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Temperature and GDP: A review of climate econometrics analysis

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ABSTRACT

Climate econometric analysis of the relationship between temperature and gross domestic product (GDP) is increasingly being used to evaluate climate risks and understand economic impacts caused by climate change. We review the literature on growth and level effects (i.e., temperature rise respectively affects the growth and level of economic output), the setting of temperature variables' forms and functional forms, and the inherent model specification of climate econometrics. Additionally, we introduce an approach for combining empirical findings with climate change integrated assessment models (IAMs) to improve damage modelling. Our findings show that estimates of damage through growth effects are generally much larger than those through level effects. Diverse impact mechanisms and adaptation effects can be revealed by changing the time resolution of temperature variables, introducing non-linearity into econometrics functions, and specifying temperature deviation. Combing the cross-sectional and panel model would enable us to examine the economic impacts at different future times.

1. Introduction

Climate change has already exerted impacts on the natural and socio-economic system and will continue to do so for centuries, and a growing body of research is focusing on how it will affect societies and economies (Stern, 2013; Carleton and Hsiang, 2016; Auffhammer, 2018; Carrilho-Nunes and Catalão-Lopes, 2022; Fabozzi et al., 2022). Further research into the economic consequences of climate change is critical for practical policymaking as it can clarify how to trade off the benefits of mitigating greenhouse gas emissions(GHGs) with the costs and value of climate change mitigation spending compared to other social investments (Wei et al., 2018; Nordhaus, 2019, 2020; Chakraborty and Mazzanti, 2021; Chen et al., 2023).

Previous research exploring the impact of climate change on the economy has relied upon process-driven models which replicated distinct physical and market equilibrium processes to simulate the consequences of climate factors on a sector or aggregate output in the socio-economic system (Tol, 2021; Rising et al., 2022). Instead, benefitting from an increasingly data-rich environment, there is a growing trend in recent research to employ the climate econometrics strategy to investigate the economic effects of climate change (Hsiang, 2016; Castle and Hendry, 2022). The approach parameterises impacts in a reduced-form empirical model capturing the connection between climate and outcome; for example, temperature and GDP which are estimated referencing historical data to directly reflect real-world settings. Climate econometrics can expand the research scope of previous literature on climate change impacts that have not been previously considered; for example, the climate effects on labour productivity, capital and total factor productivity (Fankhauser and Tol, 2005; Lecocq and Shalizi, 2007; Zivin and Neidell, 2010; Zhang et al., 2018; Henseler and Schumacher, 2019).

Research applying climate econometrics to explore climate impacts can be divided into two categories of sectoral studies and top-down, aggregate macro-economic output studies (Hsiang, 2016; Rising et al., 2022). Sectoral studies primarily examine agriculture, energy demand, mortality, crime and labour productivity (Hsiang et al., 2013; Dell et al., 2014; Carleton and Hsiang, 2016; Hsiang et al., 2017; Auffhammer, 2018). Nevertheless, these studies usually measure the socio-economic impacts by physical units such as crop yield, deaths etc., even while not always (Diaz and Moore, 2017; Sarofim et al., 2019). While, a set of

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research has focused on identifying the impacts of climate change on macro-economic output from a top-down perspective by estimating the relationship between temperature and GDP, which became a critical topic in climate econometrics research (Dell et al., 2009, 2012; Burke et al., 2015; Kalkuhl and Wenz, 2020; Colacito et al., 2021; Newell et al., 2021). There are two highlights for this strand of research. One is the use of GDP to measure economic impact as a monetary unit for measuring aggregate macro-economic output. This offers a means to quantify human welfare under the assumption that the prices of the commodities and services on the market accurately capture the costs associated with their production and use. The second is the top-down perspective, which partially avoids the need for explicit representation of impact on individual sectors and associated criticisms of the omitting of impact types, interaction effects and adaptation (Dell et al., 2012; Burke et al., 2015; Moore and Diaz, 2015; Lemoine and Kapnick, 2016).

A series of key problems and research challenges for modelling the temperature–GDP relationship using climate econometrics have been frequently discussed. We summarise them into four relevant research strands. First, does temperature affect GDP level or growth? There are numerous discussions and disagreements in the research regarding whether temperature impacts GDP level or growth. Findings in recent literature have demonstrated that the damage estimated through modelling level effects is underestimated in contrast to models of growth effects since the temperature impacts on GDP growth accumulate over time but level effects do not (Dell et al., 2012, 2014; Burke et al., 2015, 2018; Colacito et al., 2021; Newell et al., 2021). The literature related to growth effects has also involved considerable disagreement over the details, with substantial variance in resulting estimates (Dell et al., 2012; Burke et al., 2015; Carleton and Hsiang, 2016; Hsiang et al., 2017; Pretis et al., 2018; Henseler and Schumacher, 2019; Colacito et al., 2021; Kahn et al., 2021; Newell et al., 2021).

Second, how is the functional form of temperature–GDP nexus specified? The specification of the functional form of temperature–GDP varies in previous climate econometrics literature (Dell et al., 2014; Newell et al., 2021). The choice of linear or non-linear forms can dramatically influence estimations of temperature impacts. For instance, linking the aggregate per capita economic growth at the country level to a linear function with the independent variable of temperature and precipitation, Dell et al. (2012) found that temperature shocks only negatively impact growth in developing countries. In contrast, Burke et al. (2015) used a non-linear form to identify a ‘turning point’ of the annual average temperature of 13 °C for GDP growth, demonstrating that countries with lower temperatures would either have boosted growth or be harmed when temperatures rise.

Third, how are temperature variables specified? Several studies have used different temperature variables to explore the impact of temperature on GDP under different time resolutions, revealing the impact mechanism of non-linearity and identifying the adaptation effects in long-term climate change, among other considerations. For example, studies have used different time resolutions, including annual (Burke et al., 2015; Diffenbaugh and Burke, 2019; Chang et al., 2020), monthly (Pretis et al., 2018) and seasonal temperature variables (Chen and Yang, 2019; Yuan et al., 2020; Colacito et al., 2021). Some studies have investigated non-linear effects using temperature bins (Deryugina and Hsiang, 2014; Chen and Yang, 2019). In addition, recent research has revealed the inherent limitations of temperature on GDP when examined across a variety of non-climate factors using a daily temperature variable (Kotz et al., 2021), and explored the implicit adaptations required to mitigate the long-run impacts of temperature on GDP by constructing a variable of temperature deviations based on respective historical norms (Kahn et al., 2021).

Fourth, how is the climate econometrics model specified? It is crucial to investigate the model specifications for climate econometrics as they have rapidly developed from cross-sectional approaches to panel models over the past two decades (Dell et al., 2009, 2014; Hsiang, 2016; Kolstad and Moore, 2020; Castle and Hendry, 2022). More advanced models not only use different types of data which vary in time and space but can also control for the unobservable omitted variables. Moreover, different specifications help to distinguish short- and long-run climate impacts, and potential adaptation effects can also be identified using appropriate specifications. Recent hybrid models even can simultaneously consider a series of short- to long-term effects (Kalkuhl and Wenz, 2020). In addition, given that current damage functions have been criticised regarding the paucity of empirical evidence and examining the temperature–GDP relationship can directly provide a monetised indicator for measuring economic impact (Pindyck, 2013; Stern, 2013; Stoerk et al., 2018; Stern et al., 2022), estimating the relationship between temperature and GDP using the climate econometrics model can improve the accuracy of the IAMs that are commonly used to determine the optimal climate policy by examining the costs and benefits trade-offs of mitigation.

By reviewing the climate econometrics literature on the temperature-GDP nexus, this study first identifies the critical differences between the growth and level effects of temperature and the determinants of them. Also, it identifies the debate in current research on both effects and how state-of-the-art studies combine both effects to investigate the temperature effects on GDP. Secondly, this research summarises the characteristics of impact functions in both linear and non-linear forms and their application scenarios, and further identifies the shortcomings of the linear form and how it can be improved by the non-linear form. Thirdly, this study categorises the forms of temperature variables in existing studies by temporal resolution and shows how current research uses different types of temperature variables to investigate the impact mechanisms between temperatures and GDP. It also identifies the improvements brought about by the introduction of the form of temperature deviation used in recent research. Fourth, this study reviews the development of climate econometric models and sorts out the characteristics of different model specifications of the temperature-GDP relationship, comparing their advantages and disadvantages. Next, each specification of the climate econometric model is matched with its appropriate application scenario. Fifth, the study identifies the channels through which future research can combine climate econometrics with IAMs. Finally, it illuminates the limitations of existing studies and summarize a series of future potential directions.

The literature review contributes significantly to multiple facets including that firstly, it reveals the lack of consensus in identifying and interpreting growth and level effects among existing empirical studies and suggests that future research should incorporate multiple model specifications of climate econometrics into a single model to distinguish between the characteristics of growth and level effects in the short, medium, and long term. Secondly, it finds that an increasing number of studies are utilizing relevant variables that can capture climate variability to describe climate change, rather than solely relying on absolute values of climate or weather factors. Future research should focus on developing climate econometrics models that incorporate or improve these variable forms in order to avoid potential estimation bias caused by spurious regressions, ignoring the adaptation effects and so on. Thirdly, the study finds that projecting future climate change impacts on GDP by extrapolating the existing empirical temperature-GDP relationship may result in estimation bias, as these relationships do not fully reflect potential future adaptation effects, leading to biased projections of future impacts. To improve this, we suggest that future studies should use more comprehensive data and integrate long-difference econometrics models to identify climate adaptation patterns at a regional level over an extended period of time. Fourthly, we note that a substantial body of empirical research has already investigated the impact of temperature on GDP and its determinants. Therefore, we recommend that future studies incorporate these existing empirical foundations into the damage functions of IAMs. Finally, we also have identified a number of other research directions that need to be further explored, including identifying the potential empirical nexus between climate change and non-market sectors such as biodiversity, health and tipping points as well as examining the underlying temperature effects in the trading network.

2. Does temperature affect GDP level or growth?

Using growth or level effects to model the temperature-GDP relationship has been a controversial topic. The level effect assumes that temperature rises only temporarily affect the level of economic output, and once the temperature returns to the pre-warming value, the level effect disappears. In contrast, the growth effect assumes that temperature rise permanently affects economic output growth, and this effect will not disappear even if the temperature returns to the pre-warming value but will compound over time instead. The premises of these two effects are presented in Fig. 1, considering a period of rising temperatures relative to historical norms ($\Delta T > 0$), which is eventually (but not always) reversed. The red line indicates that rising temperatures could damage the GDP level; however, once temperatures have stabilised, the GDP can restart growth at the rate prior to the temperature rise. Although this generates a lower GDP level relative to the initial trajectory, the trend rate either remains unchanged (black line), or the damage would be so significant that it lowers the trend rate of GDP growth (blue line). If GDP growth is impacted by temperature changes, at some future time, the output will depend on the trajectory of temperature and output up to that time rather than just the temperature at that time (Pindyck, 2013; Batten, 2018). As growth effect can cause permanent damage to the economy rather than just reducing output in a given year as level effect does, the damages compound over time for growth effect models, resulting in projected long-term economic damage of global warming that is orders of magnitude higher than conventional estimates (Dell et al., 2014; Burke et al., 2015; Pretis et al., 2018; Piontek et al., 2021).

There is a vast body of literature concerning the micro-foundations that link temperature to various economic outcomes. For example, temperature impacts macro-economic output through various channels including energy (Auffhammer and Aroonruengsawat, 2011; Davis and Gertler, 2015), total factor productivity (TFP) (Zhang et al., 2018), capital (Zhang et al., 2018), agriculture (Schlenker et al., 2005; Schlenker and Roberts, 2009), industrial production (Hsiang, 2010; Chen and Yang, 2019), labor force (Zivin and Neidell, 2010), and capital (Zhang et al., 2018), which represent widely-accepted determinants of GDP. Some econometrics models directly aggregate related temperature to GDP levels (Dell et al., 2009; Hsiang, 2010; Deryugina and Hsiang, 2014).

However, a series of solid theoretical bases have been proposed, reasoning that GDP growth rate, not simply GDP level, might be impacted by climate change. The early theoretical model developed by Dell et al. (2012) characterises production as a multiplicative function of labour productivity, population and exponentiated temperature. The authors suggested that changing temperatures may have an impact on investment, which could impact productivity growth. According to a growing number of academics, climate change might permanently harm capital stocks and productivity, which will likely have a long-term influence on GDP growth (Dell et al., 2012; Pindyck, 2013; Stern, 2013; Hsiang and Jina, 2014; Moyer et al., 2014; Burke et al., 2015; Moore and Diaz, 2015, 2018). This research has suggested that global warming adversely affects developing countries' GDP growth (Dell et al., 2012; Henseler and Schumacher, 2019; Letta and Tol, 2019). Several studies have determined that more temperate countries face greater risks in GDP growth (Burke et al., 2015; Burke and Tanutama, 2019; Kumar and Khanna, 2019; Kalkuhl and Wenz, 2020). Similarly, some research has focused on a sub-national scale; for example, Yuan et al. (2020) and Chang et al. (2020) found that southern China, which is a relatively warmer region, will suffer more negative impacts on economic growth.

There is minimal consensus on the identification and interpretation of growth and level effects in existing empirical studies. For example, Dell et al. (2012) interpreted the coefficients of the lagged terms of temperature as indicating growth effects, assuming that if the summation of the coefficients (marginal temperature effects) of all temperature lags significantly differs from zero and the signs of different terms are reversed indicate both level and growth effects of temperature on GDP, and the results are consistent with this assumption. Similar to Dell's assumption, Burke et al. (2015) regressed distributed lag models including 1–5 lag terms of linear and quadratic temperature variables to investigate temperature effects. However, the cumulative marginal temperature effects on growth indicate that the sign reversed when more lags were included, but the increasing uncertainty caused these cumulative effects to have no statistical significance; therefore, we can't reject the hypothesis of this representing a genuine growth effect, nor can we reject the hypothesis of its representing a temporary level effect.

As reflected in the examples above, previous research has not yet fully determined whether climate change has only a level or a growth effect; however, the two effects may simultaneously exist and could manifest at different future timing. To further explore this issue, Kalkuhl and Wenz (2020) divided the climate effects on economic growth into three channels according to time scales, which included (i) the impacts of a temperature change on production in the short-run, (ii) the temporary effect on the growth rate to bring it into line with the economy's long-run growth rate and (iii) the long-run growth rate of productivity. In the model specification, the coefficients of a linear term in climate change that solely considers contemporary and one-year-lag changes in weather indicate the immediate effects, the coefficients of a model in linear and quadratic contemporaneous weather terms referencing Burke et al. (2015) indicate that there exists the short-run or long-run growth effects and the coefficients of the interaction term and linear term reflecting weather conditions consider all impact channels.

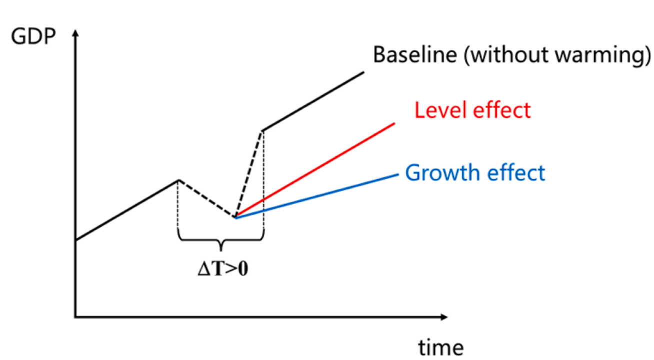

Fig. 1. The GDP pathways under different temperature effects.
Note: The black line corresponds to the baseline pathway which assumes a world without temperature warming. The red line corresponds to the pathway in which temperature change shocks GDP via the level effect. The blue line corresponds to the pathway in which temperature change affects GDP via the growth effect.

3. How is the functional form of temperature–GDP specified?

Functional form specification is among the key concerns regarding which the temperature–GDP literature varies because there are no restrictions on particular, estimable, structural links between temperature and GDP in the present paradigm (Dell et al., 2014; Burke et al., 2015; Hsiang, 2016; Schlenker and Auffhammer, 2018; Kalkuhl and Wenz, 2020). Choosing a linear or non-linear model might significantly impact the extent of damage estimations.

3.1. Linear form

The linear model is constructed assuming a linear relationship between a series of weather variables, including temperature, time trends and an explained variable, which is generally the GDP level or the first difference of the logarithm of GDP per capita. The model could include some fixed effects (FEs) but usually includes an error term. Numerous studies have examined the nexus between climate change and the economy using linear model specifications. For example, using a linear model, Hsiang (2010) determined the statistically and economically significant impacts of annual average temperature on sectoral as well as total production in the Caribbean and Central America. Dell et al. (2012, 2014) used a distributed lag linear model to explore the temperature-economic growth relationship, finding that only developing country growth will be damaged by positive temperature shocks. However, many micro-foundation studies from a sectoral perspective have demonstrated that temperature will have both negative and positive effects (Schlenker and Roberts, 2009; Auffhammer and Mansur, 2014; Deryugina and Hsiang, 2014; Graff Zivin and Neidell, 2014; Hsiang et al., 2017; Graff Zivin et al., 2018; Zhang et al., 2018; Chen and Yang, 2019).

In addition, the estimation procedure for obtaining temperature effects in a linear model has traditionally been based on temperature deviation in a certain year from each region's average value, and the temperature effect is finally estimated by averaging each region's effect, wherein only the FEs can reflect some potential differences among regions but temperature effects would not be affected by FEs. This suggests that estimations using linear models tend to capture short-term effects and temporary temperature shocks (Schlenker and Lobell, 2010). As it is difficult for this effect to reflect the response of the socio-economic system to long-run climate change, many studies using the short-run response to extrapolate climate impacts may have elicited biased estimations of GDP impacts because the approach does not account for potential adaptations (Kolstad and Moore, 2020).

3.2. Non-linear form

As noted, non-linear models have been modelled to capture the non-linear relationships (usually in a quadratic relationship) between a series of weather variables including temperature, time trends and an explained variable, which is GDP level or the first difference of the logarithm of GDP per capita. This approach allows the exploration of the marginal effects of temperature, which is also a function of temperature (Kolstad and Moore, 2020). This non-linear shape assesses positive or negative temperature effects on GDP. For example, Burke et al. (2015) proposed a temperature-GDP per capita growth nexus with quadratic temperature, precipitation and time trends. The model determined that the optimal temperature is 13 °C, and economic growth in countries with baseline temperatures which are higher than that will be negatively impacted by temperature, whereas others will be positively affected. The authors also found this relationship to be globally generalizable and robust for agricultural and non-agricultural activity in both developed and developing countries. The non-linear model can make up for the shortcomings of linear models; for example, by considering adaptations to implicitly model the marginal effect of temperature to change with climate across countries. This implies that non-linear models can capture the long-run adaptation effect by determining the changes in marginal response.

3.3. Hybrid forms

Some studies have led to a trend towards hybrid functional forms which share the advantages of both linear and non-linear functional forms. For example, Kalkuhl and Wenz (2020) used a hybrid model which includes both linear and non-linear models with interaction lag terms. This hybrid model can explicitly distinguish between short-term temperature shocks (i.e. deviations from a region's average climate conditions) and long-term climatic changes that socio-economic systems could adjust to adapt to the new world with global warming.

4. How are temperature variables specified?

4.1. Annual average temperature

Another important dimension is the specification of the forms of weather variables, particularly those for temperature. Average annual temperature has a considerable impact on economic growth, according to recent climate econometrics calculations examining spatiotemporal heterogeneity in climate variables and growth. For example, Dell et al. (2012) examined historical variations in annual temperature within countries to determine the impacts on overall economic output, determining that higher temperatures significantly reduced economic growth in developing countries. Burke et al. (2015) found global economic production to be non-linearly correlated with annual temperature across 166 countries, reaching a maximum of 13 °C and sharply dropping above that. Furthermore, Kalkuhl and Wenz (2020) employed annual panel models based on sub-national data sets, revealing robust evidence that annual temperature considerably impacts productivity levels. Also, based on a sub-national data set for China, Chang et al. (2020) found an inverted U-shaped temperature-GDP growth relationship at the provincial level, with the threshold at 12.2 °C.

4.2. Monthly temperature

However, annual temperature may not comprehensively reveal the impact mechanism of climate change on economic consequences. Summer heatwaves, prolonged cold spells, higher temperatures and precipitation variability increase uncertainty, and growing evidence has suggested that changes in the frequency and intensity of climate extremes and changes in exposure, impact socio-economic systems. This research has acknowledged that many climate-related events which may have an impact on economic growth happen over shorter time frames. As a result, only concentrating on the impacts of annual average temperature—as has been the case in the research on climate econometrics—runs the danger of overlooking the majority of extreme weather events. Therefore, Pretis et al. (2018) introduced within-year monthly variables, within-year monthly variation variables and maximum and minimum within-year monthly variables which are associated with temperature and precipitation into the climate econometrics model. The research demonstrated that, beyond global non-linear temperature impacts, within-year variability of monthly temperatures and precipitation had minimal impact on economic growth.

4.3. Seasonal temperature

In addition, some studies have determined that the varied impacts of various seasons may be hidden by prior studies' aggregating of temperature data into annually temperature averages (Dell et al., 2012). For instance, Colacito et al. (2021) showed that summer and autumn temperatures oppositely impact the gross state product (GSP) growth in US states. The average summer temperature harms the GSP growth rate, but the average autumn temperature has a positive impact. Meanwhile, beyond sectors that are traditionally seen as sensitive to changing climatic conditions, rising summer temperatures have an extensive impact on the full cross-section of industries investigated. Liddle (2018) found summer temperature to harm agricultural GDP in the US. It was found that the industrial production in China responded positively to spring temperature but adversely to summer temperature (Chen and Yang, 2019). Yuan et al. (2020) investigated whether seasonal temperatures impact the aggregate economic output of the cities in China, revealing significant negative effects from warm seasonal temperatures but positive effects from cold seasonal temperatures on economic growth. Compared with annual temperatures, examining seasonal variations in temperature can capture the complex effect mechanism; hence, it is essential to explore the impacts of seasonal temperature when investigating how global warming affects GDP.

4.4. Temperature bins

Another variable specification, temperature bins, is defined by the frequencies at which the weather events fall into different bins. This approach endeavours to uncover the non-linear effects of temperature on GDP. For instance, several regressors to record the number of days per year that are inside defined temperature ranges. (e.g. 0–5 °C, 5–10 °C, etc.) can be used to measure temperature. Deschênes and Greenstone (2011) presented an early instance of this method, the major advantage of which is the ability to avoid specifying functional forms of temperature and GDP since the econometrics model with this variable specification is relatively non-parametric. In addition, using temperature bin variable specifications, Chen and Yang (2019) identified the critical temperature threshold above and below which adverse effects can occur on industrial output, while Zhang et al. (2018) determined the significant effects of high temperatures (above 32 °C) on output. To advance the establishment of adaptation plans for a potentially unpredictable future because of climate change, the identification of such key temperature thresholds is crucial (Hallegatte, 2009). It should be noted that this specification requires high-resolution data since if data are aggregated across space or time before creating bins, extreme days could be averaged away so that the data are smoothed, and if non-linearities are significant, this may result in inaccurate estimations (Dell et al., 2014).

4.5. Daily variability

The degree of variability in daily temperature is not reflected in daily temperature bins. Kotz et al. (2021) found that daily temperature variability from seasonal expectations has significant impacts on crop yields as well as asset prices resulting from investor expectations. In contrast, numerous empirical findings have demonstrated that when investigated across a range of non-climate elements and timelines, uncertainty—measured as variability or volatility—poses an intrinsic limitation on macro-economic output. For instance, temporal fluctuations of GDP have negative effects on GDP, as well as volatility in government spending and exchange rates (Ramey and Ramey, 1994; Aghion et al., 2009). In addition, for the determinants of GDP, agricultural output and welfare would also be negatively affected by food price volatility (Myers, 2006; Haile et al., 2016). Thus, relevant contemporary research has concluded that macro-economic output and GDP would potentially be affected by the aggregate effects of daily temperature variability across these fundamental economic factors. For example, to obtain the measurement of annual daily variability, Kotz et al. (2021) calculated the intra-monthly standard deviation of daily temperature and then averaged these standard deviations across months of a given year. The study demonstrated that increases in seasonally adjusted daily temperature variability can negatively affect economic growth on a global scale, independent of (and in addition to) changes in annual average temperature.

4.6. Deviation from historical norms

Previous studies indicated a strong upward trend in temperature data for nearly all countries or regions, so it almost seems as if it is possible that the two trends are correlated in terms of the temperature-GDP growth nexus. This leaves a key problem for climate econometrics in identifying the temperature-GDP causal links which is that the temperature trend included in the regression can cause biased estimation because it introduces a linear trend to GDP growth which is spurious and unsupported by data (Kahn et al., 2021). This is an econometric pitfall related to trended variables that can be addressed by introducing variable specification of temperature deviation from its respective historical norm to explore the long-run impacts of climate change on macro-economic output across countries. This approach allows for consideration of adaptation and non-linearity in the climate econometrics model, and Kahn et al. (2021) used it to determine that consistent changes in the temperature above or below historical norms would negatively impact the growth of GDP per capita. This empirical research revealed that GDP is impacted by consistent changes in temperature, the pace of temperature change and the extent of temperature variability.

5. How is the climate econometrics model specified?

5.1. Cross-sectional model

Early research investigating the temperature–GDP relationship has largely been constructed referencing expert judgement (Fankhauser, 1995). The response functions utilised in such models, however, have little empirical basis (Mendelsohn et al., 2000). To compensate for the lack of empirical foundation, early methods focused on single points in time, estimating the marginal impact of long-term changes in the distribution of temperature and precipitation using changes in climate among cross-sections (Mendelsohn and Nordhaus, 1999). The cross-sectional model's econometric specification includes an explained variable that measures the economy, which varies throughout space at a given time point, along with a function of temperature and other control variables and an error term. In early research, Mendelsohn et al. (1992) proposed the first climate econometrics method, which was a cross-sectional model for estimating the long-run effects of climate change. This method was used to compare the results of different regions, referencing the current climate of hotter regions with analogues for regions that are currently cooler under an altered climate. Sachs and Warner (1997) and Nordhaus (2006a) then used cross-sectional regression analysis to investigate the research on climate and growth.

One of the critical advantages of utilizing the cross-sectional model lies in its ability to capture long-term equilibrium effects which reflect the net impacts after potential adaptation measures have occurred (residual damages) (Dell et al., 2014; Burke et al., 2015; Kalkuhl and Wenz, 2020). However, one important criticism of the cross-sectional approach is the biased estimation caused by omitted variables (Hsiang, 2016). In practice, a common approach to avoid such biased estimation is to control for explanatory variables as much as possible, as Nordhaus (2006b) did in his global-level geographic–economic cross-sectional model, controlling for a variety of factors such as temperature, rainfall, elevation, ruggedness and soil type. Another option for addressing omitted variable bias is to restrict the sub-samples of observations. For instance, Dell et al. (2009) examined the impact of temperature on per capita income using (prefecture) city-level data for 12 countries, controlling for national FEs and state (province) FEs in the regression analysis. It is noteworthy that adding abundant control variables to a cross-sectional regression model does not necessarily reduce the estimation bias of the model. If the control variables are endogenous or determined by the climate itself, then their introduction into the model would instead result in the so-called 'bad controls' and 'over-controlling' problems. In addition, some factors that do not vary over time (e.g. geography, culture, customs and institutions) may also affect the dependant variable (some of which may be highly correlated with the climate variable and the control variable) and have often been excluded in cross-sectional regression models because the relevant data may be difficult to obtain or is not accurately observed (Hsiang, 2016).

5.2. Panel model

A recent large body of literature associated with climate econometrics has used panel models with various FEs to identify the relationships between temperature change and GDP (Dell et al., 2014; Kolstad and Moore, 2020). In a panel model, the economically explained variables (e.g. GDP or some determinant factors of GDP such as TFP), weather variables (temperature etc.), FEs and control variables all vary over space and time. The model applies a linear or non-linear function consisting of explanatory variables, FEs (sometimes the model includes time trends) and an error term. Compared to cross-sectional regressions, this specification provides a number of advantages in terms of causal identification, due to the fact that the extended set of data utilised changes through time and space, FEs and time trends may be used to account for a variety of unobserved omitted variables, including time-invariant changes over space, which is frequently a topic of discussion in this context (Deschênes and Greenstone, 2007). Panel models have been widely utilised to analyse the temperature-economic growth nexus (Dell et al., 2009, 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019), crop yields (Schlenker and Roberts, 2009; Chen and Yang, 2019), energy demand (Auffhammer and Mansur, 2014; Wenz et al., 2017), labor productivity (Deryugina and Hsiang, 2014) and human capital (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018). These studies shed light on the possible long-term effects of climate change. In some instances, anthropogenic warming is anticipated to cause significantly greater economic losses than what prior research employing IAMs had indicated (Burke et al., 2015).

Although the problem of time-invariant omitted variables in the cross-sectional model can be addressed by introducing individual FEs into the panel model, there is also a potential problem of time-varying omitted variables. One example is the impact of seasonal temperature on industrial output, Chen and Yang (2019) used the duration of sunlight as an explanatory variable. Since sunlight is strongly correlated with temperature and has been shown to have an important effect on human health and labour productivity (Lambert et al., 2002; Patz et al., 2005; De Witte and Saal, 2010), omitting sunlight from the regression analysis could result in inaccurate estimates of the annual temperature's impacts on overall economic output. In addition to controlling for omitted variable bias, the FEs panel regression technique also has some weaknesses related to its emphasis on short-run changes in the weather rather than the long-run variability of climatic conditions. It's critical to distinguish between short-run and long-run effects because the socio-economic system could be better able to react to long-run changes than short-run ones by investing in adaptative responses. Identifying only short-term responses to weather variation and only extrapolating the short-run effects of weather variation on economic outcomes would also tend to overestimate the effects of global warming if future significant adaptation occurs (Kolstad and Moore, 2020).

Traditionally, the FE estimators utilized in the research with the panel model have assumed that climatic variables are strictly exogenous; however, there are the bi-directional feedback effects between temperature and economic growth. According to Nordhaus (1992), greater economic growth results in more GHGs, which boosts the global average temperature. Meanwhile, a rise in the global average temperature would in turn slow down economic growth. As economic growth in the previous periods could have feedback effects on future temperature, temperature may not be strictly exogenous in models that estimate the impact of temperature on economic growth (Kahn et al., 2021).Dynamic panels with a cross-section dimension (*N*) that is higher than the time series dimension (*T*) exhibit small-T bias due to the FE estimator's limitations, meaning that there is a biased estimation in the model specification based on a standard FE estimator if one or more dependant variables are not strictly exogenous (Kahn et al., 2021). To avoid this, Kahn et al. (2021) contributed by introducing the half-panel jackknife FE (HPJ-FE) estimator proposed by Chudik et al. (2016) into the model with the specification of the widely-used FE estimator. When the panel's temporal dimension is modest in terms of *N*, the HPJ-FE estimator is resilient to potential feedback effects from total economic output to the variables related to climate change and effectively corrects the bias if the regressors are weakly exogenous.

5.3. Hybrid panel model

To overcome the challenges of general panel models for capturing long-term climate impacts and to distinguish the impacts of short-, medium- and long-run variations in weather and climate, hybrid panel models have been introduced into econometric climate impact studies. Such studies usually use panel data and control for unobservable confounding variables, integrating cross-sectional, interannual and decadal variations in temperature to estimate level and growth effects of temperature from weather shocks in the short run and climate equilibrium impacts in the long run. Comparing the responses to these variations can provide information related to potential adaptation paths and produce a more accurate estimate of climate impacts (Kalkuhl and Wenz, 2020; Kolstad and Moore, 2020).

Over the recent years, researchers have developed a hybrid method called the long difference approach to quantify the climate adaptation effects. It has the same econometric expressions as the panel model, but the explained and explanatory variables in the model are averaged over time, and can be averaged over a decade, a few decades or even a century (e.g. 1960–1970 or 1970–2000). Although its econometric expressions are very similar to those of a general panel model, there are significant differences in the interpretation of the model's estimated parameters. Compared to the panel model, the hybrid describes changes that are closer to climate change rather than weather change; therefore, the temperature effects describe medium- to long-term climate effects instead of short-term effects. Dell et al. (2012) used this kind of hybrid model to estimate the effect of a 1 °C rising in temperature on GDP growth occurring over 15 years. The authors find a temperature effect that is similar to the effect estimated by a panel model with interannual changes in temperature variables, asserting that adaptation is not particularly effective throughout this period.

Another challenge is distinguishing the effects of short-, medium- and long-term variations in weather and climate. Few studies in climate econometrics have identified the effects of temperature on GDP at different temporal scales simultaneously. This kind of research can contribute to revealing whether temperature's effects on GDP are persistent (Dell et al., 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019; Rosen, 2019; Newell et al., 2021), which could impact the design of optimal future climate policies. Existing estimates of the effects of weather shocks on GDP have been criticised for methodological shortcomings, including the failure to consider trends in climate variables and the impact of average climate conditions on the marginal response to weather. Concerning spatial scope, temporal scale and particular technological challenges, Kalkuhl and Wenz (2020) addressed a number of shortcomings in earlier analyses, explicitly distinguishing between short-term weather shocks and long-term climate effects and offering potentially insightful information related to adaptation.

6. Improve damage functions in IAMs

IAMs have been created to represent the complex interactions between socio-economic and natural systems under the background of climate change to provide insights and policy suggestions to confront global warming. The damage module, which introduces a series of damage functions for calculating the economic impacts of climate change, is an essential component of IAMs. Losses in GDP and consumption are usually employed to measure economic damage (Nordhaus, 2019; Rising et al., 2022). Previously, the parameters of multiple damage functions in IAMs were calibrated to match the existing estimation results (Tol, 2009; Pindyck, 2013; Diaz and Moore, 2017). Over the previous few years, numerous empirical research has reassessed the long-term economic effects of climate change in different sectors (Carleton and Hsiang, 2016; Hsiang et al., 2017), and some studies have integrated damage assessment results using the meta-analysis approach (Howard and Sterner, 2017). These more recent empirical results can be further integrated into the modelling procedure of damage functions.

However, the current damage function approach has been criticised for being largely static and not considering the dynamic effects by which temperature changes may affect the growth of macro-economic output and, consequently, future welfare (Pindyck, 2013; Diaz and Moore, 2017; Batten, 2018; Rising et al., 2022). Projections of future economic losses vary significantly depending on whether growth or level models are specified as growth effect shocks are considered to permanently damage the economy rather than temporarily reducing output in a given year as level effects do.

Thus, an alternative for improving traditional damage functions is based on the recent empirical basis from a reduced-form temperature-GDP growth nexus (Dell et al., 2014; Burke et al., 2015; Moore and Diaz, 2015). To incorporate these growth shocks into damage assessment in an IAM, Dietz and Stern (2015) provided two key examples. The first examined the relationship between temperature impacts and physical capital stock which is boosted by capital investment (I_t) but diminished by physical depreciation (δ) and damage (D_t^K) representing the direct climate impacts on capital stock.

$$K_{t+1} = \left(1 - D_t^K\right)(1 - \delta)K_t + I_t$$

The second examined the relationship between temperature impacts and productivity, which inherently reflects the growth effect of temperature change.

$$A_{t+1} = \left(1 - D_t^A\right)A_t$$

The mechanism by which climate impacts are modelled is critical as even the smallest growth effects would ultimately outweigh large level effects. Removing growth effects from the model would significantly reduce the potential economic losses from global warming. Consequently, this may have a detrimental impact on model-based policy implications. For instance, Moyer et al. (2014) simulated the impacts of temperature on productivity growth using an IAM and discovered even a tiny growth effect to have a significant effect on the optimal climate policy. Based on the empirical results from Dell et al. (2012), Moore and Diaz (2015) calibrated climate damage to the growth rate in a simple IAM, determining that enabling climate change to directly shock GDP growth would greatly boost the optimal mitigation rate in the near term.

The majority of IAMs simply take into account the level effects of long-term climatic conditions on economic output. Kalkuhl and Wenz (2020) allowed climate change to affect level as well as growth rate of GDP, separating the effects of climate change on productivity and growth rate. Growth is impacted by (i) the short-run impact of a change in temperature by the impact on the productivity level, (ii) a temporary impact on growth rate to converge with the long-run growth rate of the economy, and (iii) the long-run productivity growth rate. This empirical evidence enabled clear identification of the macro-economic effects of climate change at various periods in the IAM to allow policymakers to make informed risk management decisions that are tailored to different periods. In addition, the model also contributes to formalising the depiction of the consequences of climate change in already-existing IAMs. Compared with the original DICE-2016 damage function predictions, the authors determined that the social cost of carbon is higher than three times higher when incorporating the damage function calibrated by their empirical results into the DICE-2016.

7. Limitations

Modelling adaptation effects based on climate econometrics is a profound and challenging research topic; however, it is one of the least researched subfields in climate economics (Burke and Emerick, 2016). This is the result of one of the most important barriers—a dearth of data regarding the aggregated costs and benefits of adaptations. In addition, current knowledge regarding the available options for future adaptation measures and adaptive capacity is extremely limited, and the actual costs and impacts of different adaptation options remain unknown (Sussman et al., 2014; Trnka et al., 2017; Chapagain et al., 2020; Rising et al., 2022). Thus, it would be very difficult to model climate adaptation explicitly using climate econometric models in comparison with implicit modelling of climate adaptation. Future research should further investigate the lack of clarity regarding adaptation options. Notably, recent advancements in methodology have allowed for assessing the benefits and costs of adaptation for some individual sectors that are derived empirically from observed variations in weather sensitivity (Carleton et al., 2022). Nevertheless, few studies have explored the impacts and costs of adaptation in macro-economic systems from a top-down perspective, using GDP as a measure, as has been done for climate impacts. This is also a research question worth exploring in the future (Sussman et al., 2014; Chapagain et al., 2020).

To identify adaptation effects more accurately, it is crucial to differentiate between short- and long-run effects as people and enterprises may adjust to long-run changes in the expected distribution of weather differently than they may to short-run, temporary, and unexpected variations in weather. If this adaptation is significant, then the effect of weather change may not offer an appropriate analogue for the long-run effects of climate change. According to Dell et al. (2009) comparison of cross-sectional and panel data, adaptation mitigates the detrimental effects of temperature shocks by 50%. If non-linearities emerging in the temperature range outside the previous data differ from those within it, extrapolating from historical temperature data may not be rational (Kahn et al., 2021). Therefore, referencing a short-term response to extrapolate climate effects will suffer a biased estimation of damages if the model ignores long-term adaptation. To overcome the bias estimation from extrapolation, future research should further refine the use of the long difference model (cross-sectional regressions) in growth rates across longer periods to model the potential adaptation effects more thoroughly. Meanwhile, in panel data analyses, the deviation from long-run averages to estimate unbiased weather impacts should also be focused on for exploring adaptation effects in climate econometrics. This change will enhance existing panel models to explicitly represent climatic variability in the calculation of long-run damage functions and enable the construction of an implicit model of adaptation (Mendelsohn et al., 2016; Kahn et al., 2021; Tol, 2021).

Since GDP does not account for the monetized effects of temperature change on non-market sectors, future research should further enrich this limitation by exploring empirical links between climate change and biodiversity impacts, health losses and tipping points, and monetizing these climate impacts (van der Wijst et al., 2023). In addition, temperature change may also shock the trade between countries or regions by some potential channels (Burke et al., 2018; He et al., 2023). Future research should also identify how this underlying factor affects the empirical relationship between temperature and GDP.

8. Conclusions

Exploring the reduced-form temperature-GDP relationship is a critical area of climate econometrics. The use of level and growth effects to evaluate climate change impacts has given rise to a long-standing and well-known controversy in the literature. We find that there are compelling theoretical justifications for thinking that climate change might affect the pace of GDP growth, not only its level, and projections of potential losses due to climate change vary significantly relying on which effect is specified. However, there is minimal empirical evidence and weak consensus regarding how to interpret this effect or specifications. Recent studies have led the trend to explore whether these two effects would both exist and how they manifest at different times, implying that future research should incorporate multiple model specifications of climate econometrics into a single model to distinguish between the two effects in the short, medium, and long term.

In terms of variable forms, in addition to annual average temperatures, the introduction of daily, monthly and seasonal temperature variables and related variants (e.g. temperature bins) would enrich the exploration of the mechanisms by which temperature affects GDP from multiple perspectives. An increasing number of studies are utilizing relevant variables that can capture climate variability to describe climate change, rather than solely relying on absolute values of climate or weather factors. Future research should focus on developing climate econometrics models that incorporate or improve these variable forms in order to avoid potential estimation bias caused by spurious regressions, ignoring the adaptation effects and so on. For instance, using a temperature variable that captures the deviations of temperature from respective historical norms could further expand the long-term climate impacts.

In terms of functional forms, the choice of linear or non-linear models significantly impacts the magnitude of damage estimates. The linear specification is suitable for estimating short-run weather impacts but it would result in a biased estimation of economic losses as it doesn't take long-term adaptations into consideration. In contrast to the linear specification, the estimation results from the non-linear panel model can reflect both short- and long-term impacts. Therefore, future studies should use more comprehensive data and integrate long-difference non-linear models to identify climate adaptation patterns at a regional level over an extended period of time. This potential improvement would reduce the bias of projecting future climate impacts by climate econometrics models.

Furthermore, concerning the reduced form of the temperature–GDP relationship, this study provides a careful review of the development of the specifications of the econometrics model along historical lines. In initial models, the temperature–GDP relationships lacked spatial and structural detail and were largely constructed on expert judgement, with minimal empirical foundations. To compensate for the lack of empirical foundations, the initial approach used a cross-sectional model to estimate the long-run equilibrium effects of climate change, rather than weather effects, by accounting for the net benefits of potential adaptation measures; however, this approach faced the challenge of biased estimation caused by omitted variables. To overcome this, a more recent strand of literature applying the panel model has offered significant advantages over cross-sectional model in terms of causal identification. The expanded set of data utilised changes with time, space and FEs, as well as the terms of time trends, controlling for various omitted factors that are not observed, especially time-invariant change across space. Other recent studies have improved the FE setting in traditional panel models to further reduce estimation bias due to the bi-directional effect between temperature and economic growth. Based on new hybrid panel models including mixed characteristics of the above model specifications, recent research trends have been distinguishing the impacts of short-, medium- and long-run variations in weather and climate to further capture the adaptation effects.

We find that one of the reasons that climate econometrics is an essentially academic pursuit is that such research can provide empirical evidence for improving damage functions in IAMs. The literature review reveals that a substantial amount of empirical studies is available to update the parameters of the damage functions and a meta-analysis approach could produce a damage function that reflects the latest empirical findings more fully. Meanwhile, according to the empirical temperature-GDP growth nexus, future research can further model temperature shocks on GDP growth in IAMs by measuring the relationship between the impacts of temperature on macro-economic factors, such as physical capital stock and productivity.

Also, it is worth noting several other directions for future research in this field, including further investigating the effects and costs of climate adaptation in the macroeconomic system from a top-down perspective based on innovative econometric models and increasingly abundant data, identifying the potential empirical nexus between climate change and some non-market sectors such as biodiversity, health and tipping points as well as examining the underlying temperature effects in the trading network.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Jun-Jie Chang: Investigation, Data curation, Methodology, Conceptualization, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Zhifu Mi:** Resources, Supervision, Funding acquisition, Validation, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – review & editing. **Yi-Ming Wei:** Resources, Supervision, Funding acquisition, Validation, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – review & editing.

Data availability

Data will be made available on request.

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