad channels through which the climate could affect economic growth, it is a global problem with complex spatial interactions, the relationship will be fundamentally nonlinear, vary between countries, and even vary over time as populations adapt to the changing environment. The channels through which climate change can affect the economy include crop yields (Keane and Neal 2020 and Schlenker and Roberts 2009), labor productivity (Dasgupta et al. 2021 and Heal and Park 2020), conflict (Hsiang et al. 2013 and Hsiang et al. 2011), asset loss from extreme weather events (Hsiang and Jina 2014), mass migration (Kaczan and Orgill-Meyer 2020 and Beine and Jeusette 2021), health impacts (Romanello et al. 2021), and other impacts.[1] It may also have devastating implications for biodiversity (Nolan et al. 2018 and Pörtner et al. 2022), which can have significant implications of its own which are difficult to price or model (Dasgupta 2021).

Earlier attempts to model aggregate impacts use either enumerative methods, where each impact channel is valued and then summed up, or cross-sectional statistical models. They are remarkable for the extremely minor impacts they predict climate change would have on the economy (see Tol 2009 for a survey), with average predictions of between -1.6% and +2.6% impact on world GDP per degree of warming. More recent articles exploit the large panel data available of economic growth and weather across the world (beginning with Dell et al. 2012). They relate a country's economic growth to weather using an econometric model, and by using fixed effects rely on idiosyncratic weather shocks for identification.[2] After estimating the relationship between temperature and economic growth, the model can use outputs from global climate models to predict impacts from future warming. These studies have predicted less ambiguous negative impacts from future climate change, with unmitigated climate change causing a decline in real GDP per capita of 7% (Kahn et al. 2021) to 23% (Burke et al. 2015) by 2100. The overly mild and mixed results from the various economic methodologies led the 2nd working group of the IPCC, in their 2022 report, to conclude that "the assessed lack of comparability and robustness of global aggregate economic damage estimates" necessitate them assigning 'low confidence' to the magnitude of the estimates.

A key assumption inherent in existing econometric models is that a country's economic growth is only related to its own weather shocks, whereas those of their neighbors, trading partners, and the rest of the world are left in the error term. Economies are highly globalised and interconnected through international trade, foreign direct investment, and financial markets. Since the spatial dependence of economic growth is not modelled, they are unable to distinguish between a local and global $+1°C$ temperature shock. This is particularly problematic for this prediction task, as future climate change is a spatially global and persistent shock, whereas the historical shocks in the data used to identify the equation are usually local or regional.[3]

This article demonstrate that even simple modifications to existing models, which al-

[1] For example, for fisheries see Free et al. (2019) and Cheung et al. (2016), for wildfires see Senande-Rivera et al. (2022) and Canadell et al. (2021), for groundswater availability see Wunsch et al. (2022), for temperature variability and its economic implications see Calel et al. (2020), and finally wildlife conflict which encourages zoonotic virus spillover see Abrahms (2021).

[2] The intuition behind this approach is that we could learn about the economic implications of two degrees of global warming for Kenya, say, by looking at times Kenya and similar countries have had heatwaves two degrees above the norm.

[3] For instance, if a local heatwave of +2°C above normal mean temperatures causes crop failures in Kenya (say), they can rely on food imports from countries that have had good harvests to cushion the economic damage from local weather shocks. In contrast, if future climate change shifts the weather draws of every country to be +2°C above normal, a key mechanism through which countries use to mitigate the harm of local weather shocks breaks down. There is also the matter of persistence, where in the past weather shocks are expected to be transitory and economic harm can be mitigated through budget deficits or foreign aid to fund recovery and compensate victims. In contrast, future climate change results in persistent temperatures well above the norm. While this could lead to adaptation, it may also compromise the ability of governments to cushion the economic impact of warmer weather.

low a country's economic growth to depend on domestic and overseas weather shocks, dramatically change the predicted effects of future climate change on the global economy in the coming century. Firstly, across three diverse models it leads to much more pessimistic predictions of aggregate GDP per capita damage in 2100. In the Dell et al. (2012) model it leads to a revision from -18% to -78%, in the Burke et al. (2015) model a revision from -67% to -94%, and in the Kahn et al. (2021) model a revision from -13% to -46%. Importantly, incorporating this additional information into the three models lead them to predict that all countries will be severely harmed from climate change to different degrees. Most studies in the past predict that some countries will benefit from climate change or barely see any effect, particularly the cooler countries of Russia, Northern Europe, parts of Eastern Europe, and Canada. The modified models suggest that the negative external weather effects will dominate any potential economic benefit from a more moderate climate in their own country.

These results suggest that the two prevailing results from the literature are dependent on a restrictive assumption in the econometric methodology. The article also outlines a second source of difficulty in producing credible economic damage predictions from future climate change: the expected temperature shock from significant climate change is wholly outside our historical experience that is available in the data (whether in terms of deviation from norms or in absolute value). Nevertheless, it is simple to devise economic models that make predictions sufficiently pessimistic to align with the characterisation in the physical sciences of the 'human imperative' to avoid significant climate change (Hoegh-Guldberg et al. 2019).[4]

2. MODELLING THE IMPACT OF FUTURE CLIMATE CHANGE

2.1. Motivating Framework

To fix ideas and motivate the econometric analysis below, consider a simple Cobb-Douglas production model that extends the framework of Dell et al. (2012) to incorporate external weather effects:

$$Y_{it} = A_{it} L_{it}^{\alpha_\ell} K_{it}^{\alpha_k} \tag{2.1}$$

where Y_{it} is aggregate output for country i at period t, A_{it} is total factor productivity, L_{it} is the labor input, K_{it} is the capital stock, and α_ℓ and α_k is the output elasticity with respect to the labor and capital factors respectively.

Assume the following transition dynamics for productivity:

$$a_{it} = \frac{\Delta A_{it}}{A_{it}} = \phi_{it} + \gamma T_{it} + \sum_{j=1}^{N} w_{ijt}(\phi_{jt-1} + \gamma T_{jt-1}) \ \forall \ j \neq i \tag{2.2}$$

where the growth of total factor productivity a_{it} is a function of a domestic innovation factor ϕ_{it}, domestic weather T_{it} (which can include temperature, precipitation, and other features), and innovation factors in the previous period in other countries weighted by w_{ijt} (to capture the diffusion of technology).

[4]Certain studies in other disciplines even consider the potential for significant climate change to cause near-extinction events (Kemp et al. 2022), such as major wars in a world with abundant nuclear weapons (Brock 2021 and Von Uexkull and Buhaug 2021).

Assume the following transition dynamics for capital:

$$k_{it} = \frac{\Delta K_{it}}{K_{it}} = ns_{it} + \lambda T_{it} + \sum_{j=1}^{N} f_{ijt} Y_{jt-1} \ \forall\ j \neq i \tag{2.3}$$

where capital growth k_{it} depends on the growth of savings net of natural depreciation of capital ns_{it}, domestic weather shocks T_{it} that generate extreme weather resulting in asset loss through $\lambda < 0$, and foreign direct investment which depends on investment rate f_{ijt} and the previous period's output of country j.

Assume the following transition dynamics for labor:

$$\ell_{it} = \frac{\Delta L_{it}}{L_{it}} = p_{it} + \sum_{j=1}^{N} x_{ijt} Y_{jt-1} \ \forall\ j \neq i \tag{2.4}$$

where p_{it} is the growth in the domestic labour supply and the external demand of domestic production is represented by foreign income Y_{jt-1} and x_{ijt} which is an exogenous propensity to import country i's goods into country j.

Taking logs in the production function and differencing over one period, we have the growth equation:

$$\begin{aligned} g_{it} &= a_{it} + \alpha_\ell \ell_{it} + \alpha_k k_{it} \\ &= (\gamma + \alpha_k \lambda) T_{it} + \sum_{j=1}^{N} (w_{ijt} \gamma T_{jt-1} + \alpha_k f_{ijt} Y_{jt-1} + \alpha_\ell x_{ijt} Y_{jt-1}) + e_{it} \ \forall\ j \neq i \end{aligned} \tag{2.5}$$

where all exogenous variables not related to weather is placed into e_{it}.[5] A local weather shock to T_{it} for country i affects the domestic economy through the growth of labor productivity and the accumulation of capital as $\partial g_{it}/\partial T_{it} = \gamma + \alpha_k \lambda$. Meanwhile, a foreign weather shock that affects T_{jt-1} for any $j \neq i$ affects economic growth through: (i) suppressed international trade and tourism (x_{ijt}), (ii) global technology trends (w_{ijt}), and (iii) lower foreign direct investment into the capital stock (f_{ijt}) as:

$$\frac{\partial g_{it}}{\partial T_{jt-1}} = w_{ijt}\gamma + (\alpha_k f_{ijt} + \alpha_\ell x_{ijt}) \frac{\partial Y_{jt-1}}{\partial T_{jt-1}}, \quad j \neq i \tag{2.6}$$

Accordingly, in this model a local weather shock is less severe on the local economy than a global weather shock that affects all countries including the local one. This will be an important issue for the econometric modelling of the relationship which is discussed later in the section. The model also formalizes two of the ways that climate change affects the economy: impacts on labor productivity and asset loss from extreme weather events. Since economic growth is affected and not simply output in levels, weather shocks will have long run effects on the economy.

2.2. The Literature on Historical Weather Shocks and Economic Growth

Many studies prior to 2010 take an ennumerative approach to quantifying the potential impact of future climate change, where individual effects are all tabulated from various means and then summed together. In 11 articles surveyed in Table 1 of Tol (2009), 2.5 to $3°C$ of warming leads to an impact of between -5% to 2.5% of world income. This range is

[5] $e_{it} = \phi_{it} + \alpha_k ns_{it} + \alpha_\ell p_{it}$.

remarkable in its smallness, and emissions mitigation could only be justified through the risk of larger damages from uncertain outcomes. Their predicted effects of climate change also vary greatly depending on country or region, where temperate regions suffer much less than tropical areas. The most badly affected regions in these studies are typically Africa or parts of Asia, while Eastern Europe and Russia stand to benefit the most.

Given the myriad channels through which climate change can effect the economy, more recent studies adopt a panel data approach that relates historic weather conditions with GDP growth directly.[6] In this approach, gridded temperature and rainfall data is spatially averaged across each country and year combination, resulting in a panel dataset that allows for fixed effects and a richer treatment of shocks over time.[7]

Dell et al. (2012) was the first to consider an equation of this type:

$$g_{it} = \alpha_i + \beta_1 T_{it} + \beta_2 T_{it} D_i + \gamma_i t + \psi_i t^2 + \epsilon_{it} \tag{2.7}$$

where g_{it} is the growth in per capita income for country i and year t, α_i is a country-specific fixed effect which can absorb all time-invariant factors that affect growth such as institutions, culture, and geographic location. γ_i and ψ_i are country-specific parameters that capture quadratic time trends of economic growth,[8] T_{it} is a vector of climate variables which in this case includes average yearly temperature and average yearly rainfall, D_i is a dummy variable for whether a country is below the median GDP per capita, and ϵ_{it} is the idiosyncratic error term which is assumed to be uncorrelated with T_{it}.

In (2.7) the relationship between weather and economic growth is linear and homogeneous through β_1, but does allow for heterogeneity between countries through D_i. Using growth g_{it} and not the level of output Y_{it} allows weather shocks to have long run effects on an economy's development path. Since they find β_1 to be statistically insignificant and β_2 both significant and negative, only poorer countries are adversely affected by temperature shocks. Their model predicts a 1°C rise in temperature reduces economic growth in poorer countries by 1.3 percentage points ('pp').

Burke et al. (2015) and Burke et al. (2018) expand on (2.7) by allowing for quadratic nonlinearity in the relationship:

$$g_{it} = \alpha_i + \beta_1 T_{it} + \beta_2 T_{it}^2 + \gamma_i t + \psi_i t^2 + \epsilon_{it} \tag{2.8}$$

The inclusion of T_{it}^2 renders the effect of temperature shocks as heterogeneous with the climate of a country (rather than its income level). Burke et al. (2015) argue that the reason β_1 is insignificant in (2.7) is that rich countries are symmetrically distributed around some 'optimal' temperature, which means some will have negative correlations

[6]By modelling the end outcome directly, the researcher doesn't need to assume which mechanisms are to be included or how they work and aggregate together (compared to ennumerative methods).

[7]The literature has placed great emphasis on discerning short from long run effects of weather shocks, see e.g. Kolstad and Moore (2020) and Hsiang (2016) for discussions.

[8]It is important to note that the original specifications of Dell et al. (2012) and Burke et al. (2015) featured time fixed effects instead of country-specific quadratic time trends. It was not found to have a meaningful impact on the coefficients on domestic weather. This change was made for three reasons. It makes forecasting easier and allows for the inclusion of country-invariant variables later in the article. Third, the use of time fixed effects in climate regressions places identification on weather shocks that are distinct relative to the global norm of that year. This arguably removes too much information, as it excludes global temperature shocks from identification. Time fixed effects are usually included in a regression due to suspected correlation between common time variation in the error term and the regressors. While there are global time-varying factors that affect economic growth, or common shocks to growth, the author could not conceive of one that contemporaneously causes global weather shocks. See Appendix A for more related discussion.

with warming and some positive ones depending on which side they sit. In comparison, poorer countries mostly sit above the optimal temperature. They predict that unmitigated climate change would reduce global output by 23% in 2100 and 77% of countries in the world will be poorer.

Kahn et al. (2021) make two modifications to the above models. They point out that if T_{it} is trended (as it would be under climate change) its inclusion in the model will introduce a linear trend on g_{it} which they argue is not supported by the data and will lead to biased estimates. Their proposed alternative is to deal with deviations in temperature or rainfall from their medium-term averages, rather than entering the regression in levels form. This will, in addition, impose a particularly optimistic form of adaptation into the model.[9] Secondly, they argue that T_{it} is only weakly exogenous (as economic growth increases greenhouse gas emissions which, in turn, increases temperature).[10]

Accordingly, they employ a Panel ARDL model of economic growth:

$$g_{it} = \alpha_i + \sum_{\ell=1}^{L} \rho_\ell g_{i,t-1} + \sum_{\ell=0}^{L} \beta_\ell \Delta \tilde{T}^{+}_{i,t-\ell} + \sum_{\ell=0}^{L} \gamma_\ell \Delta \tilde{T}^{-}_{i,t-\ell} + \epsilon_{it} \tag{2.9}$$

where $\tilde{T}_{it} = T_{it} - M^{-1} \sum_{\ell=1}^{M} T_{it-\ell}$ is the deviation in temperature and rainfall from the average of the previous M years, 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.[11] The split allows positive and negative deviations to have asymmetric effects on growth. The ARDL model also incorporates lags of the dependent variable and all of the regressors, where Kahn et al. (2021) used $L = 4$ for their main specification. They find that unmitigated warming could reduce world real GDP per capita by around 7% by 2100.

2.3. The Importance of External Weather Effects in Climate Econometrics

The models outlined in (2.7) - (2.9) restrict a country's economic growth to be a function of domestic weather shocks. To the extent that external weather shocks $T_{jt} \forall j \neq i$ affect economic growth for country i, that is left inside the error term ϵ_{it}. This causes two particular problems: (i) The estimate of the effect of domestic shocks β will be biased if domestic weather shocks are correlated with external weather shocks (also known as cross-sectional dependence in panel data, which will occur under future climate change), (ii) the counterfactual of future unmitigated climate change will affect both the domestic weather variables T_{it} and the external weather variables in the error term.

It is intuitive for external shocks to affect the domestic economy due to the globalisation of trade, technology, supply chains, and financial markets in the modern global economy, where weather shocks in other countries could result in suppressed trade, foreign direct investment, foreign aid, refugee crises, and instability in financial markets. The model in (2.1) - (2.5) sought to illustrate some of these channels. For example, if crop failures in the Horn of Africa were the result of a local heatwave, that has very different implications

[9] A form of adaptation where all climate change can be fully adapted to after a certain number of years, as weather shocks are measured relative to a moving average.

[10] Chudik et al. (2018) shows by generalising the formulation of Nickell Bias that this will lead to bias in the standard FE estimator. The topic of reverse causation is further discussed in Appendix A.

[11] Kahn et al. (2021) use $M = 30$ for their main specification, and consider $M = 20$ and $M = 40$ years as alternatives to the main specification.

for the food security of the region than the result of a global heatwave. Food prices will be much higher in the latter case, as well as a reduced capacity for foreign governments and charities to avert famine in the area. Section 3.3 outlines how unmitigated climate change causes many countries to receive extreme weather shocks (relative to historical experience) simultaneously, which severely limits the ability of an economy to rely on various cushioning mechanisms that were used during historical local weather shocks such as trade, foreign aid, and budget deficits.

One simple yet crude way to incorporate external weather effects into (2.7) - (2.9) is to include a cross-sectional weighted average of global temperature and rainfall. In this way, we allow the average weather shocks of other countries to also affect domestic economic growth. For the Dell et al. (2012) model this would be:

$$g_{it} = \alpha_i + \beta_1 T_{it} + \beta_2 T_{it} D_i + \theta \bar{T}_t + \gamma_i t + \psi_i t^2 + \epsilon_{it} \tag{2.10}$$

where $\bar{T}_t = \sum_{i=1}^{N} w_{it} T_{it}$ is a weighted cross-sectional average of weather. The Burke et al. (2015) and Burke et al. (2018) model can be modified in a similar way:

$$g_{it} = \alpha_i + \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta \bar{T}_t + \gamma_i t + \psi_i t^2 + \epsilon_{it} \tag{2.11}$$

as can the ARDL model in Kahn et al. (2021):

$$g_{it} = \alpha_i + \sum_{\ell=1}^{L} \rho_\ell g_{i,t-1} + \sum_{\ell=0}^{L} \beta_\ell \Delta \tilde{T}_{i,t-\ell}^{+} + \sum_{\ell=0}^{L} \gamma_\ell \Delta \tilde{T}_{i,t-\ell}^{-} + \sum_{\ell=0}^{L} \theta_\ell \Delta \tilde{T}_t + \epsilon_{it} \tag{2.12}$$

where $\tilde{T}_t = \bar{T}_t - M^{-1} \sum_{\ell=1}^{M} \bar{T}_t$.

If the θ coefficients in these equations are significant and negative, it is evidence that a domestic economy is impacted by weather shocks in other countries. Accordingly, regressions that exclude $\bar{T}_t$ will undercount the potential economic impacts of future climate change, as the counterfactual of future climate change will affect both T_{it} and $\bar{T}_t$.

2.4. Data Sources

Real GDP per capita, used to construct g_{it}, was taken from Feenstra et al. (2015).[12] Following the conventions of previous studies, T_{it} is defined as annual average temperature and rainfall that has been spatially averaged (or summed in the case of rainfall) across each country. Monthly air temperature mean and cumulative precipitation were obtained from Matsuura and Willmott (2018). They were compiled from several sources of station data and interpolated over a 0.5 by 0.5 degree grid of the globe. This data was then mapped into countries by taking a weighted average of the temperature gridpoints in the raw data. The gridded population estimates for the year 2000 from Center for International Earth Science Information Network CIESIN (2018) were used as weights. The result is an unbalanced panel dataset with $N = 159$ and $T = 56$ on average.

Lastly, to predict the effects of future climate change on economic growth the models require projections of future annual average temperature for each country through to 2100. This requires outputs from a general circulation model ('GCM'), which in turn relies on assumptions regarding global emissions growth over the coming century. The CMIP protocol, or 'Coupled Model Intercomparison Project', was introduced by The

[12] Real GDP per capita data from World Bank (2022) was also collected and the results are available upon request. They did not meaningfully change the conclusions of this paper.

World Climate Research Program as part of the Working Group on Coupled Modelling. The protocol ensures the outputs of GCMs are comparable and able to be analyzed systematically, allowing scientists to directly compare the outputs of many GCMs. The sixth version of CMIP is the most recent effort to date from the IPCC Sixth Assessment Report.

This article uses the multi-model ensemble median temperature projections from the World Bank's Climate Change Knowledge Portal (see Zermoglio et al. 2022). Each GCM uses as an input the exogenous path for the atmospheric concentration of greenhouse gases. CMIP6 uses a variety of shared socioeconomic pathways (or 'SSPs'), which this article uses four: SSP1-1.9, SSP2-4.5, SSP3-7.0, and SSP5-8.5.[13]

3. RESULTS

3.1. Models of Historical Economic Growth

Table 1 presents the results from estimating (2.7) - (2.12) on the historical temperature and real GDP per capita growth data outlined in Section 2.4. It presents both the closed versions of the three models, which means that they exclude the global average temperature as a regressor (akin to the model specifications in the original papers), and the open models which include the global average temperature as a regressor.[14] The Dell et al. (2012) model includes a linear temperature variable, as well as an interaction with a 'poor country' dummy varible. The Burke et al. (2015) model includes a quadratic temperature specification. In both of these models, the coefficients can be interpreted as the effect on GDP per capita percentage point growth for a 1°C increase in annual average temperature. For the Kahn et al. (2021) model we report the long run effect of a normalized 1°C increase in temperature relative to the 50 year average on economic growth, with the p-values reported in brackets.

First, we consider the Dell et al. (2012) model. Both the open and closed models estimate for poorer countries a marginal effect of -0.01 on economic growth per degree of warming. Meanwhile, there is no evidence that the economic growth of richer countries are directly harmed by temperature increases. If the closed model was used to forecast the economic effects of climate change, which was not the intent of the original authors, it would predict a further divergence between rich and poor countries over the coming century and an ambiguous impact on world GDP.[15]

The open version of the Dell et al. (2012) model reveals how sensitive these predictions are to model specification. The cross-sectional average of annual average temperature has a highly negative coefficient of -0.013, rendering the marginal effect of a global temperature increase of one degree for richer countries to be -0.008 (95% CI -0.017 to 0.001) and for poorer countries -0.028 (95% CI -0.038 to -0.018). By taking into account the interdependence of modern economies when assessing the effect of climate on economic

[13] These pathways correspond to different radiative forcing values in 2100. For example, SSP-1.9 denotes a forcing of $+1.9W/m^2$ above pre-industrial levels. The larger the radiative forcing value, relative to pre-industrial levels, indicates greater greenhouse gas concentrations in the atmosphere and more extreme climate change.

[14] For the sake of brevity, certain parameter estimates aren't reported such as the results for rainfall, time trends, and fixed effects.

[15] The results are entirely consistent with the idea that some countries will benefit and some will lose from climate change, except in this model the wealth of the country is the prime determinant of which will benefit and not the preexisting climate of the country.

Table 1. Models of Economic Growth as a Function of Weather

Models of $g_{i,t}$:	Dell et al. (2012) Closed	Dell et al. (2012) Open	Burke et al. (2015) Closed	Burke et al. (2015) Open	Kahn et al. (2021) Closed	Kahn et al. (2021) Open
Domestic Temperature:						
$T_{i,t}$	0.002	0.005	0.007	0.011		
	(0.003)	(0.003)	(0.005)	(0.005)		
$T_{i,t}^2/100$			-0.035	-0.040		
			(0.014)	(0.014)		
$T_{i,t} * D_i$	-0.013	-0.015				
	(0.004)	(0.004)				
$\Delta\tilde{T}_{i,t}^{+}$					-0.027	-0.012
					{0.002}	{0.162}
Global Temperature:						
$\bar{T}_t$		-0.013		-0.013		
		(0.004)		(0.004)		
$\Delta\tilde{T}_t$						-0.106
						{0.000}
Diagnostics:						
R^2	0.142	0.145	0.142	0.144	0.078	0.087
N	8736	8736	8736	8736	8100	8100

Note: Precipitation was included in all models but excluded from the table for the sake of brevity. Robust standard errors are reported in parentheses, while brackets contain p-values. For the Kahn et al. (2021) model, the coefficient attached to $\Delta\tilde{T}_{i,t}^{+}$ is $(1-\sum_{\ell=1}^{L}\rho_\ell)\sum_{\ell=0}^{L}\beta_\ell$ from (2.9), while the coefficient attached to $\Delta\tilde{T}_t$ is $(1-\sum_{\ell=1}^{L}\rho_\ell)\sum_{\ell=0}^{L}\theta_\ell$ from (2.12). $M = 50$ and $L = 4$.

growth, even in a simplistic way, the predictions of the model are turned on their head. While the model will still predict that poorer countries are more adversely affected by climate change than richer countries, the implications for richer countries are now negative. Furthermore, the model no longer predicts that some countries will gain from future climate change.

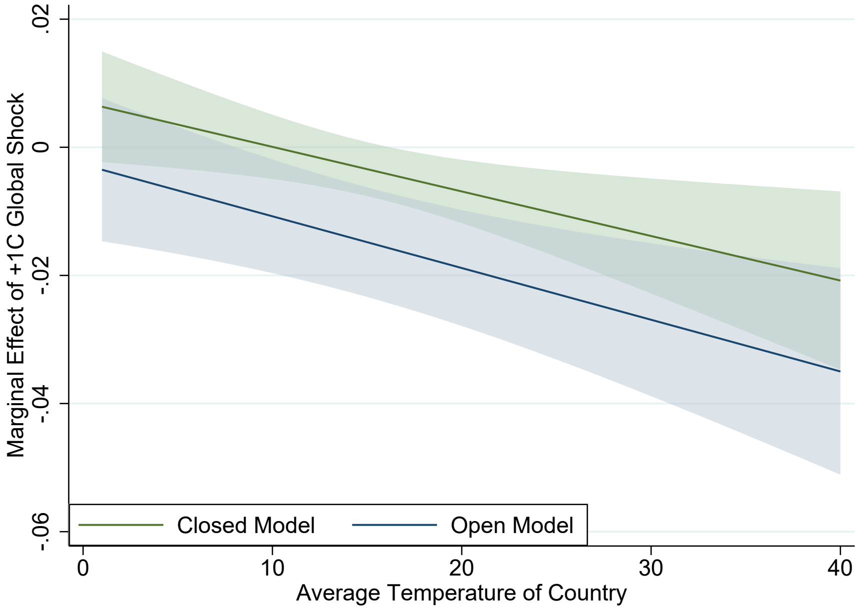
With the Burke et al. (2015) or Burke et al. (2018) model, the marginal effect of temperature shocks on economic growth varies by the climate of the country rather than per capita wealth. One degree of warming might be beneficial to a cold country yet damaging to already warm countries under this approach. The results of the closed model estimate that this is the case, although the linear term is not statistically significant. The optimal average annual temperature is estimated to be 10.1 degrees Celsius (95% CI 2.9 to 17.27 degrees), with warming above this temperature associated with lower economic growth. As above, it allows for the conclusion that future climate change (even if severe) is going to benefit some countries and hurt others.[16]

The results once again change significantly with the open model. Holding the domestic climate fixed, the marginal effect of a one degree temperature increase elsewhere in the world has a large effect on domestic economic growth of -0.013. It also lends to a more pronounced quadratic curve between domestic temperature and economic growth, with both the linear and quadratic term's coefficients further from zero. The optimal

[16] Albeit benefit fewer countries in this model relative to the Dell et al. 2012 model.

temperature in the open version of the model is now 13.1 degrees Celsius (95% CI 7.4 to 18.7 degrees).

Figure 1. Marginal Effect of a Global Temperature Shock in the Burke et al. (2015) Model



Note: This figure plots the marginal effect on economic growth from a +1° C global shock conditional on the average annual temperature experienced prior to the shock.

It predicts that future climate change will cause economic damage in all countries, even those that are particularly cold, due to its effect on global economic conditions. Figure 1 illustrates this by plotting the marginal effect of a 1°C global temperature shock. In the closed model this is equivalent to a 1°C local shock, while in the open model economic growth is affected by both the coefficients on T_{it} and $\bar{T}_{it}$. Importantly, the figure shows that while the marginal effect worsens with the country's average temperature, in the open model the marginal effect is negative in all contexts. Meanwhile, the closed model suggests that the marginal effect is not negative until average temperature crosses the optimal threshold of 10.1 degrees.

For the Kahn et al. (2021) model we report the coefficients $(1 - \sum_{\ell=1}^{L} \rho_\ell) \sum_{\ell=0}^{L} \beta_\ell$ from (2.9) and (2.12) with the p-values in brackets, and in the latter case also $(1 - \sum_{\ell=1}^{L} \rho_\ell) \sum_{\ell=0}^{L} \phi_\ell$. These algebraic expressions represent the long run effect that temperature shocks have on economic growth.[17] In the closed model, there is significant evidence that positive temperature shocks above the 50 year average have a detrimental effect on economic growth. In the open model, we find that the effect of global temperature increases are substantial and negative. Amazingly, the marginal effect of an external weather shock of one degree (holding domestic temperatures fixed) is roughly four times

[17] $M = 50$ in this specification, which means that all temperature and rainfall is measured relative to the country's 50 year average.

larger than a domestic temperature increase in the closed model. In the open model, the effect of domestic temperature shocks halve and the p-value is above 0.1.[18]

Across all three specifications, external weather effects dominate local weather effects. The closed models implicitly hold the climates of other countries fixed while exploring the counterfactual of future climate change as a large domestic weather shock. If external conditions are actually important, this will systematically bias the predicted effects of future climate change towards zero. The effect this has on predicting the macroeconomic impacts of future climate change is discussed in Section 3.4.

3.2. Robustness of the External Weather Effect

It is worthwhile considering whether the external weather effect estimated in Table 1 is sensitive to model specification and particular subsamples of the data. Appendix A presents results showing that the external effect is robust to the addition of global greenhouse gas emissions into the model, which explicitly addresses the potential for reverse causation to bias the coefficient estimate. Furthermore, it shows that the open models provide a minor yet meaningful improvement to out-of-sample forecasting performance, further supporting the idea that they are important for predicting the economic impacts of future climate change.

Table 2 presents the estimated external weather effect across all three models when applied to different subsamples of the data. It will provide insight on whether the magnitude (or existence) of the effect depends on certain types of countries or time periods. Interestingly, the external weather effect is much stronger in 1984-2017 relative to the earlier 1950-1983 period. This is intuitive given that the stylistic model outlined in (2.1) - (2.5) suggested that countries more reliant on trade would have stronger external weather effects, and the last four decades has seen significant globalization and trade liberalization across the world. The external weather effect is consistent across small and large economies in the first two models, while the Kahn et al. (2021) model estimates a much stronger effect for larger economies. The Dell et al. (2012) and Burke et al. (2015) models suggest that the effect is stronger for poorer countries on a per capita basis, but the reverse is true in the Kahn et al. (2021) model so there is no strong evidence in either direction. However, across all three models the effect is somewhat weaker for colder countries. This is intuitive, as the disruption caused by global weather shocks can be offset somewhat by more favourable conditions at home. In all, Table 2 provides evidence that the external weather effect is significant across a range of contexts and is not fragile to specification. More evidence of this is provided in Appendix A.

3.3. Median Projections of Future Climate Change

This section compares the projections of future climate change with the historical climate data across three dimensions: (i) the magnitude of weather shocks measured relative to a common norm, (ii) the distribution of temperature, and (iii) the global average annual temperature. It shows that unmitigated future climate change is completely outside our realm of experience in regards to deviation from the norm, the persistence of shocks, and global averages. This has important ramifications for the ability to use econometric

[18] In contrast to the other models, neither version of the Kahn et al. (2021) model allow for climate change to affect some countries much less harshly than others.

Table 2. Subsample Analysis on External Weather Effects

Models of $g_{i,t}$:	Dell et al. (2012)	Burke et al. (2015)	Kahn et al. (2021)
Coefficient:	$\bar{T}_{i,t}$	$\bar{T}_{i,t}$	$\Delta\bar{T}_{i,t}$
Years 1950-1983	-0.015	-0.015	-0.013
	(0.007)	(0.007)	{0.390}
Years 1984-2017	-0.031	-0.031	-0.133
	(0.006)	(0.006)	{0.000}
GDP < \$48 Bil	-0.013	-0.013	-0.062
	(0.007)	(0.007)	{0.000}
GDP > \$48 Bil	-0.014	-0.014	-0.166
	(0.006)	(0.006)	{0.000}
GDP P.C. < \$6.6K	-0.016	-0.016	-0.084
	(0.006)	(0.006)	{0.000}
GDP P.C. > \$6.6K	-0.010	-0.010	-0.129
	(0.007)	(0.007)	{0.000}
Avg. Temp < 20.56 ° C	-0.010	-0.010	-0.071
	(0.006)	(0.006)	{0.000}
Avg. Temp > 20.56 ° C	-0.016	-0.016	-0.131
	(0.007)	(0.007)	{0.000}

Note: Robust standard errors are reported in parentheses, while brackets contain p-values. The coefficient attached to $\Delta\tilde{T}_t$ *is* $(1-\sum_{\ell=1}^{L}\rho_\ell)\sum_{\ell=0}^{L}\theta_\ell$ *from* (2.12).

models to estimate the functional relationship between the cliamte and economy in the range that is relevant to explore the counterfactual of future climate change.

Table 3 outlines the frequency distribution of the deviation in annual average temperature from the 1900-1960 country-level historical average, with numbers representing the proportion of country-year observations that fit within a specific band of temperature change in period t and $t+1$. By delineating observations by the temperature deviation in t and $t+1$, the matrix conveys the magnitude of deviation as well as the persistence of significant weather shocks from one period to the next. Consider first the 1960-2017 historical data, which is shown in the top third of the table. A sizable majority of observations occur in the 0-2 degree range above the 1900-1960 country-level average. Of these, 19% revert below the 1900-1960 average in the following year, while the vast majority remain in the band for a subsequent year. Less than 1% of observations contain annual average temperatures 2 to 4 degrees above the 1900-1960 average, which represents 86 observations in the dataset. Of these observations, only two observations in the 1960-2017 historical data features temperatures at least three degrees above the 1900-1960 historical average.

Next, consider the median GCM projections of annual average temperature in the SSP1-1.9 scenario. This scenario of emissions growth, more than any other scenario considered under CMIP, represents extreme and quick decarbonization of the global economy from the present day with temperatures stabilizing around 2040 and beginning to decline in the remainder of the century.[19] There are no median projections of temperature that are below that of the 1900-1960 average, and as expected the vast majority occur within

[19]It broadly corresponds to the planet keeping warming under 1.5°C, and any effect on economic growth from future climate change will mostly be from climate change that has already been locked in from historical emissions.

Table 3. The Distribution of Temperature Deviation (%)

Δ in Temp. in t	Δ in Temp. in $t+1$ <0	0-2	2-4	4+
1960-2017 Historical Data				
<0	0.183	0.132		
0-2	0.126	0.543	0.007	
2-4	0.001	0.006	0.002	
4+				
Median SSP1-19 Projections				
<0				
0-2		0.849	0.007	
2-4		0.006	0.174	
4+				
Median SSP5-85 Projections				
<0				
0-2		0.296	0.012	
2-4			0.416	0.011
4+				0.301

Note: This table outlines the deviation in annual average temperatures from the 1900-1960 historical average for each country. The proportion of observations are reported for the 1960-2017 historical data, and the median of the GCM projected values of future observations in the 2018-2100 period using the two SSP scenarios. The table presents numbers conditional on the observation in the following period.

the 0-2 degree band. However, even with strong climate change mitigation, 17.4% of observations occur within the +2-4 degree band of weather shocks. To identify the effects within this band, we rely on the paltry 86 observations in the historical data to provide some insight. Furthermore, unlike in the historical data, most of the observations within this band also persist into the subsequent year.

Turning to the SSP5-8.5 scenario, which represents inaction on climate change, temperature deviation is far beyond any historical precedent. More than 40% of observations occur within the 2-4 degree band. Moreover, 30% of observations exceed four degrees of deviation, where there is no historical data with shocks this large. When an econometric model is used to forecast economic growth for deviations this large, it is extrapolating the functional form far beyond any observable data, which could be highly misleading given the relationship is likely to be nonlinear.

Another aspect in which the projections of the climate change scenarios differ from the historical data is the persistence of shocks. A big shift in the mean annual temperature under future climate change causes shocks that persist, unlike in the historical data. We do not have sufficient information about severe weather shocks over an entire country that persist for long periods of time. One inevitable conclusion from this table is that econometric models that rely on temperature deviation to identify the effect of weather on economic growth, such as panel fixed effects models or the Kahn et al. (2021) ARDL model, are fundamentally limited in estimating the area of the function that is relevant.

Given that future climate change causes temperature deviations far beyond historical experience, it is worthwhile considering whether exploiting cross-sectional variation in

Table 4. The Distribution of Annual Average Temperature

	Average Temp. in t			
	<10	10-25	25-30	30+
Historical Data	0.182	0.527	0.291	
SSP1 1.9	0.137	0.530	0.363	0.006
SSP5 8.5	0.079	0.518	0.358	0.081

Note: This table outlines the distribution of the annual average temperatures. It lists the proportion of observations by temperature bucket in the 1960-2017 historical data, and the median of the GCM projected values of future observations in the 2018-2100 period using the two SSP scenarios.

average temperature will alleviate this problem.[20] Table 4 outlines the distribution of average temperature in levels, with bands for annual average temperatures of below 10 degrees, between 10 and 25 degrees, between 25 and 30 degrees, and above 30 degrees Celsius.[21] In the historical data, just over half of the observations occur in the wide 10 to 25 degree annual average range. In the SSP1-1.9 scenario, we observe a mild shift away from annual averages below 10 degrees Celsius, and greater weight on the 10-25°C and 25°C+ bands. Also, for the first time, we observe a small number of observations with annual averages above 30°C, which is unprecedented in the historical data.

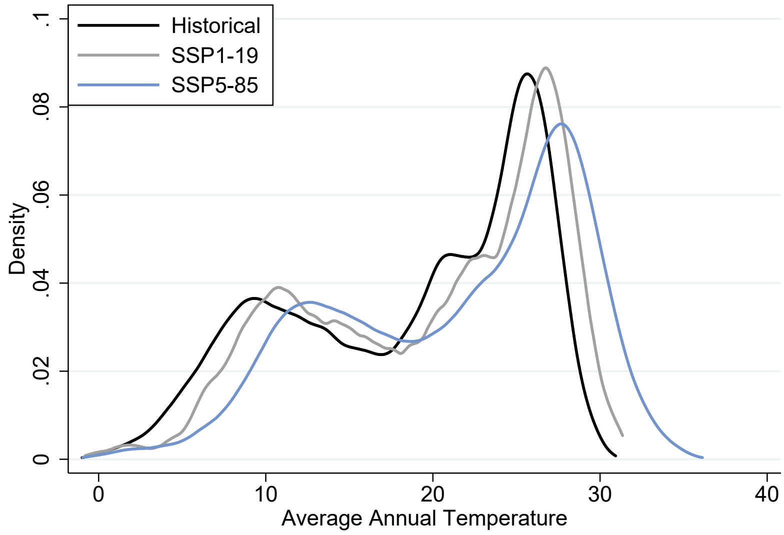
As expected, the SSP5-8.5 scenario exhibits a significant shift in observations into the 25-30°C band and away from the <10°C band. Most dramatically, there are roughly 8% of observations with annual average temperatures above 30°C. Figure 2 illustrates the shift in the annual average from future climate change. Under SSP5-8.5, there is not only a significant rightward shift in the distribution but a flattening of annual averages below 10 degrees, with a fat tail going upward to 36°C. Despite the significant differences, 92% of observations from the median climate change projections have precedent in history. Accordingly, allowing for cross-sectional variation makes the econometric model more relevant for forecasting, but does introduce the problem of omitted variable bias. Even in a cross-sectional model, we see that unmitigated climate change pushes some countries into extremes not observed anywhere in the world with a measurable economy.

Lastly, it is worthwhile to consider the projected increase in global average temperatures from different emission growth trajectories. Figure 3 plots both the historical average and the median projections (across GCMs) of the global average temperature for five scenarios of emissions growth: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5. Unsurprisingly, average temperatures increase over time and with higher emission scenarios. The most striking fact is that the increase in the range from future climate change is far larger than the idiosyncratic variation over the historical period. The stan-

[20] Using such information in a panel data regression would be akin to excluding fixed effects from the regression, and the idea would be that the experience of the Mediterranean might be indicative for the future of cooler countries in Northern Europe, while the experience of Central America might be more indicative of the future of the Mediterranean, and so forth. There are many problems with this notion. Notably, there might be important time-invariant factors other than climate that make these regions of the world different. The reason researchers include fixed effects in these regressions is because they expect the current economic growth dynamics of countries with warmer climates is not reflective of future growth dynamics of cooler countries experiencing climate change. See Hsiang (2016) for a discussion.

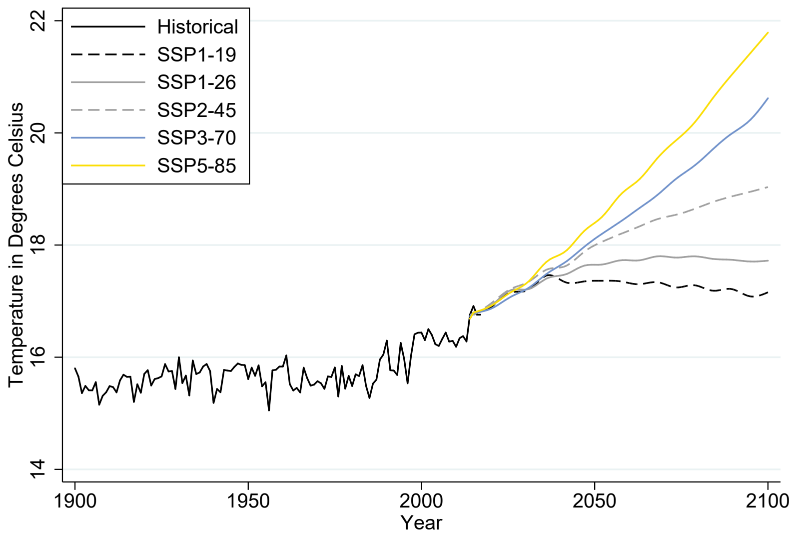
[21] Note that many countries with average temperatures in the 20s will experience days or spells of temperatures in the 30s or even 40s.

Figure 2. The Distribution of Annual Temperature



Note: This figure presents kernel densities of average annual temperature by country and year from the historical data and median values from two climate change scenarios.

Figure 3. Yearly Average Temperature Weighted by Income Per Capita



Note: This figure plots the global yearly temperature, which is averaged across countries and weighted by income per capita, for the historical period as well as the median projection for several future emissions trajectories according to the CMIP6 collection of GCM models.

dard deviation over the historical period is 0.37 degrees, with the global average hovering between 15 and 16 degrees until the late 1990s when warming starts to accelerate.[22]

In the SSP1-1.9 scenario, climate change is expected to increase global average temper-

[22]Note that this series is a weighted global average from country-level averages that is weighted by

atures to 17.6 degrees in 2050 (using this particular weighted average) before declining back to 17.4 degrees in 2100. The 2050 value represents an increase in 0.8 degrees above that observed in the preceding decade, and is more than 4 standard deviations above the historical mean. With SSP5-8.5, average temperatures increase up to five degrees more than the maximum observed in the historical period. In 2050 global average temperatures are seven standard deviations above that of the historical mean, and in 2100 it is 16 standard deviations above the historical mean. Accordingly, the idiosyncratic variation in historical global temperatures is far too small to allow an econometric model to estimate the function between external weather and growth at close to a relevant range.

3.4. Prediction Experiments of Future Climate Change

The research question that motivates the above models is the potential economic impacts of future climate change, and accordingly their ability to predict this is their most important feature. Appendix A presents an out-of-sample forecasting exercise which shows that the open models provide an improvement to prediction error. This section conducts experiments where projected temperature changes are fed into these models to determine their prediction of future economic growth under climate change. The end outcome of interest in this experiment is global GDP under each of the climate change scenarios, where:

$$WGDP_{mst} = \sum_{i=1}^{N} GDP_{msit} \tag{3.13}$$

for econometric model m, SSP climate change scenario s, country i and year $t = 2018$, 2019, ..., 2100 where $GDP_{msit} = GDP_{msi,t-1} * (1 + \hat{g}_{msit})$ and $\hat{g}_{msit}$ is the predicted economic growth from model m.

For the Dell et al. (2012) model, we have:

$$\hat{g}_{m=1,sit} = \hat{\alpha}_i + \hat{\beta}_1 T_{sit} + \hat{\beta}_2 T_{sit} D_i + \hat{\theta}\bar{T}_{st} + \hat{\gamma}_i t + \hat{\psi}_i t^2 \tag{3.14}$$

where the parameters were estimated from the historical data and $\hat{\theta}$ is constrained to be zero for the closed model or freely estimated in the open model. For the Burke et al. (2015) or Burke et al. (2018) model we have:

$$\hat{g}_{m=2,sit} = \hat{\alpha}_i + \hat{\beta}_1 T_{sit} + \hat{\beta}_2 T_{sit}^2 + \hat{\theta}\bar{T}_t + \hat{\gamma}_i t + \hat{\psi}_i t^2 \tag{3.15}$$

and finally for the Kahn et al. (2021) model we have:

$$\hat{g}_{m=3,sit} = \hat{\alpha}_i + \sum_{\ell=1}^{L} \hat{\rho}_\ell g_{i,t-1} + \sum_{\ell=0}^{L} \hat{\beta}_\ell \Delta\tilde{T}^{+}_{i,t-\ell} + \sum_{\ell=0}^{L} \hat{\gamma}_\ell \Delta\tilde{T}^{-}_{i,t-\ell} + \sum_{\ell=0}^{L} \hat{\theta}_\ell \left(\bar{T}_t - M^{-1} \sum_{\ell=1}^{M} \bar{T}_t \right) \tag{3.16}$$

where $t = 2018, 2019, ..., 2100$. In place of historical values of T_{sit}, we use the median of the CMIP6 model ensemble projections of future temperature generated for each country by Zermoglio et al. (2022). To reflect econometric uncertainty underlying the relationships, the parameter values of (3.14) - (3.16) are estimated 1,000 times using a weighted bootstrap method (see e.g. Hall and Maesono 2000), where a random weight is used to

the country's GDP per capita. The level of the average might not be consistent with global average temperatures that are derived in other ways, but the trends will likely be similar.

determine the incidence of observations in each bootstrapped sample.[23] These 1,000 parameter estimates from bootstrapped samples are used to form 95% prediction intervals by taking the 5th and 95th percentile prediction.

Table 5 outlines the result of this prediction experiment for: the three models in both a closed and open specification, the years 2050 and 2100, and three CMIP6 emissions scenario that are used for the temperature projections (SSP2-4.5, SSP3-7.0, and SSP5-8.5). Importantly, each number is the percentage change in world GDP relative to that predicted in the SSP1-1.9 scenario, which indicates that it is the prediction of the economic damage that accrues from any climate inaction that results in slower emissions reductions relative to the ambitious SSP1-1.9 scenario.[24] This results in 36 distributions of projections, and we summarize them with the mean prediction as well as the 5th and 95th percentiles from the bootstrap procedure outlined above. The top panel of the table shows results for closed models, while the lower panel shows results for open models.

First consider the closed Dell et al. (2012) model, which is unique in that temperature is linearly related to economic growth with a dummy variable for poorer countries. The closed model predicts a mildly positive relationship for richer countries and a negative one for poorer countries. Accordingly, the projected impacts of climate change are highly uncertain. In 2050, only the SSP-8.5. scenario shows tangibly negative impacts from climate change. In 2100 the mean projection is more negative but not cardinal with the amount of emissions growth (i.e. the SSP3-7.0 scenario is worse for the economy than SSP5-8.5), and that is because this model predicts a divergence in growth rates between rich and poor countries. This also leads to the problem of extremely uncertain projections, with the impact of SSP5-8.5 ranging from -50% to +50% of world GDP in 2100 relative to SSP1-1.9.

The Burke et al. (2015) model relates temperature to growth through a quadratic function, allowing the relationship to vary by country according to their preexisting climate. The closed model predicts minor economic damage from future climate change in 2050, yet the damage becomes very severe in 2100 and depends meaningfully on the planet's emissions trajectory. While economic damage is severe in any scenario beyond SSP2-4.5, it is catastrophic in SSP5-8.5. While the range of predictions remains large, they are more precise than in the Dell et al. (2012) for reasons outlined above.[25]

The Kahn et al. (2021) model is distinct in that it relates economic growth to temperature shocks above the fifty year moving average, and allows for dynamic effects through the ARDL specification. This model assumes that the world can fully adapt to any severity of climate change in 50 years. Accordingly, we might expect that it would predict less severe economic damage from climate change. The results for 2050 are slightly more

[23] Essentially, a draw from a uniform distribution is assigned to each observation and weighted OLS is used to estimate the parameter values of (3.14) - (3.16), and the predictions of economic growth under climate change are then formed. This is repeated 1,000 times to form a distribution of predictions in each scenario and model. The benefits of this approach is that it doesn't break the panel structure of the dataset and is computationally efficient to implement.

[24] An alternative to this approach is to freeze the current climate of the planet and use that as the benchmark. Since a certain amount of future climate change is locked in even if emissions plummeted tomorrow, the more policy-relevant research question is the implications of slow emissions reductions relative to very fast emissions reductions.

[25] The predicted economic damage presented here exceeds the headline result presented in the original Burke et al. (2015) paper. This is due to a different prediction experiment design, but they are broadly consistent with the ones presented in Extended Data Table 3 in their paper, as the 'pooled with 5 lags' specification predicted a loss of 73% relative to a world without climate change.

Table 5. World GDP Per Capita Relative to SSP1-1.9 (%)

Models of $g_{i,t}$:	Dell et al. (2012)	Burke et al. (2015)	Kahn et al. (2021)
Models Excluding World Temperature / Closed Models			
2050:			
SSP2-4.5	-0.007	-0.016	-0.029
	(-0.019, 0.004)	(-0.025, -0.007)	(-0.040, -0.019)
SSP3-7.0	-0.005	-0.012	-0.037
	(-0.015, 0.004)	(-0.020, -0.005)	(-0.050, -0.024)
SSP5-8.5	-0.034	-0.052	-0.054
	(-0.061, -0.012)	(-0.076, -0.027)	(-0.073, -0.035)
2100:			
SSP2-4.5	-0.178	-0.371	-0.032
	(-0.371, 0.059)	(-0.535, -0.181)	(-0.045, -0.019)
SSP3-7.0	-0.202	-0.512	-0.092
	(-0.450, 0.203)	(-0.724, -0.278)	(-0.125, -0.061)
SSP5-8.5	-0.184	-0.671	-0.125
	(-0.540, 0.503)	(-0.850, -0.361)	(-0.169, -0.083)
Models Including World Temperature / Open Models			
2050:			
SSP2-4.5	-0.070	-0.092	-0.134
	(-0.097, -0.043)	(-0.114, -0.067)	(-0.152, -0.112)
SSP3-7.0	-0.058	-0.076	-0.170
	(-0.081, -0.035)	(-0.095, -0.055)	(-0.193, -0.143)
SSP5-8.5	-0.129	-0.164	-0.224
	(-0.171, -0.088)	(-0.195, -0.125)	(-0.254, -0.190)
2100:			
SSP2-4.5	-0.579	-0.729	-0.155
	(-0.713, -0.415)	(-0.806, -0.601)	(-0.180, -0.129)
SSP3-7.0	-0.699	-0.861	-0.361
	(-0.831, -0.491)	(-0.924, -0.742)	(-0.407, -0.307)
SSP5-8.5	-0.784	-0.944	-0.464
	(-0.906, -0.528)	(-0.976, -0.848)	(-0.517, -0.400)

Note: This table presents the mean prediction, as well as the 5th and 95th percentile prediction in parentheses, of world GDP relative to that predicted for the SSP1-1.9 scenario of climate change. Numbers are in percentage change and are split by year, model, SSP scenario, and whether the model includes average world temperatures.

pessimistic than the Burke et al. (2015) model, particularly in scenarios with less strong emissions growth. The predictions for 2100 are very optimistic relative to the other two models, in line with the results from the forecasting exercise in the original Kahn et al. (2021) paper. For the SSP5-8.5 scenario the model expects future climate change to damage the world's gdp per capita by 12.5% relative to the SSP1-1.9 scenario. This is not an insignificant amount of economic harm, by any means, but is not severe and arguably trivial relative to potential economic growth from technological development over the coming century.

Turning to the open models, which are presented in the lower panel of Table 5, they each offer fundamentally different projections than the closed models. The Dell et al. (2012) closed specification predicted that only poor countries will be harmed by future climate change, yet with the inclusion of the global average temperature both rich and poor countries are affected negatively by future climate change to different degrees. We see this in the results, where economic damage is minor yet meaningful at 2050, and dramatically worsens by 2100 with catastrophic levels of economic damage on the global economy. The bands around the point projections have also tightened significantly.

The open Burke et al. (2015) model is even more pessimistic than the closed model. Economic damage is more severe across all the emission growth scenarios and years considered, which is remarkable considering the degree of economic damage that was predicted under the closed model. The same is true of the open Kahn et al. (2021) model. In fact, the projected economic damage in 2050 for the SSP2-4.5 scenario is worse than that of the SSP5-8.5 scenario in 2100 from the closed model. In the open model, the mean projection of economic damage in 2100 for the SSP5-8.5 is -46% which is severe. This is notable given the model assumes that humanity can fully adapt to any amount of climate change within fifty years.

In summary, this section has shown that once the existing models are made to account for external weather effects, their predictions of economic damage change in three important ways. The first is that future climate change has the potential to have dire and catastrophic implications on economic prosperity. The second is that all three open models agree much more closely on the severity of the global consequences of future climate change relative to the three closed models. The third is that all open models predict that all country will be adversely affected from climate change, which is in contrast to the closed models of Dell et al. (2012) and Burke et al. (2015).

The catastrophic predictions offered by the open models suggest that unmitigated climate change has the potential to dwarf all other economic trends in the coming century and have an unprecedented and devastating impact on the global economy. More work is needed to provide plausible projections of climate change damage. One example is adaptation. The Burke et al. (2015) model is not able to take adaptation into account, while the Kahn et al. (2021) model assumes perfect adaptation over time. Allowing for data-driven estimates of adaptation will likely lead to more sensible predictions. Another area for future research is utilising more disaggregated weather data to mitigate the stark gap between the historical data used in econometric models and the projections of future climate change. The intent of this article is not to arrive at a final estimate, but to demonstrate that prior mild estimates of macroeconomic climate change damage, where some countries even benefit or are unaffected, is dependent on assumptions which aren't supported in the data. Even simple modifications to existing models produce far more pessimistic estimates of climate change damage, which are arguably more in line with the warnings coming from the physical sciences.

4. CONCLUSION

The future effects of climate change on the global economy is arguably one of the most pressing and unsolved questions in economics. Recent work on the topic has exploited the panel nature of weather data to employ econometric models that estimate the relationship between economic growth and historical weather shocks, which are then used to estimate the damage from future climate change scenarios. The main contribution of this article is to demonstrate that existing models are unable to appropriately distinguish between the impacts of local and global weather shocks. By leaving external weather effects in the error term, the models are unable to plausibly forecast the effects of future climate change given that it represents a global and persistent shock.

By modifying existing models to incorporate the weather events of other countries, this article finds strong evidence across all three models that external weather effects are important in the relationship between economic growth and the climate. A forecasting exercise revealed that this addition made three significant changes to the model's predictions about future climate change: (i) the economic damage from future climate change is much greater than previously predicted, (ii) no countries stand to benefit from climate change, and (iii) model predictions agree much more closely than previously.

The article also demonstrates that the projections of future climate change lie well beyond the range of observations that can be seen in the historical weather data, whether in terms of temperature in levels, deviation from some norm, or the global average temperature. Accordingly, econometric models that are specified using annual average temperatures are unable to estimate the relevant range of the function between weather and economic growth.

While the evidence from the open models is that existing closed models could be significantly understating the economic damage of future climate change, there remains a great deal of uncertainty. What is clear is that the two consensus views from the literature, that future climate change will have mild to moderate impact on the world economy and some countries are likely to benefit or be unaffected, are very fragile to the specification of the model. In this way, the results are complementary with Newell et al. (2021) who found that out-of-sample forecasting performance for these models are insensitive to large changes in the model specification which lead to very different predictions of future impacts.

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A. SUPPLEMENTARY RESULTS

A.1. Reverse Causation in Climate Regressions

One potential complication of climate regressions, which regress economic growth on some function of weather, is the reverse causation between economic activity and weather itself. Just as weather can impact economic activity, economic activity influences the future climate. This motivates the use of integrated assessment models for forecasting future economic activity under climate change, as economic growth trends will feedback into the severity of future climate change. If we construct a simple economic system whereby:

$$\begin{aligned} g_{it} &= f(T_{it}, \bar{T}_t, GDP_{i,t-1}, A_{it}), \\ T_{it} &= g(GHGc_{it}) = g(\sum_{i=1}^{N}\sum_{\ell=1}^{L} GHGe_{it-\ell}), \\ GHGe_{it} &= h(GDP_{it}) \end{aligned} \tag{1.17}$$

where economic growth of country i at year t g_{it} is some function $f()$ of domestic temperature/climate T_{it} (assume that larger values of T_{it} represents hotter climates), global temperature $\bar{T}_t = N^{-1}\sum_{i=1}^{N} T_{it}$, preexisting economic conditions $GDP_{i,t-1}$, and some factor A_{it} incorporating productivity shocks. In turn, the weather draw during period t will be some function $g()$ of the global greenhouse gas concentrations in the atmosphere $GHGc_{it}$, which in turn is determined by global greenhouse gas emissions $\sum_{i=1}^{N} GHGe_{it}$ in the last period and all previous periods up to L which is the number of years until greenhouse gas emissions disperse from the atmosphere and cease to have influence over temperature.[26] Greenhouse gas emissions are in turn some function h of economic activity. In this way, prior economic conditions affect both temperature draws and economic growth in the current period.

This leads to the weather variables, T_{it} and $\bar{T}_t$ being technically weakly exogenous or predetermined as they are related to lags of the dependent variable in any regression. However, two features of the above system prevent this from being a meaningful econometric problem. First, weather draws in country i are affected by global greenhouse gas emissions, which substantially weakens the correlation with local emissions $GDP_{it-\ell}$ (with the strength of the correlation dependent on the size of the domestic economy). Second, weather draws are assumed to be unrelated to emissions in period t, reflecting the fact that it takes time for GHG emissions to affect temperature due to the ocean's thermal inertia (e.g. see Zickfeld and Herrington (2015) for simulations showing the peak warming effect from an emission pulse starts at 10 years following the emission). This prevents T_{it} from being even a little endogenous in the main regressions of (2.10) - (2.12).

The potential for reverse causation or omitted variable bias from biasing the estimate of the coefficient on $\bar{T}_{i,t}$ can be directly tested by including atmospheric concentrations of greenhouse gas emissions $GDPc_t$ and its lag directly into the model. The system set out in (1.17) would suggest that $GHGc_{it}$ is not related to g_{it} independently of T_{it}, while the lag $GHGc_{it-1}$ will be correlated with g_{it} due to its correlation with $GDP_{i,t-1}$. Table 6 reports regression results from the three models where changes in greenhouse gas concentrations are included in the model. For the sake of brevity, only the results pertaining to external weather effects and GHG concentrations are reported.

Across all three models, the inclusion of greenhouse gas concentration changes did not affect the coefficient estimates of external weather effects nor their standard errors. As expected, the contemporaneous value of $\Delta GHGc_t$ is statistically insignificant with a magnitude close to zero, while the lag $\Delta GHGc_{t-1}$ is significant and positive. The results support the argument that the estimated effect of external weather effects in the main body of the paper is not biased due to reverse causation or other endogeneity concerns arising from the timing assumptions relating to emissions and their influence on weather draws.

A.2. Out-of-sample Forecasting Performance

Another test of the robustness of the open models is to see if they lead to better out-of-sample predictions of economic growth relative to the closed models. This is particularly relevant given that the models are primarily used to predict the potential impact of climate change on the future economy. Table 7 reports the results from an out-of-sample forecasting exercise. The six model specifications are estimated using data from 1950-2013, and then tasked with predicting GDP per capita growth from 2014 to 2017. The

[26] In the case of carbon dioxide, it takes roughly 100 years for it to disperse.

Table 6. Regression Results with GHG Concentrations

Models of $g_{i,t}$:	Dell et al. (2012)	Burke et al. (2015)	Kahn et al. (2021)
$\bar{T}_{i,t}$	-0.013	-0.013	
	(0.004)	(0.004)	
$\bar{\theta}_{i,t}$			-0.104
			{0.000}
$\Delta GHGc_t$	0.000	0.001	
	(0.002)	(0.002)	
$\Delta GHGc_{t-1}$	0.008	0.008	
	(0.002)	(0.002)	
$\bar{\lambda}_{i,t}$			0.005
			{0.072}

Note: Local temperature and precipitation was included in all models but excluded from the table for the sake of brevity. Standard errors are reported in parentheses, while brackets contain p-values. See the note to Table 1 for details on the construction of $\bar{\theta}_{i,t}$, while $\bar{\lambda}_{i,t}$ represents the total long term effect from an impulse shock to $GHGc_t$ in the Kahn et al. (2021) model.

table lists both the root mean squared error ('RMSE') and median absolute error ('MAE') across countries for each of the out-of-sample years.

The results are conclusive. The Kahn et al. (2021) offers significantly better prediction performance relative to the other models, which is unsurprising given it is a dynamic model. The Burke et al. (2015) is occasionally a slight improvement over the Dell et al. (2012) model, but are otherwise indistinguishable. Accordingly, the inclusion of the quadratic on temperature in the Burke et al. (2015) is fairly comparable to the interaction with the poor country dummy of the Dell et al. (2012) model. The open models yield a small yet meaningful improvement in RMSE in all cases save the Kahn et al. (2021) model in 2016 and 2017. The improvement in MAE is much more pronounced, with the value smaller than half that of the closed models in most situations. Given the robustness of the sign and magnitude of external weather effects to subsample analysis and the inclusion of greenhouse gas emissions, along with the improvement to out of sample forecasting performance evident in the open models, the more general models appear to be a real improvement which may offer much more realistic predictions of the impact of future climate change on the global economy.

Table 7. Out of Sample Forecasting Results for 2014-2017

Years	2014	2015	2016	2017
Root Mean Squared Error				
Dell et al. (2012):				
Closed	0.090	0.159	0.124	0.163
Open	0.087	0.154	0.122	0.161
Burke et al. (2015):				
Closed	0.090	0.158	0.123	0.163
Open	0.087	0.153	0.121	0.161
Kahn et al. (2021):				
Closed	0.072	0.132	0.083	0.127
Open	0.071	0.127	0.085	0.128
Median Absolute Error				
Dell et al. (2012):				
Closed	-0.017	-0.021	-0.029	-0.004
Open	-0.006	-0.005	-0.023	0.003
Burke et al. (2015):				
Closed	-0.016	-0.021	-0.028	-0.004
Open	-0.006	-0.006	-0.024	0.002
Kahn et al. (2021):				
Closed	-0.007	-0.016	-0.016	0.006
Open	-0.001	-0.000	-0.014	0.012

Note: The table reports root mean squared error and median absolute error for the six models when used to forecast out of sample. All models were run using data from 1950-2013 and the estimated parameters were used to predict economic growth for 2014-2017.