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Revalidation of temperature changes on economic impacts: a meta-analysis

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Abstract
To identify appropriate strategies for temperature change adaptation, the economic impacts of temperature changes are critical to be understood. Despite a wide investigation about this issue, the obtained evidence is still mixed, including positive linear, negative linear, U-shaped, inverted U-shaped, or even irrelevant relationships. To address this question, we investigated the findings of collected studies through a meta-analysis based on 87 studies with 2977 estimates. We first examined the genuine effects between temperature changes and economic impacts based on statistical models (i.e., funnel plots, MST and FAT-PET-PEESE tests). Then, we adopted the meta-regression method to identify the sensitive modeling characteristics influencing the research outcomes. The results illustrate four major conclusions. First, there is a negative relationship between temperature changes and economic outputs in linear regression analysis, and an inverted U-shaped relationship in quadratic regression specifications. Second, research areas and temperature variables involved in individual studies have significant effects on current economic consequence analysis. Particularly, rich countries located in colder climates can even benefit from temperature changes, whereas poor countries located in hotter climates suffered adverse impacts. Third, the resilience factors should be involved in future prediction models to investigate the mitigation effects. Fourth, the sensitive modeling specifications were different according to different research sub-objects. The results obtained can provide implications for the sustainable development of the economy and human society caused by climatic change, and can also make contributions to advance the theory and practice of future temperature change consequence analysis.

Keywords Temperature change · Economic impact · Meta-analysis · Empirical research

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1 Introduction

Climate change has created serious challenges for the sustainable development of human society at a global scale, including the increase in frequency/severity of natural disasters, rising sea levels, and loss of biodiversity. Particularly, the earth has witnessed many extreme temperature events and greater temperature fluctuations at an unprecedented speed due to global climate change since the turn of the twentieth century (Acevedo et al. 2020; Grotjahn et al. 2016; Peterson et al. 2013). According to the 2020 report of the World Meteorological Organization (WMO), the global mean surface temperature was 1.2 ± 0.1 °C warmer than the pre-industrial baseline (1850–1900) (World Meteorological Organization 2020). Inevitably, the influence caused by temperature changes creates serious effects to economic development. To address this issue, researchers and policymakers have already raised warnings of the potential for dramatic economic consequences to identify better strategies to conduct risk management and implement appropriate mitigation tactics.

Currently, there is a large and growing research literature of temperature changes on economic impacts based on global or regional datasets over the past few decades, such as investigating the potential relationship between temperature changes and mortality, worker productivity, aggregate output, agricultural output, manufacturing, and service sectors (Chen and Yang 2019; Henseler and Schumacher 2019; Hsiang 2010; Korhonen et al. 2019; Seetanah and Fauzel 2019). However, the empirical findings are mixed. For instance, several studies suggested that the rising temperature has a negative effect on total output, especially for developing countries (Colacito et al. 2019; Henseler and Schumacher 2019; Hsiang et al. 2017; Jain et al. 2020; Lanzafame 2014). Conversely, some studies suggested that the rising temperature has not decreased the growth in economic output yet, and some countries can even benefit from the warming climate (Acevedo et al. 2020; Copiello and Grillenzoni 2020; He et al. 2020; Ng and Zhao 2011). Even for samples from the same country, different conclusions can also be drawn. For, instance, in the USA, Fisher et al. (2012) showed that global warming caused severe adverse impacts to US agriculture, whereas Cui (2020) suggested that temperature changes increased the yield of agricultural crops over the past 30 years. Thus, although there are increasing studies that have attempted to examine the relationship between temperature changes and economic impacts, there is still a large heterogeneity in this field.

Our motivation stemmed from the variation in current empirical findings and attempted to reach an overall understanding, as well as identify the sensitive modeling characteristics influencing the research outcomes. Our main research questions are as follows: Do temperature changes enhance or impede economic development? Which factors influence the heterogeneity in estimates? Thus, we employed a meta-analysis to answer these questions. The meta-analysis technique uses a set of rigorous statistical methods designed to review and evaluate the empirical evidence from different but comparable empirical studies, to explore a range of findings in different contexts, for different outcome variables, and different units of analysis, thus reaching an overall understanding of a problem, as well as identifies sources of variation (Gurevitch et al. 2018; Stanley et al. 2008), which is well accepted in medicine and psychology and also becoming more and more popular in economics (Melo et al. 2009; Gunby et al. 2017). In terms of climate change impacts, previous meta-analyses have summarized climate change impacts in agricultural production and human capital impacts. For instance, Knox et al. (2012) assessed the impacts of climate change on the yield of eight major crops in Africa and South Asia and found decreases in the mean change in yield of all crops. Challinor et al. (2014)

evaluated crop yield impacts of climate change and adaptation based on meta-analysis, and they found likely increases in yield variability without adaptation. In addition, Beine and Jeusette (2019) and Šedová et al. (2021) conducted meta-analysis to investigate the impact of climate change on migration. Different from their research, this paper, for the first time, examined the macroeconomic impacts of the temperature changes from multiple dimensions, including empirical findings on the association between temperature changes and human capital, aggregate output, the output of primary sectors, secondary sectors, and tertiary sectors.[1] Due to the heterogeneous situation in current research results, and there is no research to systematically summarize and update the latest research information, thus, a meta-analysis is worth exploring to help improve the understanding of the genuine effects and how the economic outcomes of temperature changes are influenced by various modeling factors, to advance the theory and practice of economic consequence analysis in the future.

The rest of the research is organized as follows. Section 2 describes data sources and presents some tests. Section 3 and Section 4 present the research approach and research results, while Section 5 offers conclusions.

2 Meta-dataset construction

2.1 Data sources

The original literature included in this paper was collected and identified through a four-step process.

- First, search terms were used to collect studies in search engines and databases. The search terms in terms of temperature included "temperature," "global warming," or "climate change," and words denoting economy included "economic development," "economic growth," "output," "economic loss," or "GDP." The deadline for literature searching was December 31, 2020. The search engines and databases used included Google Scholar, Web of Science, Elsevier, and Emerald.
- Second, the title, keywords, and abstract were screened. The screening process was conducted according to the following two principles: (1) the remaining studies must be empirical studies that have produced quantitative results; thus, theoretical research and review studies were excluded. (2) The question examined was the economic impacts of temperature changes. Thus, the title, keywords, and abstract of these studies were screened to determine whether the collected studies were related to the research question.
- Third, the full texts of the remaining studies were reviewed to collect key information.
- Fourth, due to the high probability that studies would reference similar topics, some studies that have not been searched in the search engine were also available to minimize the missing studies.

In the same study, scholars often obtained regression results from different sample characteristics (e.g., different time periods and involved countries). In this paper, we collected all the regression results because the variations in the research findings can also be observed in

[1] Primary sectors, secondary sectors, and tertiary sectors in this paper referred to agriculture, manufacturing, and services, respectively.

different regression characteristics within the same study. In addition, we can make an empirical analysis according to the significance levels of the research findings from collected studies. That is, studies without *t*-values or coefficients and standard errors, but with regression coefficients and significance levels, can also be analyzed. Under the circumstances, the sample size has increased by 5.64%.[2]

Eventually, we extracted 87 studies and 2977 estimates, including 2809 *t*-values and 168 findings without *t*-values, but with regression coefficients and significance levels. The range of the publication dates of these collected studies is 1994–2020. According to the research objectives, there were 17 studies that investigated the economic impacts of temperature changes on human capital, containing 874 estimates (i.e., the associations between temperature changes and labor factor input or labor income). There were 25 studies that investigated the economic impacts on aggregate output, including 630 estimates (i.e., the associations between temperature changes and GDP or total income). There were 53 studies that investigated the economic impacts on the output of the primary sectors, containing 1039 estimates (i.e., the associations between temperature changes and agricultural output or yield). There were 14 studies that investigated the economic output of the secondary sectors, containing 253 estimates. Also, there were 11 studies that investigated the economic output of the tertiary sectors, including 185 estimates. The specific review of the included studies is shown in Appendix Table 1.[3]

Moreover, various estimation methods were used to evaluate the relationship between temperature changes and economic impacts. Overall, the regression coefficients obtained from the collected 87 studies were derived from linear regression analysis and quadratic regression specifications. For the coefficients obtained from linear regression analysis, a positive and linear coefficient means that the higher temperature is associated with higher economic development, whereas a negative and linear correlation means that higher temperature could reduce economic output. For the coefficients obtained from quadratic regression specifications, a positive and quadratic coefficient means that the economy could decline to the lowest point at a particular temperature, and then rise at higher temperatures (i.e., a U-shaped relationship between temperature changes and economic impacts), whereas a negative and quadratic coefficient means that the economy could peak at a particular temperature and then decline at higher temperatures (i.e., an inverted U-shaped relationship between temperature changes and economic impacts). From the collected 87 studies, 30 studies obtained empirical evidence both from linear regression analysis and quadratic regression specifications.

2.2 Genuine effects and publication bias

Here, we conducted some tests to check the genuine effects and publication biases in temperature change consequence analysis based on empirical findings both from linear regression analysis and quadratic regression specifications.

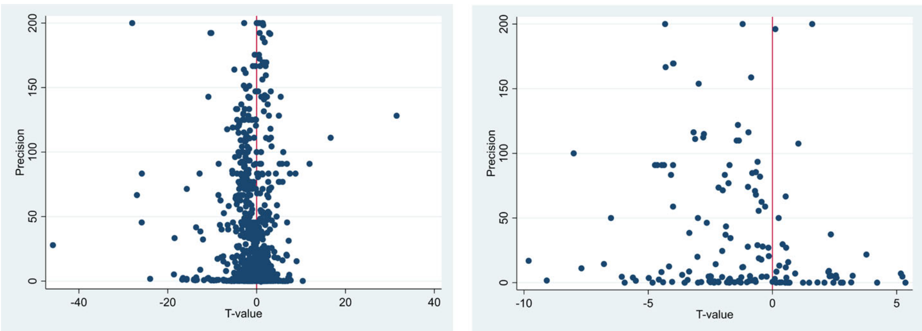
[2] If there were no clear *t*-values in the original studies, but both the regression coefficient and the standard error were presented, then *t*-value = regression coefficient/standard error. For ease of discussion, this paper reports *t*-values always in a way that "negative" impact means that the costs of temperature changes were larger. However, if the studies investigated the relationship between temperature changes and diseases or deaths, then the positive *t*-values indicated that temperature changes were positively correlated with the effects of diseases and deaths. Therefore, we changed the signs of the coefficients to evaluate them between different studies.

[3] Due to the word limit, Appendix Table 1–4 and Appendix Figure 1–5 were included in the supplementary materials.

First, the funnel plot is a widespread and intuitive method to detect the existence of research finding bias. In this paper, the *t*-values of economic outcomes with temperature changes collected and their accuracy (the inverse of the standard error) were plotted (Fig. 1). If no bias occurs, the funnel plot will be symmetric (Havranek and Irsova 2017). If asymmetry exists, it indicates that the current research outcomes are biased, and the potential sources of bias can also be detected. In this paper, the funnel plot of temperature changes on economic outcomes from both linear regression analysis and quadratic regression specifications was asymmetric, with slightly inclined to negative *t*-values in linear regression analysis (i.e., a negative relationship between temperature changes and economic outputs), and a clear bias towards reporting negative *t*-values in quadratic regression specifications (i.e., an inverted U-shaped relationship between temperature changes and economic outputs) (Fig. 1).

Second, the meta-significance test (MST), precision-effect test (PET), funnel-asymmetry test (FAT), and precision-effect estimate with standard error (PEESE) test were also adopted to evaluate the genuine effects objectively. The MST examines the genuine empirical effects based on the variation of the magnitude of a standardized test statistic with its degrees of freedom (Stanley 2008). Further, the PET-FAT can overcome the possible bias of the MST by considering both the influence of publication selection and the existence of genuine effects (Stanley and Doucouliagos 2014), and the PEESE test can even correct the non-linear relationship and take heteroscedasticity into account, to better evaluate the existing effects (Lazzaroni and van Bergeijk 2014). Here, we used these three tests together to examine and evaluate the genuine effects of temperature changes on economic outcomes.

Table 1 provides the results of genuine effects and publication bias obtained by the MST, FAT-PET, and PEESE test. Although the MST obtained insignificant results, the FAT-PET and PEESE test showed a genuine effect between temperature changes and economic outcomes in current research findings. The precision coefficients of PEESE testing results indicated that there were genuine effects. In addition, the publication selection effects (FAT) were negative and significant both in linear regression analysis and quadratic regression specifications, indicating that there was a publication bias with negative estimates among temperature changes and economic outcomes. Therefore, based on the research results of genuine effects and publication bias through the above tests, the negative effects of temperature changes on economic outputs can be observed in current research findings.



(a) Linear regression analysis (b) Quadratic regression analysis

Fig. 1 Funnel plot between temperature changes and economic impacts. **a** Linear regression analysis. **b** Quadratic regression analysis

Table 1 Tests for genuine effects and publication bias

Dependent variable	Linear regression analysis			Quadratic regression analysis		
	MST ln|t-value|	FAT-PET t-value	PEESE t-value	MST ln|t-value|	FAT-PET t-value	PEESE t-value
lnNobs	0.034 (0.035)			0.084 (0.057)		
Precision		−4.90e−08*** (8.69e−09)	−4.01e−08*** (1.46e−09)		−9.4E−05 (1.44E−04)	−2.88E−04** (1.33E−04)
Standard error			−5.2E−05 (4.14E−05)			3.12E−04*** (9.03E−05)
Cons	0.012 (0.302)	−0.569* (0.298)		−0.071 (0.462)	−1.474*** (0.270)	
N	1984	2137	2137	447	311	311
R^2	0.005	0.000	0.000	0.016	0.010	0.083

Note: The small R^2 can be found in Table 1. We focus on the correlation between variables, rather than trying to use the independent variable to explain or predict the change of the dependent variable, so a small R^2 is also feasible. Compared with Lazzaroni and van Bergeijk (2014), they also reported a small R^2 in the tests of genuine effects (i.e., 0.0008). The statistics exclude 1 outlier. Robust standard errors, clustered by studies. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Values in parentheses represent the standard errors

3 Meta-regression analysis: approach

3.1 Analytical framework for heterogeneity

Meta-regression analysis is the statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating research findings (Glass 1976). A key assumption of this method is that each study provides estimates of the relationship between variables in the population, and when the results across studies are aggregated, the statistical association between the change of the estimate outcomes and the variables in the population can be observed (Zhou and Chen 2020). When using meta-analysis, each estimation is taken as one single observation containing information on the nature of the relationship between temperature changes and economic impacts. The method helps researchers to identify key modeling factors that may influence the nature of a relation between variables.

However, there are also several limitations associated with this method. The first issue of meta-regression analysis is the publication bias problem. This is because the research findings of the individual studies may be obtained by authors with a prominent reputation or published in prestigious journals. To address this issue, it is recommended that a distinction should be made between journal publications and non-journal publications. The second issue of meta-analysis is the small sample problem. To address this problem, our assessment used a relatively large sample set which includes 2977 estimates derived from 87 empirical studies, which can overcome the small sample problem to some extent. The third issue is the heterogeneity of methods being analyzed in individual studies. It reflects the fact that the methods used in studies are dissimilar, and because of the differences in measures, samples, and contexts, it can be challenging to determine if the same phenomenon is investigated (Zhou and Chen 2020). To address this problem, a correlation test of variables should be conducted to make sure that the modeling variables are sufficiently heterogeneous before the meta-regression analysis.

Despite these limitations associated with meta-regression analysis, it is still a useful tool that could help to improve the overall understanding of how the research outcomes are influenced by various modeling factors and thus advance the theory and practice of economic consequence analysis of temperature changes. In this paper, the sensitive modeling factors that may influence the research outcomes potentially were incorporated in the heterogeneity analyses. The heterogeneity framework contained seven groups of moderator variables, and the descriptive statistics are shown in Table 2.

- The first group of moderator variables was data specifications. The observations used in the included studies were incorporated in the meta-regression analysis, and the research periods divided into 10 years were also incorporated to investigate whether there were periodic characteristics between temperature changes and economic outcomes.
- The second group of moderator variables was country characteristics, which referred to the geographical location of the involved country, and whether the investigated countries were rich countries or poor countries.
- The third group of the moderator variables controlled estimation techniques. The estimation methods extensively used in the included studies were the OLS method, Ricardian method, quantile regression method, and IV and GMM method. Among them, the OLS method, quantile regression method, and IV and GMM method are commonly used econometric methods, whereas the Ricardian method is an empirical approach developed by Mendelsohn et al. (1994) to capture the effects of agricultural production to climate change based on cross-sectional data. In this paper, we focused on the direct impacts of temperature changes on yields of different crops based on the historical data. In addition, the differences in research findings may also be associated with whether panel data was used and whether the country effect, regional effect, and time effect were controlled. Therefore, eight dummies were set for estimation techniques.
- The fourth group of moderator variables was research objects. The studies included mainly concentrated on changes in temperatures over time within a given spatial area and demonstrated the impacts of these changes on various economic outcomes. The objects investigated could influence the research findings across the studies since different studies account for the different links between temperature changes and economic outcomes. Accordingly, we set five dummies for estimation subjects, including human capital, aggregate output, and the output of primary sectors, secondary sectors, and tertiary sectors.
- The fifth group of moderator variables controlled the temperature indicators. Annual, quarterly, monthly, and daily average temperatures were all defined across different studies as temperature variables to investigate temperature effects. Maximum temperature, minimum temperature, temperature variation, and temperature bins were also used as temperature variables for the time period explored. Besides, to overcome simultaneity problems between variables, some studies insert interaction structures on temperature indicators. Moreover, lagged temperature effects were also explored to investigate the differences between the long-term and immediate impacts of temperature changes; thus, we set dummy variables with 1 if the studies involved lagged structures of temperature indicators in the regression models. The focus of this paper is to explore economic impacts from historical data, and we found that the lagged years included in the collected studies are all within 10 years. In sum, we included 10 dummy variables that captured temperature indicator differences across studies.
- The sixth group of moderator variables referred to resilience factors. Resilience factors are also essential in the economic impact assessment of temperature changes as it helps the

Table 2 Description of variables and basic statistics

Variable	N	Mean	Type	Description
t-value	2808	−1.014	Continuous	T-Statistic coefficients related to temperature changes and economic effects, estimated in studies included
Moderator variables: data specifications				
N observations	2542	80,448[a]	Continuous	Number of observations, estimated in studies included
N years	2976	35.30	Continuous	Time period used in studies included
Yr50s	2976	0.211	Dummy	1 if data referred to 1950s (0 otherwise)
Yr60s	2976	0.348	Dummy	1 if data referred to 1960s (0 otherwise)
Yr70s	2976	0.562	Dummy	1 if data referred to 1970s (0 otherwise)
Yr80s	2976	0.840	Dummy	1 if data referred to 1980s (0 otherwise)
Yr90s	2976	0.871	Dummy	1 if data referred to 1990s (0 otherwise)
Yr00s	2976	0.875	Dummy	1 if data referred to 2000s (0 otherwise)
Yr10s	2976	0.622	Dummy	1 if data referred to 2010s (0 otherwise)
Moderator variables: country characteristics				
Africa	2976	0.302	Dummy	1 if African country was included (0 otherwise)
Asia	2976	0.366	Dummy	1 if Asian country was included (0 otherwise)
Europe	2976	0.394	Dummy	1 if European country was included (0 otherwise)
North America	2976	0.429	Dummy	1 if North American country was included (0 otherwise)
South America	2976	0.205	Dummy	1 if South American country was included (0 otherwise)
Oceania	2976	0.192	Dummy	1 if Oceanian country was included (0 otherwise)
Rich	2976	0.463	Dummy	1 if the analyzed country was a rich country (0 otherwise)
Poor	2976	0.673	Dummy	1 if the analyzed country was a poor country (0 otherwise)
Moderator variables: estimation techniques				
Panel	2976	0.924	Dummy	1 if panel data was adopted (0 otherwise)
OLS	2976	0.698	Dummy	1 if OLS technique was adopted (0 otherwise)
Ricardian	2976	0.142	Dummy	1 if Ricardian technique was adopted (0 otherwise)
QR	2976	0.0460	Dummy	1 if quantile regression was adopted (0 otherwise)
IV	2976	0.0410	Dummy	1 if IV technique was adopted (0 otherwise)
GMM	2976	0.00269	Dummy	1 if GMM technique was adopted (0 otherwise)
Fixed_Cou&Reg	2976	0.640	Dummy	1 if country or region fixed effects were adopted (0 otherwise)
Fixed_Year	2976	0.694	Dummy	1 if year fixed effects were adopted (0 otherwise)
Moderator variables: research categories				
Aggregate output	2976	0.212	Dummy	1 if aggregate output was explored (0 otherwise)
Human capital	2976	0.294	Dummy	1 if human capital was explored (0 otherwise)
Primary	2976	0.349	Dummy	1 if the output of primary sectors was explored (0 otherwise)
Secondary	2976	0.0850	Dummy	1 if the output of secondary sectors was explored (0 otherwise)
Tertiary	2976	0.0622	Dummy	1 if the output of tertiary sectors was explored (0 otherwise)
Moderator variables: temperature indicators				
Tem_Annual	2976	0.268	Dummy	1 if the temperature variable was annual temperatures (0 otherwise)
Tem_Quarter	2976	0.137	Dummy	1 if the temperature variable was quarterly temperatures (0 otherwise)
Tem_Month	2976	0.288	Dummy	1 if the temperature variable was monthly temperatures (0 otherwise)
Tem_Day	2976	0.310	Dummy	1 if the temperature variable was daily temperatures (0 otherwise)

Table 2 (continued)

Variable	N	Mean	Type	Description
Tem_Max	2976	0.0393	Dummy	1 if the temperature variable was maximum temperatures (0 otherwise)
Tem_Min	2976	0.00874	Dummy	1 if the temperature variable was minimum temperatures (0 otherwise)
Tem_Var	2976	0.0598	Dummy	1 if the temperature variable was temperature variations (0 otherwise)
Tem_Bins	2976	0.226	Dummy	1 if the temperature variable was temperature bins (0 otherwise)
Tem_Inter	2976	0.156	Dummy	1 if temperature interaction structures were used (0 otherwise)
Tem_long	2976	0.0974	Dummy	1 if the long-term impacts were investigated (0 otherwise)
Moderator variables: resilience factors				
Res_Economy	2976	0.222	Dummy	1 if the economic conditions were taken into account (0 otherwise)
Res_Education	2976	0.0168	Dummy	1 if the education conditions were taken into account (0 otherwise)
Res_Investment	2976	0.0474	Dummy	1 if the investment conditions were taken into account (0 otherwise)
Res_Openness	2976	0.0346	Dummy	1 if the openness level was taken into account (0 otherwise)
Res_Population	2976	0.0638	Dummy	1 if the population density was taken into account (0 otherwise)
Res_Climate	2976	0.618	Dummy	1 if the climate factors were taken into account (0 otherwise)
Res_Geography	2976	0.0692	Dummy	1 if the geographical factors were taken into account (0 otherwise)
Res_Aid	2976	0.00403	Dummy	1 if the aid capacity were taken into account (0 otherwise)
Res_Institution	2976	0.0363	Dummy	1 if the institution conditions were taken into account (0 otherwise)
Res_Adaptation	2976	0.0144	Dummy	1 if the adaptation measures were taken into account (0 otherwise)
Moderator variables: publication characteristics				
Pub_Year	2976	2015	Continuous	Publication year
Published	2976	0.840	Dummy	1 if the study was published in a peer-reviewed journal (0 otherwise)

Note: reported descriptive statistics exclude 1 outlier

[a] The mean observations are so high because the observations in some studies are special. For instance, Zhang et al. (2018) and Chen and Yang (2019) used data from many industrial firms, and their observations in the regression model are 1,833,408 and 1,803,482, respectively. Except for the six studies with the highest observations, the mean observations of the remaining 81 studies are 5932.943

economic system maintain its functions. To analyze the economic impacts of temperature changes on specific regions, the included studies involved different resilience factors of research areas, such as economic development level, education level, government investment, opening level, population density, and climate conditions. Therefore, we set dummy variables with 1 if the included studies involved these resilience factors.

- The final group of moderator variables controlled publication differences. First, a dummy variable was adopted to indicate whether a study was a peer-reviewed article. Besides, the publication years were also included in the meta-regression analysis, allowing us to analyze differences over time in reported economic effects.

3.2 Explaining heterogeneity: econometric model

A total of 52 variables were identified as possible sources of heterogeneity. Before performing meta-regression analysis, a correlation test was conducted to prevent the model estimates from being distorted or difficult to estimate due to the high correlation between the explanatory variables in the regression models. Generally, when the mean value of the variance inflation factor (VIF) is greater than 2 and the maximum value of the VIF approaches or exceeds 10, it is generally considered that there is a relatively serious multicollinearity (Miles 2005). The correlation between explanatory variables in this research was strong (the mean VIF was 20.44), so the collinearity problem did exist. Therefore, stepwise regression and lasso regression were adopted to perform the meta-regression to solve the collinearity problem, exclude some variables with insignificant effects, and establish an optimal subset of independent variables, thereby improving the model structure.

The principle of stepwise regression is to select appropriate variables to determine the optimal regression model (Nomura et al. 2016). Least squares regression models (LSM) are commonly adopted in stepwise regression to find the coefficient β that can minimize the residual sum of squares (RSS). The equation that we specified can be expressed as

$$\left(\widehat{\alpha}^{(ols)}, \widehat{\beta}^{ols}\right) = \underset{(\alpha,\beta)}{arg\ min} \sum_{i=1}^{n} \left(y_i - \alpha - \sum_{j=1} X_{ij}\beta_j\right)^2 \tag{1}$$

where $\hat{\alpha}^{(ols)}$ is the intercept of the stepwise regression model, $\hat{\beta}^{(ols)}$ denotes the coefficient of the stepwise regression model, and X_{ij} and y_i are the observed values of the explanatory and explained variables respectively.[4]

Lasso regression can effectively estimate the coefficients in the regression model, and solve the multicollinearity problem between variables. The estimator $\left(\hat{\alpha}^{(lasso)}, \hat{\beta}^{(lasso)}\right)$ of the lasso method can be defined as

$$\left(\widehat{\alpha}^{(lasso)}, \widehat{\beta}^{(lasso)}\right) = argmin\left\{ \sum_{i=1}^{n} \left(y_i - \alpha - \sum_{j=1} X_{ij}\beta_j\right)^2 + \lambda \sum_j \left|\beta_j\right| \right\} \tag{2}$$

The first part of Eq. (2) represents the goodness of model fitting, and the second part represents the penalty of parameters, where λ is the harmonic coefficient, a smaller λ indicates that the punishment intensity of the model is smaller, and more variables will be retained. Conversely, a larger λ indicates that the punishment intensity of the model is greater, and fewer variables will be retained.

In addition, following Lazzaroni and van Bergeijk (2014), this paper divided the *t*-values into three categories, including negative and significant relationships, insignificant relationships, and positive and significant relationships based on the collected estimates. This method can not only increase the observations of the model, but also can verify the results of stepwise regression and lasso regression. Before using the meta-regression model to conduct further analysis, the brand test was adopted to examine the parallel line assumption. If the meta-dataset constructed in this paper can meet the parallel line assumption, then the ordered logit model was appropriate to conduct further meta-analysis. However, the Brant tests reject the parallel line assumption, then the generalized ordered probit (GOP) model was adopted instead. To

[4] Two stepwise regression models were performed (forward-stepwise and backward-stepwise) to extract variables at 5% level of significance.

explain heteroscedasticity and study dependency, we estimated that both stepwise regression model and GOP model with robust standard errors clustered by studies. The estimated GOP regression model for meta-analysis is specified as follows:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_1 x_{1ij} + \cdots + \beta_n x_{nij} + u_{ij} \tag{3}$$

where y_{ij} is the estimated effect i drawn from study j, and the estimated effect includes three categories. Based on the 5% significance level, $y = 1$ means that the reported estimate is negative and significant at least 5% ($t \leq -1.96$); $y = 2$ means that the reported estimate is insignificant ($-1.96 < t < 1.96$); $y = 3$ means that the reported estimate is positive and significant ($t > 1.96$). Meanwhile, the OLS model using the reported t-values of the collected studies was also conducted.

4 Meta-regression analysis: results

4.1 Empirical results

The results of lasso regression, stepwise regression, and GOP model are reported in Table 3. After eliminating those variables which were insignificant in the heterogeneity framework through lasso regression and stepwise regression, there were ten variables in linear regression analysis and four variables in quadratic regression specifications were obtained as modeling factors of heterogeneity.

As expected, the regression results suggested that the study areas involved in individual studies affected the research outcomes. *T*-values of temperature changes varied when using different regional or country data, especially when the research data was from rich countries. According to the results of the marginal effect, using data from rich countries was more likely to report positive and significant relationships. This finding was consistent with current studies, such as Hsiang et al. (2017) who pointed out that the risk of temperature changes was distributed unequally across locations that increase economic inequality. As Dell et al. (2008) demonstrated that the effects of temperature changes in rich and poor countries are different, with wide-ranging effects in poor nations, such as reducing agricultural output, industrial output, and aggregate investment, and increasing political instability, but have little effect in rich countries. Moreover, with sufficient capital and technical support to adapt to the changing climate, rich countries could even benefit from temperature changes in numerous ways (Cui 2020). Meanwhile, poor countries do not have the economic and institutional capabilities to withstand extreme temperature events and greater temperature fluctuations (Moore and Diaz 2015).

Moreover, the meta-regression results reflected a significant effect of using the Ricardian method and IV and GMM methods in linear analysis, as well as the OLS method in quadratic regression analysis. Specifically, using the Ricardian method as the assessment method increased the probability of reporting positive and significant relationships. Using IV and GMM methods as the assessment methods increased the probability of reporting negative and significant relationships. Also, using the OLS method to conduct the investigation increased the probability of reporting inverted U-shaped relationships between temperature changes and economic impacts. This can be

Table 3 Meta-regression results on the estimated economic effects of temperature changes

Dependent variable	Lasso	Stepwise regression		OLS	Generalized ordered probit — marginal effects		
		Forward stepwise	Backward stepwise		(1) Neg. sig.	(2) Insignif.	(3) Pos. sig.
	t-value				*t*-value categories (1.96)		
Linear regression analysis							
North America	−3.930		−5.232***	−5.200***	0.676***	−0.40***	−0.273***
			(0.660)	(0.909)	(0.084)	(0.09)	(0.074)
Oceania	3.256		3.066***	3.279***	−0.327***	0.07	0.254**
			(0.678)	(0.714)	(0.046)	(0.14)	(0.125)
Rich	1.710		2.082***	2.059***	−0.299***	−4.00E−03	0.303***
			(0.474)	(0.485)	(0.075)	(0.09)	(0.058)
Ricardian	1.533		1.748***	1.536**	−0.109*	−0.02	0.132*
			(0.489)	(0.637)	(0.061)	(0.06)	(0.063)
IV	−2.101		−2.228***	−1.883***	0.369***	−0.29**	−0.078***
			(0.407)	(0.552)	(0.120)	(0.13)	(0.013)
GMM	−2.568		−1.233*	−1.696**	0.316**	−0.24*	−0.076***
			(0.482)	(0.736)	(0.138)	(0.14)	(0.012)
Tem_Max	−0.945	−2.384***	−2.816***	−2.479***	0.221***	0.17***	−0.048
		(0.434)	(0.734)	(0.516)	(0.038)	(0.05)	(0.058)
Tem_Bins	−1.925		−1.534***	−1.192***	0.178***	−0.11	−0.072**
			(0.318)	(0.301)	(0.058)	(0.07)	(0.031)
Res_Aid	0.470	1.080***	0.716**	0.804***	−0.147***	0.06	0.086**
		(0.161)	(0.234)	(0.251)	(0.043)	(0.08)	(0.044)
Published	−1.126		−1.316**	−1.286**	0.143***	−0.16***	0.022
			(0.473)	(0.593)	(0.046)	(0.05)	(0.058)
Constant	8.268	−2.424***	−1.540	−1.025			
		(0.312)	(0.824)	(0.784)			
N		2042	2042	2042	2542	2542	2542
R^2		0.073	0.105	0.110			
Dependent variable	Lasso	Stepwise regression		OLS	Generalized Ordered Probit — marginal effects		
		Forward stepwise	Backward stepwise		(1) Inverted U-shaped	(2) Insignif.	(3) U-shaped
	t-value				*t*-value categories (1.96)		
Quadratic regression analysis							
OLS	1.562		4.211***	0.023*	0.379*	0.280	−0.658***
			(0.491)	(0.643)	(0.202)	(0.253)	(0.154)
Tem_Day	3.927		−15.093***	9.061**	−0.266**	0.211*	0.055

Table 3 (continued)

			(1.957)	(3.133)	(0.124)	(0.128)	(0.067)
Tem_Long	2.156	2.433**	2.142***	1.497*	−0.319***	0.320***	−1.278E−03
		(0.773)	(0.351)	(0.743)	(0.085)	(0.085)	(1.456E−03)
Res_Climate	1.792	2.836**		3.753**	−0.034	0.019	0.016*
		(0.775)		(1.712)	(0.157)	(0.158)	(0.009)
Constant	209.644	−1.669***	970.972***	290.819			
		(0.371)	(206.321)	(194.060)			
N		448	448	448	468	468	468
R^2		0.249	0.325	0.311			

Note: Some estimates have to be excluded from the meta-analysis due to missing number of observations in the collected studies. Robust standard errors, clustered by studies. ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Values in parentheses represent the standard errors attributed to the fact that each method has its own special principles of evaluation. For instance, the Ricardian model was mainly used to evaluate the temperature effects on the agricultural economy, and this method assumes that each farmer wishes to have maximized income subject to the exogenous conditions. Thus, given this assumption, using the Ricardian method as the assessment method was more likely to report positive and significant relationships.

In terms of the selection of different temperature variables, significant differences were observed across the studies, represented by using maximum temperatures, temperature bins, daily temperature, and long-term effects of temperatures as temperature variables. Specifically, using maximum temperatures and temperature bins as temperature variables increased the probability of reporting negative and significant relationships. The studies involved used a wider temperature range, from − 60 °C to above 30 °C. Similar to estimates reported from maximum temperature, extreme temperatures may reduce the productivity in agricultural production, manufacturing processes, and worker productivity (Cai et al. 2018; Chandio et al. 2020). Also, using daily temperatures as temperature variables and investigating the long-term effects of temperatures decreased the probability of reporting inverted U-shaped relationships. The finding of different temperature variables was basically consistent with the conclusion from Chen and Yang (2019) that more findings can be obtained by utilizing different temperature variables for investigation.

In addition, we presented 10 resilience factors from current empirical findings, including economy, education, investment, opening level, population, climate conditions, geographical factors, aid capacity, institutions, and adaptations. The results showed that the evaluation models taking aid capacity into account were more likely to report positive and significant relationships. This result may be explained by the fact that the improvement of aid capacity could improve the ability to respond to temperature changes by obtaining relief funds or financial support. Also, regression models taking climate conditions into account were more likely to report U-shaped relationships. Moreover, if the estimates were collected in peer-reviewed journals, then negative and significant associations between temperature changes and economic impacts were easier to find.

Moreover, to test the accuracy and robustness of the results found above, two robustness checks were performed from data source bias and model selections. The results of the robustness checks are reported in Appendix Tables 2 and 3. First, we presented in Appendix Table 3 with FAT-PET-PEESE tests on economic outcomes excluding observations from specifications with interaction terms and unpublished studies based on linear regression analysis. Then, we performed a robustness check to further investigate the GOP regression results with the conventional thresholds at 10% level and 1% level based on linear regression analysis. In general, the main regression results were basically unchanged and relatively robust.

4.2 Heterogeneity analysis

The above results demonstrated that temperature changes have negative impacts on economic output in current studies and sensitive modeling factors have also been identified. Subsequently, we further analyzed the economic impact of the temperature changes on different research objects (Appendix Fig. 1–5 and Appendix Table 2). The funnel plots revealed a similar conclusion with total economic impacts in investigating the impacts of temperature changes on human capital, aggregate output, and the output of primary sectors, secondary sectors, and tertiary sectors. In sum, a bias towards reporting negative *t*-values was also observed in all research sub-objects (Appendix Fig. 1–5). Then, the sensitive modeling factors in research sub-objects were also identified through meta-regression analysis (Appendix Table 2).[5]

First, in the studies of aggregate output, two sensitive modeling factors were identified, including rich country in country characteristics and aid capacity in resilience factors. Using data from rich countries and taking aid capacity into consideration increased the probability of reporting positive and significant relationships between temperature changes and aggregate output. Second, in the studies of human capital, three sensitive modeling factors were identified, including country or region fixed effects in estimation techniques, climate factors in resilience factors, and whether the research findings were published in peer-reviewed articles. Specifically, if country or region fixed effects were involved in the assessment method, then the probability of reporting negative and significant relationships was decreased. Also, taking climate conditions into account also decreased the probability of reporting negative and significant relationships. Moreover, research findings published in peer-reviewed journals were more likely to report negative and significant associations between temperature changes and human capital.

Third, in the studies of the output of primary sectors, eight sensitive modeling factors were identified. Using data from the 2000s and 2010s was more likely to report negative and significant associations. One possible reason is that the temperature has changed more rapidly in recent years, and the resulting impact has become more serious. Also, using data from rich countries increased the probability of reporting positive and significant associations between temperature changes and the output of primary sectors. Using panel data and IV techniques decreased the probability of reporting negative and significant relationships, whereas using the OLS method increased the probability of reporting negative and significant relationships. Moreover, taking education conditions into account decreased the probability of reporting positive and significant relationships, and research findings published in peer-reviewed journals were more likely to report negative and significant associations between temperature changes and the output of primary sectors.

Fourth, in the studies of the output of secondary sectors, four sensitive modeling factors were identified, including number of observations in data specifications, rich country and poor country in country characteristics, and country or region fixed effects in estimation techniques. Specifically, the increase in observations was more likely to report negative and significant relationships. Using data from rich countries increased the probability of reporting positive and significant associations, whereas using data from poor countries was more likely to show negative and significant associations. Several research findings reveal that higher temperatures substantially reduce economic growth in poor countries but have little effect in rich countries (Dell et al. 2008; Falco et al. 2019; Pretis et al. 2018). In addition, taking country or region fixed effects into consideration decreased the probability of reporting positive and significant relationships. Fifth, in the studies of the output of tertiary sectors, two sensitive modeling factors were identified. The increase in observations was more likely to report negative and significant results. Moreover, using data from European countries was significantly more likely to report positive and significant estimates. This could be explained by the fact that in Europe the climate is cooler and there are more developed countries, with strong economic strength and the ability to deal with the impact of temperature changes.

[5] Due to the small number of estimates from quadratic regression analysis, the funnel plots of quadratic regression analysis were performed between temperature changes and aggregate output, human capital, and the output of primary sectors. Also, the meta-regression analysis on different research objects was performed based on estimates derived from linear regression analysis.

5 Conclusion

Although the rapid increase of temperature has stimulated an extensive academic investigation, it remains unclear about the genuine effects of temperature changes on economic output and how the economic outcomes are influenced by factors pertaining to modeling specifications. Current empirical findings provide heterogeneous evidence on the association between temperature changes and economic output, with some studies indicating that temperature changes can significantly promote economic development, while others prove that temperature changes have serious negative economic impacts. With the fact that global temperatures have increased at a historically unprecedented pace, understanding the genuine effects, as well as improving the future modeling structure and prediction robust, is a pressing issue.

In order to explore the genuine effects and characterize the heterogeneity in estimates, we investigated the relationship between temperature changes and economic impacts of the extant literature through a meta-analysis based on 87 studies with 2977 estimates. Several important results were found. First, this paper demonstrated that there were genuine effects between temperature changes and economic impacts. Through tests of MST, FAT-PET-PEESE, and funnel plot, publication selection bias towards negative and significant results in linear regression analysis and inverted U-shaped relationship in quadratic regression specifications seemed relevant. In addition, the similar impacts of temperature changes can also be observed in research sub-objects, including the impact of temperature changes on human capital and aggregate output, as well as the output in primary sectors, secondary sectors, and tertiary sectors. Second, the results indicated that regional differences and temperature indicator selections have significant effects on the economic consequence analysis of temperature changes. Particularly, rich countries located in colder climates can even benefit from temperature changes, whereas poor countries located in hotter climates seemed to suffer negative effects of temperature changes. Third, resilience factors are important in individual studies. Different countries have various adaptabilities to meet the challenges of temperature changes in terms of geography, population density, socio-economic situation, education, and aid ability. Therefore, we stressed the need of future studies to carefully include and deal with resilience on to mitigate the adverse impacts of temperature changes.

This article provides the following implications for future temperature change consequence analysis: First, the majority of empirical studies focused on the primary sector. Further research could explore sectors that were rarely evaluated. Second, future research could also advance empirical specifications. According to our meta-regression results, the sign and significance of the estimates vary according to the choice of modeling factors. Thus, it is important that future authors increase consideration and transparency concerning the selection of modeling factors. In addition, as for temperature variable selections, the process of the variable adopted should be improved, to secure sufficient robustness in the research outcomes. For instance, average temperatures, maximum temperatures, minimum temperatures, and temperature variations were commonly used temperature variables in current studies. The problem is that these variables are correlated, which means multivariable methods that assume independence are not necessarily established when using these interrelated variables together. An effective way to solve this problem is to check the degree of correlation between the included variables and screen out the independent and effective variables for analysis before starting to conduct further analysis. Third, in furthering the empirical studies, scholars are encouraged to present a detailed characteristic of the samples used across the whole regression analysis. This will help conduct more comprehensive meta-analyses in the future that can contribute to temperature change economics.

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Data availability The datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

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