



The uneven impact of temperature on the macroeconomy: a perspective on total factor productivity

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Abstract

The economic ramifications of climate change have drawn growing attention, yet empirical evidence on how temperature dynamics influence total factor productivity (TFP) in China remains limited. This study constructs a city-level TFP index based on a Cobb–Douglas production function, using balanced panel data from 278 Chinese cities spanning 2000–2022. A fixed effects model is employed to identify the nonlinear impact of temperature on TFP. The results reveal a statistically significant inverted U-shaped relationship, with the marginal effect of temperature on TFP peaking at 13.34 °C. The mechanism analysis indicates that temperature affects TFP through internal factor inputs, by altering the efficiency of labour and capital utilisation efficiency, and external environmental channels such as air pollution, energy consumption, and ecosystem service degradation. The heterogeneity analysis further suggests that urban sensitivity to climate change varies by region, industrial structure, income level, and resource dependence. These findings uncover the mechanisms linking climate variability and economic productivity, and provide empirical support for differentiated climate adaptation policies aimed at sustaining long-term productivity under environmental constraints.

Keywords Total factor productivity · Climate change · Temperature shock · Nonlinear · Capital productivity

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1 Introduction

Enhancing total factor productivity (TFP) constitutes a key pathway to achieving high-quality economic development and remains one of the principal drivers of long-term economic growth (Yiğiteli and Şanlı, 2024). TFP reflects the efficiency with which input factors contribute to economic output, and its growth captures the portion of the production that cannot be attributed to changes in capital or labour inputs alone (Pan et al. 2022). However, climate change has been shown to erode factor productivity, triggering widespread concern about the long-term sustainability of economic growth across countries (Desmet and Rossi-Hansberg 2024; Moore and Diaz 2015). Globally, the accelerating pace of climate change and the surge in extreme weather events have elevated their physical and economic consequences to central priorities in policy and governance agendas. In the pioneering work by Nordhaus (1992), climate change was characterised by the increase in global average temperature. Empirically defined damage functions entail substantial discretionary assumptions, and owing to their sensitivity to parameter choices, they cannot be readily generalised or directly applied across different regional contexts (Newell et al. 2021). Moreover, the impact of temperature change is far from uniform across the globe; certain regions, particularly those with already high baseline temperatures, are experiencing accelerated warming, underscoring the need to identify localised effects on economies and populations (Rantanen et al. 2022). China remains the world's largest developing economy amid rapid industrialisation and urbanisation. Intensifying climate change poses a significant obstacle to economic progress and adversely affects the well-being of its population (Adger 2010). The “China Climate Change Blue Book 2023” indicates that the rate of warming in China is higher than the global average for the same period. In 2022, the average surface temperature in China was 0.92 °C higher than the long-term average, and from 1961 to 2022, the frequency of extreme high-temperature events in China showed a significant increasing trend, reaching a peak in 2022. The growing severity of climate-related challenges calls for a more urgent and systematic identification of climate risks from theoretical and empirical perspectives. However, the current literature remains limited in addressing this issue comprehensively.

Building on the preceding discussion, this paper aims to address the following research questions. First, it examines how to reconcile the economic growth framework of climate change in integrated assessment models (IAMs) with the macroeconomic measurement of TFP. IAMs typically simulate growth using empirically defined Cobb–Douglas production functions under the assumption of constant returns to scale. However, macro-level TFP estimation approaches often rely on non-parametric methods, such as data envelopment analysis, which lack a clear structural link to the production function. Conversely, parametric models may deviate from the constant returns to scale assumption, creating a conceptual mismatch with IAMs. This paper proposes an adjusted set of coefficients to modify the Cobb–Douglas function, thereby deriving a TFP estimation model that can be harmonised with the economic growth component of IAMs. Second,

the paper investigates the impact of climate change on regional TFP across China. Given China's vast territorial expanse and wide latitudinal span, regional climate patterns exhibit significant heterogeneity. Since labour and capital exhibit temperature sensitivity in production, deviations from optimal temperature, whether excessively high or low, can adversely affect productivity. Accordingly, changes in average temperature may either enhance or hinder TFP. To test this hypothesis, the study employs a non-linear fixed effects model. Third, the paper seeks to identify the underlying mechanisms by which climate change influences TFP, considering both factor input channels and external environmental effects. On the input side, climate change may reshape the composition and efficiency of factor inputs. Externally, factors such as air pollution, energy consumption, and ecosystem service quality will likely mediate the relationship between temperature and productivity. The empirical model incorporates both perspectives to test the significance of these mediating pathways.

This study offers four significant contributions compared to existing research. First, drawing upon the Cobb–Douglas production function, the study introduces a set of coefficients and integrates empirical and mathematical economic methods to formally derive and verify that TFP is the geometric weighted mean of labour and capital productivity, thereby unifying TFP and single-factor productivity within a consistent analytical framework. Second, it constructs a framework for assessing the impact of average temperature on TFP within the structure of IAMs of climate change, and fits the heterogeneous effects of temperature variation on TFP using historical data. Third, it investigates the mechanisms through which climate change affects TFP from the perspective of factor input structures. It also incorporates external factors such as air pollution, energy consumption, and ecosystem services, thereby enhancing the comprehensiveness of the explanatory framework. Fourth, in response to the widespread absence of complete labour force statistics at the city level in China, the study proposes a practical estimation strategy to improve the completeness and consistency of the dataset used for TFP measurement.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the research design. Section 4 presents the empirical analysis of the impact of temperature variation on TFP. Section 5 explores heterogeneity across different dimensions. Section 6 concludes with a summary of findings, policy implications, and a discussion of the study's limitations.

2 Literature review

2.1 The concept and measurement methods of total factor productivity

TFP is an essential economic concept that measures how efficiently resources are used in national economies, industries, and enterprises (Balk et al. 2020). Solow (1957) introduced TFP in his seminal paper, attributing the portion of economic growth not explained by labour and capital inputs to TFP, and he used the “Solow residual” method to measure its growth rate. As research has progressed, the importance of TFP in economic growth has been increasingly recognised.

Initially seen as technological progress, TFP includes factors like management quality and labour force skills (Hang et al. 2024; Xia and Xu 2020). To measure TFP more precisely, labour and capital have been further subdivided. For example, labour is classified into high-skilled and low-skilled categories (Zhibiao and Yonghui 2022), and capital into tangible and intangible assets (McGrattan 2020). These subdivisions address the quality of labour and capital. Economic growth fundamentally comes from two sources: resources and the effectiveness of their use, which can be measured by productivity, output equals factor input multiplied by productivity (Wu and Yao 2023). Suppose only labour is considered, and it is measured by quantity. In that case, the quality of labour or other technical factors can still be reflected in differences in labour productivity, i.e., output per unit of labour. When both labour and capital are considered, TFP becomes a composite measure of both, explaining the part of total output growth not due to the growth of input factors (Ren et al. 2022).

The methods of measuring TFP can be broadly classified into parametric and non-parametric approaches. The parametric approach requires the pre-specification of a production function. The Cobb–Douglas production function (Felipe and McCombie 2020; Oryani et al. 2021) and the Constant Elasticity of Substitution (CES) production function (Obrosova et al. 2023) are the most widely used. Farajzadeh et al. (2023) examined the applicability of the CES and Cobb–Douglas production functions to Asian economies, concluding that the Cobb–Douglas form best represents the basic production technology of Asian economies. This supports the use of the Cobb–Douglas production function in studies of Asian economic issues. However, using the Cobb–Douglas production function has faced criticism (Liu et al. 2012), particularly regarding the subjectivity in parameter setting and parameter estimation accuracy. Additionally, the assumption of constant returns to scale, which is generally required, is often debated despite its suitability for economic modelling. In contrast, non-parametric methods have gained wide application, as they do not require pre-specification of a functional form. Data Envelopment Analysis (DEA) is a commonly used non-parametric method that can handle multiple inputs and outputs by constructing a production frontier to assess the production efficiency of decision-making units. However, under radial and angular assumptions, the calculated TFP results may not align with reality when there is excessive input or insufficient output (Zeng et al. 2022). To address this, Tone (2001) developed the Slack-Based Measure (SBM) model, which is non-radial and non-angular. Extensive research has been conducted on expanding the DEA model (Färe et al. 2007; Halkos et al. 2014).

Several issues exist in the current measurement of TFP. First, there is often confusion between TFP levels and TFP indices. Labour productivity represents economic output per unit of labour input, while the TFP level represents economic output per unit of combined inputs like labour and capital. The TFP index, however, refers to the growth rate of TFP, indicating a dynamic concept. Another issue concerns the selection of input data, especially in studies measuring TFP in Chinese cities. Labour input data should align with capital and output data. However, due to data source limitations, inaccuracies in the selection of labour indicators by scholars have led to measurement results that do not accurately reflect reality.

2.2 The impact of temperature changes on total factor productivity

Climate change, characterised by rising temperatures and an increasing frequency of extreme weather events, adversely affects economic development and human welfare. Scholars have developed numerous theoretical foundations and empirical models to identify the effects of temperature changes on economic systems. Regardless of the measurement methods or their types, the fundamental aim is to understand the damage caused by climate change to economic systems. The findings from these studies provide deep insights into climate change and assist various countries and industries in designing effective mitigation and adaptation policies (Kalkuhl and Wenz 2020; Newell et al. 2021). Given the importance of TFP to economic growth, researchers have examined the impact of temperature changes on TFP at different scales. Within the framework of endogenous economic growth models, it has been shown that TFP can be adversely affected if the global average temperature exceeds pre-industrial levels, leading to a rapid increase in the social cost of carbon (Dietz and Stern 2015). Cruz and Rossi-Hansberg (2024) estimate the damage function associated with global warming and identify how climate change affects productivity and human comfort within this framework. Economic agents in different regions or sectors respond heterogeneously to temperature variations. Such diversity in climate change impacts is shaped by factors including baseline climatic conditions, industrial structure, stage of development, and the extent of adaptive capacity (Bijmens et al. 2024). Zhang et al. (2018) show that rising temperatures substantially negatively affect timber manufacturing, while the impact on pharmaceutical manufacturing is statistically insignificant. This highlights the variation in climate exposure across industries, leading to differential productivity losses. Among major sectors, agricultural productivity is most severely threatened by climate change, given its direct reliance on climatic conditions (Bouteska et al. 2024). From a broader perspective, numerous studies have indicated that temperature changes significantly negatively impact TFP, with the effects being most pronounced in poorer countries (Letta and Tol 2019). Kumar and Khanna (2019), using a stochastic frontier function, discovered a concave relationship between temperature and TFP growth, with developing countries experiencing more severe negative impacts from temperature changes compared to developed economies. However, the effect is not always linear, as Burke et al. (2015) identified a nonlinear relationship between temperature and TFP. Kumar and Maiti (2024), using a sample of emerging economies, find that changes in average temperature exhibit a non-linear impact on TFP, with moderate warming fostering productivity in the short term, but extreme temperatures exerting significantly detrimental effects. Although population and economic activity can, in theory, be reallocated to mitigate the economic damage caused by climate warming, Desmet and Rossi-Hansberg (2024) argue that spatial frictions limit this adjustment, resulting in persistently high productivity costs. Collectively, these findings contribute to a deeper understanding of how climate change affects productivity, thereby informing the design of more effective mitigation and adaptation policies across countries and industrial sectors (Kalkuhl and Wenz 2020; Newell et al. 2021).

Concerning the fundamental components of TFP, climate change exerts differentiated effects on labour and capital inputs and their respective productivities. In

estimating climate-induced economic damages, damage functions map altered weather patterns into corresponding economic costs and benefits (Auffhammer 2018). Some sectors are inherently more vulnerable to climate change, with rising temperatures particularly impacting heat-intensive industries such as agriculture and construction (Shayegh and Dasgupta 2024). In addition, elevated temperatures impair the effectiveness of industrial lubricants in reducing friction between mechanical components, which increases material input requirements, elevates failure rates, and slows operational efficiency, ultimately constraining capital accumulation (Kumar and Maiti 2024). Zhao et al. (2024), employing a computable general equilibrium model, reveal that China's economic losses from high temperatures are unevenly distributed across regions, industries, and labour types, with disproportionately adverse effects on heat-sensitive workers. Economic systems often adopt anticipatory or adaptive strategies to mitigate productivity losses in response to rising temperatures. Theoretically, if climate adaptation were complete and frictionless, both present and future economic losses from climate change could be entirely avoided (Carleton and Hsiang 2016). Effective climate adaptation entails short-term reallocating production factors and sustained investment in research and development over the long term. Colacito et al. (2019) demonstrate that rising temperatures significantly reduce labour productivity growth during summer and autumn, whereas no such effect is observed in winter or spring. In response to temperature impacts, workers may adjust leisure and work schedules (Huang et al. 2020). Systemically, the optimal adaptive response involves reallocating capital and labour to sectors and regions with comparative advantages to minimise climate-related losses (Albert et al. 2021). Capital investment is redirected away from polluting assets towards clean investments, which can lead to higher welfare and efficiency (Baldwin et al. 2020). These findings emphasise the considerable influence of temperature variations on the productivity of both labour and capital, which in turn impacts overall economic efficiency, known as total factor productivity. The analysis demonstrates that fluctuations in temperature can either enhance or impair workforce efficiency and capital utilisation, thereby affecting the broader economic output. Nevertheless, it is also crucial to note that market participants are not merely passive observers of these effects. There is evidence that the adverse impacts of temperature on productivity can be substantially reduced through proactive strategies.

2.3 Research review

A brief literature review is a solid foundation for presenting the novelty and innovation of current research, and it is essential for identifying research gaps. Many approaches currently exist for measuring TFP, encompassing parametric and non-parametric techniques. Within integrated assessment models of climate change, the classical DICE model specifies an economic growth framework incorporating TFP, labour, and capital, assuming constant returns to scale. However, discrepancies between prevailing TFP estimation methods and the specification of TFP within such models introduce conceptual misalignments that undermine the applicability and consistency of the framework. While existing literature has explored the effects

of climate change on TFP from global and firm-level perspectives, there is a relative paucity of research at the scale of Chinese cities, and the mechanisms through which these effects materialise remain insufficiently examined. Accordingly, this study proposes a novel TFP accounting approach that integrates total factor productivity with single-factor productivity, while exploring the underlying mechanisms associated with both factor inputs and partial productivity. Building on this framework, the analysis is further extended to consider the potential mediating effects of external factors beyond the traditional components of TFP.

3 Research design

3.1 The interaction framework between output, temperature, and productivity

It has been indicated in the existing literature that an increase in average temperature affects productivity levels or their growth. This study follows the conceptual framework of Letta and Tol (2019) to illustrate how climate change impacts TFP. The model assumes a final output production function that costlessly aggregates intermediate goods produced across different regions. In each region, a single variety of goods is produced using local labour and capital inputs. It is further assumed that economic activity in each region generates localised negative externalities. The overall rise in temperature is assumed to impair total factor productivity (Kumar and Maiti 2024). The production model is formalised in Eq. (1), which reflects a widely adopted structure for simulating the economic impacts of climate change (Kalkuhl and Wenz 2020):

$$y_{i,t} = [(1 + \Omega_{i,t})A_{i,t}]K_{i,t}^a L_{i,t}^{1-a} \quad (1)$$

where i and t represent individuals and time respectively; $y_{i,t}$ denotes the output of the economic system, typically measured by regional gross domestic product; $A_{i,t}$ represents total factor productivity, which captures the efficiency with which inputs are transformed into output in the production process, and is commonly used as a proxy for technological progress.; K refers to capital input, which encompasses fixed assets such as infrastructure, machinery, and buildings; L denotes labour input, typically quantified by total hours worked or the number of employed individuals; $\Omega_{i,t}$ denotes the functional relationship capturing the effect of average temperature on total factor productivity, which is empirically estimated using a fixed effects model in this study; and a represents the weight coefficient of capital. The equation is assumed to satisfy the constant returns to scale hypothesis.

The output $y_{i,t}$ is utilised for consumption and savings:

$$y_{i,t} = I_{i,t} + C_{i,t} \quad (2)$$

$$C_{i,t} = cr_{i,t} \times y_{i,t} \quad (3)$$

where $I_{i,t}$ and $C_{i,t}$ denote investment and consumption, respectively; $cr_{i,t}$ denotes consumption rate; Labour indicators are specified exogenously; the capital movement equation is applied in the form of the perpetual inventory method:

$$K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t} \quad (4)$$

where $K_{i,t-1}$ represents the capital stock of the previous period, and δ denotes the capital depreciation rate, which is set at 9.60% in this study. The change in TFP $A_{i,t}$ without considering climate damage is as follows:

$$A_{i,t} = A_{i,t-1} / (1 - g_{i,t-1}) \quad (5)$$

$$g_{i,t} = g_{i,t-1} \times e^{-\theta_i} \quad (6)$$

where $g_{i,t-1}$ represents the exogenous growth rate of total factor productivity, and θ_i denotes the decay index of the total factor productivity growth rate for region i .

Building on the conceptual framework established in Eqs. (1) through (6), this study assumes that climate change may induce losses in TFP, with temperature-related damages transmitted via a damage function. These losses in TFP are expected to persistently impact economic output in the context of future economic growth. Accordingly, this study seeks to empirically estimate the historical impact of temperature variation on TFP, alongside the underlying transmission mechanisms. The findings aim to inform the design of targeted and differentiated climate mitigation and adaptation policies by providing robust empirical evidence.

3.2 Measurement of total factor productivity

3.2.1 Accounting framework

The measurement of TFP relies on determining the structural parameters α , specifically the weight of capital. The integrated assessment model of global climate change by Barrage and Nordhaus (2024), α is set at 0.3. Statistically, this implies that labour is more significant than capital in driving economic growth, which aligns with the future economic growth model, where labour is expected to play an increasingly important role. Historically, China achieved rapid economic development by attracting investment and leveraging its demographic dividend, during which capital was critical in promoting economic growth. Therefore, setting the capital weight at 0.3 for historical periods may be unreasonable. To ensure the objectivity of the weight setting and to adhere to the assumption of constant returns to scale, a new method for measuring and decomposing TFP based on the Cobb–Douglas production function is proposed. The resulting Cobb–Douglas production function is derived by assuming labour and capital as the input factors. For simplicity, the subscripts i and t are omitted:

$$y = AL^\alpha K^\beta \quad (7)$$

In this context, the output elasticities of labour and capital are represented by α and β , respectively. The logarithm of both sides of the equation is then taken, resulting in:

$$\ln y = \ln A + \alpha \ln L + \beta \ln K + \varepsilon \quad (8)$$

By fitting the equation parameters using the least squares method, issues may arise where TFP is treated as a constant and the presence of error terms ε . Therefore, Eq. (7) is strictly valid only under specific conditions, such as:

$$\bar{y} = A \bar{L}^{-\alpha} \bar{K}^{\beta} \quad (9)$$

where $\bar{y}$, $\bar{L}$, and $\bar{K}$ represent the average values of output, labour, and capital, respectively. For general statistical data, an error term ε causes Eq. (8) not to hold strictly, leading to inaccuracies in economic efficiency analysis. Based on the basic principle that output equals input multiplied by production efficiency, TFP is treated as a constant in Eq. (8), representing the average total factor productivity. Important production information of the economy is implicitly contained within the error term ε . This paper introduces a set of coefficients to quantify the error term and derive TFP. By incorporating these coefficients into Eq. (7), the identity of the Cobb–Douglas production function is obtained:

$$y \equiv A(r_L L)^{\alpha}(r_K K)^{\beta} \quad (10)$$

where r_L and r_K are the introduced coefficients, while α and β are parameters obtained by fitting Eq. (8). By combining Eqs. (9) and (10), it follows that:

$$1 = \frac{A}{\bar{y}} \bar{L}^{-\alpha} \bar{K}^{\beta} \quad (11)$$

$$1 = \frac{A}{y} (r_L L)^{\alpha} (r_K K)^{\beta} \quad (12)$$

By combining Eqs. (11) and (12), and constructing the dummy parameter t_1 , Eq. (13) can be obtained:

$$1 = \frac{A}{\bar{y}} \left[\left(\frac{\bar{y}}{y} \right)^{t_1} \left(\frac{L r_L}{\bar{L}} \right)^{\alpha} \right] \bar{L}^{-\alpha} \left[\left(\frac{\bar{y}}{y} \right)^{t_2} \left(\frac{K r_K}{\bar{K}} \right)^{\beta} \right] \bar{K}^{\beta} \quad (13)$$

For Eqs. (13) and (11), by introducing the separation condition (Chen and Yao 2024a), the following can be obtained:

$$\left(\frac{\bar{y}}{y} \right)^{t_1} \left(\frac{L r_L}{\bar{L}} \right)^{\alpha} = 1, \quad \left(\frac{\bar{y}}{y} \right)^{t_2} \left(\frac{K r_K}{\bar{K}} \right)^{\beta} = 1 \quad (14)$$

where $0 < t_1, t_2 < 1$ and $t_1 + t_2 = 1$. Within this range, you are free to choose any value, but it is essential to opt for a value that simplifies the resolution of r_L and r_K ,

and can be logically justified. We take here, $t_1 = \frac{\alpha}{\alpha+\beta}$, and then $t_2 = \frac{\beta}{\alpha+\beta}$. Let $m = \alpha + \beta$, then we can get.

$$r_L = \frac{y_m^{\frac{1}{m}}}{L} / \frac{\bar{y}_m^{\frac{1}{m}}}{\bar{L}}; r_K = \frac{y_m^{\frac{1}{m}}}{K} / \frac{\bar{y}_m^{\frac{1}{m}}}{\bar{K}} \quad (15)$$

By combining Eqs. (9) and (10), and solving the simultaneous equations, Eq. (15) can be obtained:

$$\begin{cases} A = \frac{\bar{y}}{\bar{L}^{\alpha} \bar{K}^{\beta}} \\ m = \alpha + \beta \\ y \equiv A \left[\left(\frac{y_m^{\frac{1}{m}}}{L} / \frac{\bar{y}_m^{\frac{1}{m}}}{\bar{L}} \right) L \right]^{\alpha} \left[\left(\frac{y_m^{\frac{1}{m}}}{K} / \frac{\bar{y}_m^{\frac{1}{m}}}{\bar{K}} \right) K \right]^{\beta} \end{cases} \quad (16)$$

Finally, Eq. (17) is obtained, deriving the identity for determining weights under the least squares regression method:

$$y \equiv \left(\frac{y_m^{\frac{1}{m}}}{L} \right)^{\alpha} \left(\frac{y_m^{\frac{1}{m}}}{K} \right)^{\beta} L^{\alpha} K^{\beta} \quad (17)$$

Let $\alpha^* = \frac{\alpha}{\alpha+\beta}$, $\beta^* = \frac{\beta}{\alpha+\beta}$. Then:

$$y \equiv \left(\frac{y}{L} \right)^{\alpha^*} \left(\frac{y}{K} \right)^{\beta^*} L^{\alpha^*} K^{\beta^*} \quad (18)$$

$$\alpha^* + \beta^* = 1 \quad (19)$$

Thus, by combining the fundamental principle that output equals input multiplied by productivity, TFP can be derived:

$$TFP = \left(\frac{y}{L} \right)^{\alpha^*} \left(\frac{y}{K} \right)^{\beta^*} = P_L^{\alpha^*} P_K^{\beta^*} \quad (20)$$

where P_L and P_K represent labour productivity and capital productivity, respectively, while α^* and β^* denote the standardised structural parameters, i.e., the weights of labour and capital. An objective method for obtaining the weights of labour and capital from the Cobb–Douglas production function using the least squares method has been derived, and TFP has been decomposed. In the literature, TFP represents technological progress, managerial behaviour, etc. (Pan et al. 2022). However, in this paper, TFP is derived from the perspective of single factor productivity, showing that TFP is the geometric weighted average of labour productivity and capital productivity. This approach integrates the accounting of TFP and single-factor productivity into a unified framework, satisfying the basic assumption of constant returns

to scale. Generally, due to the law of diminishing marginal returns, economic production tends to exhibit constant returns to scale.

3.2.2 Output and input variables

(1) Capital input

The perpetual inventory method has been used to calculate the capital stock of various prefecture-level cities in China after 2000 (Xu et al. 2022). The calculation formula is:

$$K_t = (1 - \delta_t)K_{t-1} + I_t \quad (21)$$

where K_t and K_{t-1} represent the current and previous periods' asset stocks, respectively. The depreciation rate of fixed assets, δ_t , is 9.6%, and I_t denotes the total social fixed asset investment for the year. The fixed asset investment price index has eliminated price factor interference, with 2017 as the base year. Since the total social fixed asset investment data is available up to 2017 and only growth rates are published thereafter, 2017 is the base year to calculate the total social fixed asset investment after 2017. In 2000, Zhang (2008) provided the fixed asset stock for each province in China. Using the total social fixed asset investment data for each prefecture-level city and its respective province in 2000, the actual capital stock in 2017 prices for each city was proportionally estimated. The perpetual inventory method was then used to calculate the capital stock from 2001 to 2022.

(2) Output variable

The output data is the regional real GDP (Cheng et al. 2023). The GDP was adjusted to real GDP at 2017 prices based on the regional GDP index to standardise the price level.

(3) Labour input

Labour data should measure the total number of workers in each city at the end of the year. The indicators used to calculate TFP should maintain consistent accounting standards, with capital stock and real GDP data calculated city-wide. In current literature on measuring TFP at the city level, the number of employed persons in urban units or the number of urban private and individual employees, as published in the China City Statistical Yearbook, is used (Lyu et al. 2023; Zheng et al. 2023). This results in differing statistical standards for labour and other indicators. This method closely approximates the total employment for regions with high urbanisation rates. However, a significant discrepancy exists for areas with low urbanisation rates, leading to an overestimation of TFP levels in less urbanised areas. The ideal method would be to use total employment data, which is severely lacking for most cities. The China Regional Economic Statistical Yearbook published the annual total number of workers for each town until 2014, when it ceased to update. In this paper, the following method is employed: in the absence of data from local provincial statistical yearbooks and the city's statistical yearbook, the ratio of the city's total workforce to the provincial workforce in 2014 is used as a basis. This ratio and annual provincial workforce data are then used to estimate the total workforce for prefecture-level cities (Chen and Yao 2024b). The calculation formula is:

$$\psi_i = \frac{CL_{i,2014}}{PL_{j,2014}} \quad (22)$$

$$CL_{i,t} = PL_{j,t} \times \psi_i; j > 2014 \quad (23)$$

where ψ_i represents the ratio of the total workforce of city i to the total workforce of its province. $CL_{i,2014}$ and $PL_{j,2014}$ represent the total workforce of city i and its province j in 2014, respectively. $CL_{i,t}$ and $PL_{j,2014}$ represent the total workforce of city i and its province j after 2014, with t denoting the year. The total workforce data for provinces can be obtained from the China Provincial Economic Statistical Yearbooks.

Using this method to estimate the total workforce at the city level helps to overcome the limitations associated with calculating using urban labour data. Furthermore, provincial data are adjusted following a population census to reflect the previous decade's employment figures. Consequently, this method allows for reasonable adjustments for each city's data, ensuring synchronisation and continuity between city-level and provincial-level research.

(4) Weight determination

Labour, capital inputs, and economic output were determined, and Eq. (8) was applied. The initial weight coefficients for labour and capital were determined using the least squares method. The regression results are shown in Table 1, with an R-squared value of 0.9178, indicating a good fit.

Table 1 shows that the initial weights for labour and capital, α and β , were 0.4173 and 0.6485, respectively. Further analysis determined the final weights, α^* and β^* , to be 0.3915 and 0.6085, respectively. In contrast to the parameter setting adopted by Nordhaus (2019) in his seminal study, this paper estimates the labour share at 0.3915, which is notably lower than the benchmark value of 0.7. This deviation can be attributed to two primary sources of divergence. First, the DICE model assumes a labour share of 0.7 based on future projection scenarios. In developed economies, industrialisation and urbanisation have largely been completed, meaning that capital investment contributes less to growth, with technological progress and human capital becoming the dominant engines of economic expansion. Vollrath (2024), examining the elasticity of output in the United States, found that the capital elasticity ranged between 0.24 and 0.37 from 1996 to 2018. However, the employment elasticity concerning output tends to be higher for OECD countries, encompassing a broader set of less-developed economies. Long-run panel estimates range from 0.3 to 0.4, while short-run estimates lie between 0.5 and 0.6 (Görg et al. 2023). When the focus shifts to developing countries, research suggests that their economies are

Table 1 Initial weight

lny	Coefficient	Robust std. err	t-value	P
lnL	0.4173	0.0077	54.21	0.0000
lnK	0.6485	0.0036	181.55	0.0000
_cons	2.7861	0.0551	50.58	0.0000

generally capital-intensive, with estimated capital elasticity around 0.602 and labour elasticity around 0.455, alongside evidence of increasing returns to scale. These elasticity estimates are broadly consistent with those reported in Table 1 of this study, though the coefficients here have been standardised using the novel estimation method proposed in this paper. This indicates that during the historical process of China's economic development, capital has contributed more significantly than labour to overall growth.

3.2.3 Method comparison

This paper proposes a method for calculating TFP based on the Cobb–Douglas production function. To verify the reasonableness of the calculation results and the robustness of the model settings, other methods for calculating TFP were also employed. First, Barrage and Nordhaus (2024) set the weights of labour and capital at 0.7 and 0.3, respectively, in the economic growth module of their integrated assessment model. This scheme was referenced in this study to calculate TFP for robustness testing. Second, Data Envelopment Analysis (DEA) is a popular method for measuring efficiency (Zhang and Chen 2022; Zhu 2022). This method, based on the input–output perspective, can handle multiple inputs and outputs, although there are many extended versions of this model, each with its advantages and disadvantages. This paper uses the non-radial, non-angular SBM model proposed by Tone et al. (2020) and Tone (2002).

3.3 Empirical model

To empirically examine the historical relationship between average temperature and TFP, a two-way fixed effects model was established (Song et al. 2022).

$$\ln TFP_{i,t} = \alpha_0 + \alpha_1 Tem_{i,t} + \alpha_2 Tem_{i,t}^2 + \sum \alpha_j X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (24)$$

where i and t represent individuals and time respectively; $\ln TFP_{i,t}$ denotes the natural logarithm of TFP; $Tem_{i,t}$ and $Tem_{i,t}^2$ respectively indicate the quadratic terms of the average temperature; $X_{i,t}$ is the control variable affecting TFP; α_1 and α_2 represent the coefficients of the impact of the average temperature on TFP; α_j denotes the coefficient of the control variable's effect on TFP; α_0 is the constant term; μ_i and ν_t respectively signify the individual fixed effect and the time fixed effect; $\varepsilon_{i,t}$ represents the random disturbance term.

Utilising the mechanism utility analysis framework proposed by Kumar and Maiti (2024), the following regression model has been established:

$$\ln Med_{i,t} = \beta_0 + \beta_1 Tem_{i,t} + \beta_2 Tem_{i,t}^2 + \sum \beta_j X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (25)$$

where $\ln Med_{i,t}$ represents the natural logarithm of the mediating variable, with the meanings of the other variables being the same as in Eq. (24). Combining theoretical analysis, the mechanism testing section considers the adaptability to temperature changes. It examines the relationship between average temperature and both

labour productivity and capital productivity, while also investigating the adjustment responses in the allocation of labour and capital under changes in average temperature.

3.4 Data Sources, sample composition, and descriptive statistics

Combining climate and economic variables, this study collected a comprehensive balanced panel dataset for 278 prefecture-level cities in China from 2000 to 2022. Organisations such as the European Union and the European Centre for Medium-Range Weather Forecasts provided the ERA5-Land dataset, which includes 2-m air temperature data (Hersbach et al. 2019). The dataset has a spatial resolution of $0.1^\circ \times 0.1^\circ$, offering a high degree of surface representativeness. Given that the raw dataset is structured at the gridded level, this study constructs a spatial overlay between vectorised urban boundaries and the ERA5-Land grid system. Grid-level temperature values are aggregated to the city scale using weighted averaging, thereby ensuring that each city's temperature indicator accurately reflects the climatic conditions of its primary built-up area. Finally, daily temperature values are averaged over time to derive annual city-level observations. The original monthly temperature raster data were averaged to obtain the annual average temperature and precipitation data for each prefecture-level city in China. The annual "China City Statistical Yearbook" provided the economic variables required for this analysis. TFP for prefecture-level cities was calculated at constant prices using 2017 as the base year. Additionally, variables such as average precipitation, urbanisation level, government investment, financial development level, human capital investment, and infrastructure construction were included. Table 2 provides a detailed description of the data, including sources and selection criteria.

Table 3 provides the description of each variable.

4 Empirical results

4.1 Benchmark regression results

Column 1 of Table 4 reports the results of the baseline specification, illustrating the relationship between annual average temperature and $\ln TFP$. The estimates indicate that the quadratic term of average temperature has a statistically significant negative impact on TFP, consistent with the findings of Zhang et al. (2018). The relationship between average temperature and TFP exhibits an inverted "U" shape, suggesting the presence of a critical temperature point where the marginal impact of temperature on TFP shifts from positive to negative. The estimated results reveal that the marginal impact of average temperature on TFP is zero at 13.34°C ($-0.0667/(2 \times -0.0025)$). These nonlinear results align with previous studies; for instance, Burke et al. (2015) found that the relationship between overall economic productivity and temperature is nonlinear across all countries, with productivity peaking at an annual average temperature of 13°C and then sharply declining. Unlike this

Table 2 Summary of variable definitions

	Variables	Abbreviation	Calculation method	References
Dependent variable	Total factor productivity	lnTFP	Cobb–Douglas production function	Chen and Yao (2024a)
Independent variable	Average temperature	Tem	Weighted geographic average	Graff Zivin et al. (2020)
Control variable	Average precipitation	Pre	Weighted geographic average	Kotz et al. (2022)
	Urbanization	lnUrban	Natural logarithm of the ratio of the urban population to the total population	Wang et al. (2022)
	Government Investment	lnGov	Natural logarithm of government budget expenditure	Onifade et al. (2020)
	Financial Development Level	lnFin	The natural logarithm of the year-end balance of deposits and loans of financial institutions	Wen et al. (2021)
	Human capital investment	Humpay	The proportion of education and science and technology investment in total government investment	Neycheva (2010)
Mechanism variable	Infrastructure	Pernode	Per capita road area	Zou et al. (2022)
	Labour productivity	lnL	The natural logarithm of output per unit of labour	Song et al. (2022)
	Capital productivity	lnK	The natural logarithm of output per unit of capital	
	Labour force	lnPl	The natural logarithm of the total number of employed individuals	
	Capital stock	lnPk	The natural logarithm of capital stock	
	Air pollution	lnEnv	The natural logarithm of PM2.5 concentration	Wei et al. (2021)
	Energy consumption	lnEner	The natural logarithm of energy consumption	Hao et al. (2024)
	Ecosystem services	lnEco	The natural logarithm of vegetation cover	Zhou et al. (2025)

Table 3 Descriptive statistics of main variables

Variables	N	Mean	SD	Min	Max
lnTFP	6394	− 0.0002	0.3243	− 0.8665	0.8563
Tem	6394	13.9677	5.2315	1.4625	23.7155
Pre	6394	0.3089	0.1476	0.0505	0.6491
lnUrban	6394	− 0.7887	0.4207	− 1.9995	− 0.0287
lnGov	6394	14.0509	1.2947	11.1902	17.0621
lnFin	6394	16.7338	1.3831	13.8954	20.3884
Humpay	6394	0.1979	0.0501	0.0099	0.9615
Perrode	6394	4.1035	4.7043	0.2420	30.0247
lnL	6394	5.2595	0.7212	3.2847	6.9318
lnK	6394	17.1147	1.3977	14.0634	19.9819
lnPl	6394	1.6087	0.8541	− 0.3132	3.3828
lnPk	6394	− 1.0335	0.5284	− 2.1795	0.2611
lnEnv	6394	3.7379	0.3659	2.8642	3.7692
lnEner	6394	11.2232	0.9330	7.9696	11.2564
lnEco	6394	− 0.1379	0.2758	− 2.7522	− 0.0548

Table 4 Benchmark regression results

	(1) lnTFP	(2) TFP1	(3) EG_V	(4) EG_C
Tem	0.0667*** (0.0135)	0.0314** (0.0143)	0.0741*** (0.0176)	0.0774*** (0.0249)
Tem ²	− 0.0025*** (0.0006)	− 0.0013** (0.0006)	− 0.0023*** (0.0008)	− 0.0038*** (0.0011)
C.V	YES	YES	YES	YES
u	YES	YES	YES	YES
v	YES	YES	YES	YES
R ²	0.829	0.943	0.749	0.704
Obs	6394	6394	6394	6394

This notation applies throughout

lnTFP denotes the natural logarithm of TFP, estimated using the method proposed in this study; lnTFP1 represents the TFP measure calculated using a capital weight of 0.7 and a labour weight of 0.3; EG_V denotes TFP estimated under the assumption of variable returns to scale using the data envelopment analysis (DEA) method; EG_C represents TFP estimated under the assumption of constant returns to scale using the DEA method. C.V refers to the set of control variables, with “YES” indicating their inclusion in the regression specification; u and v denote individual and time fixed effects, respectively; “YES” indicates their inclusion in the regression model; Obs. indicates the number of observations; Standard errors in parentheses

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

study, which focuses on the impact on TFP levels, Letta and Tol (2019) provided evidence of the negative impact of temperature on TFP growth rates, while the inverted “U” shape in TFP levels reflects this negative impact on TFP growth rates. The present study finds a negative coefficient on the quadratic term of temperature, consistent with the findings of Kumar and Maiti (2024) based on a sample of emerging economies. This result is further supported by Letta and Tol (2019), who report similar evidence of a non-linear relationship between temperature and productivity. Similarly, Chen et al. (2023) show that in China’s provincial capitals and municipalities, both extreme high and low temperatures exert significantly negative effects on the growth rate of TFP. In contrast, moderate temperatures have only limited effects on TFP, highlighting the non-linear nature of climate impacts on urban productivity.

Optimal temperatures can improve the working environment and reduce the external environmental load on assets and equipment. However, further increases in average temperature are often accompanied by extreme weather events and other anomalies. These conditions can cause heat stress for workers and machinery, increase cooling demands, and disrupt supply chains, ultimately leading to a decline in TFP. As noted by Magazzino et al. (2021), deviations from optimal temperatures to extreme conditions, including high heat and cold, impede economic productivity. Adaptive behaviours are inherent to the impact of temperature changes on TFP. With technological and economic advancements, the development of heat-resistant and cold-resistant production materials, as well as the use of cooling measures such as air conditioning during high summer temperatures, can mitigate the damage caused by climate change to TFP. At the same time, proactive mitigation efforts—such as enhancing the efficiency of non-renewable energy use (Özkan et al. 2023) and expanding the deployment of renewable energy sources (Adebayo and Özkan 2024)—can contribute to environmental improvement and help reduce future climate-related damages.

To validate the accuracy of the TFP estimation method proposed in this study, three additional methods were employed. In the model in Column 2, the weights for labour and capital are set to 0.7 and 0.3, the dependent variable is denoted as TFP1. Columns 3 and 4 use the SBM-DEA model to calculate TFP under conditions of variable returns to scale and constant returns to scale, the dependent variable is denoted as EG_V and EG_C in Table 4, respectively. The results indicate that the nonlinear impact of average temperature on TFP remains significant, confirming the validity of the proposed estimation method and the robustness of the model specifications.

4.2 Robust test

Table 4 uses different methods to calculate TFP, providing a preliminary validation of the model’s stability. Since municipalities are provincial-level administrative units, robustness checks were conducted by excluding observations from municipalities (Lin and Wang 2023). The fitted results in Column (1) of Table 5 indicate that the relationship between average temperature and TFP remains statistically significant. During 2020–2022, the pandemic had a substantial impact

Table 5 Robust test

	(1) Excluding municipali- ties	(2) year < 2020	(3) Add C.V	(4) Pro C
	lnTFP	lnTFP	lnTFP	lnTFP
Tem	0.0681*** (0.0136)	0.0350*** (0.0105)	0.0738*** (0.0141)	0.0667*** (0.0135)
Tem ²	− 0.0026*** (0.0006)	− 0.0011** (0.0004)	− 0.0027*** (0.0006)	− 0.0025*** (0.0006)
C.V	YES	YES	YES	YES
<i>u</i>	YES	YES	YES	YES
<i>v</i>	YES	YES	YES	YES
<i>Province</i>	NO	NO	NO	YES
<i>R</i> ²	0.824	0.836	0.831	0.829
<i>Obs</i>	6302	5560	6394	6394

Excluding municipalities indicates that the model is re-estimated after excluding centrally administered municipalities from the sample. *year < 2020* indicates that the estimation is based solely on observations prior to the year 2020. *Add C.V* denotes the inclusion of additional control variables beyond the baseline specification to reduce omitted variable bias. *Pro C* refers to high-dimensional controls, where the model further incorporates province-level fixed effects. *Province* indicates whether provincial fixed effects are included in the model, with “YES” denoting inclusion and “NO” denoting exclusion

on the economy, so the sample period was shortened. Column (2) of Table 5 shows that the model remains robust.

To avoid the impact of omitted variables, Column (3) of Table 5 includes variables for industrial structure, degree of openness, and per capita GDP. The data still support the statistical significance of the nonlinear impact of average temperature on TFP. Additionally, in the fixed effects model, city and year fixed effects were controlled for, and provincial fixed effects were considered to account for potential biases due to provincial differences. The data in Column (4) show that even after including provincial fixed effects, the model remains robust (Table 5). A series of model tests confirm that the model specification is robust, supporting further research and analysis.

Table 6 presents the results of further robustness checks. Including an excessive number of control variables may result in over-controlling, potentially attenuating the estimated effect of temperature. To address this, a more parsimonious model is employed, in which only temperature and precipitation are retained; the corresponding results are reported in Column (1) of Table 6. In the baseline regression, the temperature threshold at which its effect on TFP switches from positive to negative is estimated to be 13.34 °C. To assess the robustness of this threshold, a piecewise regression model is employed, as specified in Eq. (26):

Table 6 Further robustness checks

	(1) Parsimonious model lnTFP	(2) Spline regression lnTFP	(3) Dynamic GMM lnTFP	(4) Lagged climate variables lnTFP
Tem	0.0838*** (0.0147)	0.0276*** (0.0076)	0.0660*** (0.0172)	0.0700*** (0.0115)
Tem ²	− 0.0032*** (0.0006)		− 0.0029** (0.0014)	− 0.0027*** (0.0005)
Pre	0.0922*** (0.0341)			0.0901*** (0.0331)
spline		− 0.0494*** (0.0119)		
L1.lnTFP			0.9204*** (0.0800)	
C.V	YES	YES	YES	YES
AR (1)			−5.34***	
AR (2)			0.72	
Hansen test			2.50	
<i>u</i>	YES	YES	YES	YES
<i>v</i>	YES	YES	YES	YES
<i>R</i> ²	0.818	0.829	—	0.847
<i>Obs</i>	6394	6394	3336	6116

$$\ln TFP_{i,t} = \delta_0 + \delta_1 Tem_{i,t} + \delta_2 (Tem_{i,t} - \tau)^+ + \sum \delta_j X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

$$(Tem - \tau)^+ = \begin{cases} 0 & \text{if } Tem \leq \tau \\ Tem - \tau & \text{if } Tem > \tau \end{cases} \quad (26)$$

Here, τ denotes the estimated threshold temperature, while $(Tem_{i,t} - \tau)^+$ is represented by a spline variable. The corresponding regression coefficient is examined, and the estimation results are reported in Column (2) of Table 6. The results show that the temperature variable yields a significantly positive coefficient, whereas the spline term is significantly negative, indicating that once the threshold is surpassed, the marginal effect of temperature on TFP reverses from positive to negative, confirming the stability of the estimated threshold value. The study also addresses potential endogeneity issues. Adebayo (2025) argues that economic growth may have adverse environmental consequences, particularly through increased CO₂ emissions, which raise greenhouse gas concentrations and accelerate global warming. To account for such endogeneity, this study employs a dynamic GMM estimation strategy, which is well-suited to datasets with a large cross-sectional dimension and a short period, and mitigates the problem of instrument proliferation. The model is estimated using data from 2010 to 2022. Lagged values of the temperature variable are used as instruments. The diagnostic tests indicate the presence of first-order autocorrelation in the first-differenced residuals, but no evidence of second-order

autocorrelation, which is consistent with the assumptions of the dynamic GMM framework. The Hansen test is not statistically significant, suggesting that the instruments are valid. Estimation results are presented in Column (3) of Table 6 and confirm that the impact of temperature on TFP remains statistically significant. Lastly, the analysis replaces current-period climate variables with their first-order lags to further mitigate reverse causality, thereby constructing a lagged-response model. Given that reverse causality—i.e., the influence of output on temperature—may operate through contemporaneous channels, using lagged explanatory variables helps reduce such bias. Estimation results, presented in Column (4) of Table 6, indicate that the inverted U-shaped relationship between temperature and TFP continues to hold.

4.3 Mechanism analysis

4.3.1 Mechanism through factor inputs

The model in this study demonstrates that TFP is a geometric weighted average of labour productivity and capital productivity, with annual average temperature impacting TFP by influencing the production efficiency of input factors. Labour productivity is measured by the ratio of output to labour input, while capital productivity is measured by the ratio of output to capital. Additionally, short-term adaptation and mitigation of climate change may necessitate the reallocation of factors to alleviate its impact. Table 7 presents the regression results of average temperature on input factors and production efficiency.

Existing microeconomic evidence suggests that temperature affects various aspects of labour production, including labour productivity and labour supply (Adhvaryu et al. 2020). This study finds evidence that average temperature impacts labour employment. The data in Column (1) of Table 7 report the nonlinear effect of average temperature on labour employment. In hot climates, workers may start earlier or

Table 7 Temperature shocks and mechanisms

	(1) lnL	(2) lnK	(3) lnPl	(4) lnPk
Tem	− 0.0754*** (0.0162)	− 0.1420*** (0.0237)	0.0027 (0.0186)	0.0878*** (0.0202)
Tem ²	0.0030*** (0.0007)	0.0048*** (0.0011)	− 0.0003 (0.0008)	− 0.0032*** (0.0009)
C.V	YES	YES	YES	YES
<i>u</i>	YES	YES	YES	YES
<i>v</i>	YES	YES	YES	YES
<i>R</i> ²	0.963	0.975	0.964	0.869
<i>Obs</i>	6394	6394	6394	6394

lnL, lnK, lnPl, and lnPk denote the natural logarithms of labour input, capital input, labour productivity, and capital productivity, respectively

spend more time to maintain the same total output (LoPalo 2023). Somanathan et al. (2021) suggest that on extremely hot or cold days, absenteeism rates among individual workers or teams increase, prompting firms to hire more workers to ensure expected output. Extremely cold or hot conditions reduce working hours, leading to a decline in labour productivity (Garg et al. 2020; Lai et al. 2023). However, this study does not find statistically significant evidence supporting the impact of average temperature on labour productivity, although the coefficients suggest a nonlinear effect. This could be due to the short-term reallocation of labour across industries or sectors, or short-term unemployment, mitigating the impact on labour productivity. Additionally, the measurement only considers labour participation as an indicator, neglecting factors such as work intensity, working hours, and work capacity, which ultimately affect labour productivity.

This study identifies the effects of climate change on both the quantity of capital input and capital productivity. Average temperature exhibits a U-shaped relationship with capital input (see Column (2) of Table 7), consistent with the findings of Tsigaris and Wood (2019); whereas its effect on capital productivity follows an inverted U-shape, mirroring the non-linear impact of temperature on TFP observed earlier. This non-linear pattern may stem from the interplay of two underlying mechanisms: (i) direct climate-induced stress on capital depreciation and operational efficiency; (ii) firms' adaptive investment behaviour in response to prolonged high-temperature risks. Under low temperature conditions, extreme cold often leads to poor mechanical lubrication, material embrittlement, and equipment freezing, which in turn increases the failure rate of industrial equipment and maintenance frequency, thereby accelerating capital depreciation and reducing both usable lifespan and operational efficiency. In regions with widespread electrification, cold weather has been shown to shorten battery life (Ruhatiya et al. 2024). In colder regions, firms are often compelled to incur additional expenditures on heating, snow removal, and anti-freezing infrastructure to ensure operational stability (Chen et al. 2024b), and such inflexible expenditures manifest as implicit depreciation, thereby compressing the marginal productivity of capital.

Within a moderate temperature range, fixed capital assets tend to operate under stable conditions, energy systems function efficiently, and the marginal return on capital remains relatively high. As temperatures rise beyond this range, fixed capital assets are increasingly exposed to physical stress and energy burdens, including motor overheating, increased strain on cooling systems, and elevated energy expenditures for ventilation and air conditioning. These conditions collectively accelerate capital depreciation and lead to a decline in capital's marginal productivity. Concurrently, high-temperature conditions often trigger firms' adaptive investment responses, prompting increased capital expenditure to cope with climate-induced disruptions. As highlighted by Kong et al. (2024), firms adopt various forms of direct liquid cooling, such as immersion, jet, and microchannel systems, to manage excess heat. Although these investments constitute fixed capital expenditure, they are characterised by substantial upfront costs and limited short-term productivity gains, and in the presence of unstable financing or underdeveloped financial markets, they may heighten firms' exposure to climate-related vulnerabilities. Hence, in the early stages of temperature escalation, rising heat compresses capital efficiency

via increased depreciation and operational stress, and even when adaptive capital investments are introduced in later stages, capital productivity continues to decline (Chen et al. 2024a), resulting in a dual dynamic pattern: a U-shaped capital response coupled with an inverted U-shaped productivity trajectory.

Theoretically, changes in average temperature can influence both labour productivity and capital productivity. Nevertheless, businesses and workers mitigate the impact of rising temperatures by adjusting working hours and increasing investment. This adaptation reduces the adverse effects on labour productivity. Such natural and proactive climate adaptation behaviours lessen the damage caused by temperature changes to TFP. This evidence suggests that researchers should objectively estimate the damage caused by temperature changes to economic systems, avoiding the underestimation of the adaptability of economic and social systems and thereby preventing the overestimation of the economic damage caused by climate change.

4.3.2 Mechanism through air pollution

Air pollution poses not only public health risks, but also leads to severe environmental consequences. Numerous studies worldwide have examined the relationship between meteorological conditions, such as temperature and humidity, and $PM_{2.5}$ concentrations (Danek et al. 2022). Using average $PM_{2.5}$ concentration as a key proxy for air pollution, this study explores its mediating role in the relationship between climate change and TFP. Estimation results are presented in Column (1) of Table 8. The dependent variable is defined as the natural logarithm of the average $PM_{2.5}$ concentration at the city level. Results show that the coefficient on the quadratic temperature term is -0.0043 , while the linear term is 0.0973 . Both coefficients are statistically significant at the 1% level, with a calculated turning point of approximately $11.31^{\circ}C$, beyond which the impact of temperature on $PM_{2.5}$ shifts from positive to negative. Against the backdrop of rising average temperatures, elevated heat appears to reduce $PM_{2.5}$ concentrations. As noted by Zender-Świercz et al. (2024),

Table 8 Mechanisms through air pollution, energy consumption, and ecosystem services

	(1) lnEnv	(2) lnEner	(3) lnEco
Tem	0.0973*** (8.9469)	− 0.1319*** (− 8.3773)	0.0072* (1.6569)
Tem ²	− 0.0043*** (− 8.6945)	0.0049*** (7.0266)	− 0.0008*** (− 3.7100)
C.V	YES	YES	YES
<i>u</i>	YES	YES	YES
<i>v</i>	YES	YES	YES
<i>R</i> ²	0.8993	0.9606	0.9643
<i>Obs</i>	6394	6394	6394

lnEnv, lnEner, and lnEco denote the natural logarithms of environmental quality, energy consumption, and ecosystem services, respectively

rising temperatures reduce PM_{2.5} levels by suppressing the formation and dispersion of particulate matter, limiting the condensation of volatile compounds, and decreasing heating-related emissions. Air pollution represents a global risk, and elevated PM_{2.5} concentrations are negatively associated with total factor productivity. A survey-based study among workers indicates that exposure to elevated PM_{2.5} levels can cause obstructive pulmonary dysfunction, increasing both mortality and broader health risks (Li et al. 2024). Poor worker health hampers labour performance, ultimately reducing productivity (Dong and Wang 2023).

4.3.3 Mechanism through energy consumption

This study further investigates the mediating role of energy consumption in the relationship between temperature and TFP. As a critical intermediate input in economic production, energy consumption is susceptible to climatic conditions. Existing research suggests that temperature variation may alter heating and cooling demand, generating non-linear shifts in energy use, which in turn influence urban production costs and economic output capacity (Yuan et al. 2024). Using city-level energy consumption as a proxy variable, regression results presented in Column (2) of Table 8 reveal a significant U-shaped relationship between temperature and energy consumption. At lower temperatures, an increase in temperature reduces heating demand, resulting in more energy-efficient outcomes; however, once temperature surpasses a critical threshold, rising demand for cooling, coupled with the adverse effect of heat on equipment efficiency, drives up energy consumption. Energy consumption plays a vital role in sustaining industrial activity and in maintaining a high-income economic status (Bashir et al. 2025). In the absence of effective regulatory mechanisms, exogenous increases in energy consumption can result in a series of systemic efficiency losses. First, rising energy consumption may crowd out investment in areas that enhance productivity, such as technological advancement and management improvement, thus diminishing TFP. Second, in contexts of constrained energy supply, priority may be given to traditional high-consumption sectors, potentially crowding out high-productivity industries, exacerbating resource misallocation, and further depressing TFP.

4.3.4 Mechanism through ecosystem services

Climate change may also reshape ecosystem service functions, diverting ecological resources towards climate mitigation efforts. This study employs vegetation cover as a proxy indicator for ecosystem service capacity. Regression results in Column (3) of Table 8 suggest an inverted U-shaped relationship between temperature and ecosystem services. At lower temperature ranges, moderate warming promotes vegetation growth and enhances photosynthetic activity, thereby strengthening ecosystem service provision in urban areas. However, once a threshold is surpassed, excessive heat induces stress that accelerates transpiration and moisture loss, suppresses vegetation growth, and may ultimately lead to dieback and ecosystem degradation, heightening the risk of urban green space deterioration (Phelan et al. 2024). A decline in urban vegetation cover undermines ecosystem functioning, leading to

weakened environmental regulation, intensified urban heat island effects, deteriorating air quality, and reduced water retention capacity. These consequences collectively deteriorate the urban production environment, elevate public health risks, and place additional strain on infrastructure. The decline in ecosystem service capacity can influence TFP through a variety of pathways. Ecosystem degradation may increase the risk of zoonotic disease transmission, worsen public health outcomes, drive up healthcare costs, and reduce labour productivity—thereby exerting a downward pressure on TFP (Kumar and Maiti 2024).

5 Further analysis

5.1 Regional heterogeneity

This paper provides a multi-faceted discussion on the relationship and mechanisms between average temperature and TFP. However, it is crucial to recognise that estimating China's optimal temperature effect using a single equation is inherently biased. China's vast geographical area, diverse topography, and significant economic and social disparities across different regions contribute to this complexity (Rosen 2019). Due to sample size limitations, estimating a TFP loss function for each province presents considerable challenges. Nevertheless, the issue of the impact of heterogeneity must be addressed. China's temperature distribution exhibits a clear north–south disparity. The Qinling Mountains block most northern cold air from moving southward, creating a geographical divide between northern and southern China. Economically and socially, the northern regions primarily focus on heavy industry and agriculture, while the southern regions are dominated by manufacturing, light industry, and services. Given the differences in topography, economic sectors, and infrastructure development between northern and southern regions, this paper delineates these areas along the Qinling-Huaihe Line. Subsequently, the study investigates the differences in TFP loss functions between these two sample groups. Columns (1) and (2) of Table 9 report the regression results for two model specifications,

The average temperature in southern China is relatively higher, while it gradually decreases in the northern regions. This variation implies that each region's economic structure, characteristics, and infrastructure development have historically adapted to the local climate and temperature. For instance, regions with lower average temperatures, such as northern China, have implemented heating systems, whereas regions with higher average temperatures mitigate climate effects by installing high-power cooling air conditioners. This adaptation suggests that the critical point at which average temperature shifts from positively to negatively impacting TFP varies across regions due to differing adaptive capacities. Generally, regions with higher average temperatures have a higher critical point. The empirical tests in this paper support this observation. As shown in Table 9, columns (1) and (2), the critical points of the impact of average temperature on TFP are 8.90 °C for northern regions and 18.28 °C for southern regions. In southern regions where average temperatures are comparatively higher, cities face greater exposure to heat-related

Table 9 Regional and sectoral heterogeneity analysis

	(1) North	(2) South	(3) Low share of primary industry	(4) High share of primary industry
	lnTFP	lnTFP	lnTFP	lnTFP
Tem	0.0765*** (0.0171)	0.1353* (0.0768)	0.0358** (0.0177)	0.0817*** (0.0166)
Tem ²	− 0.0043*** (0.0011)	− 0.0037* (0.0022)	− 0.0016* (0.0009)	− 0.0027*** (0.0007)
C.V	YES	YES	YES	YES
<i>u</i>	YES	YES	YES	YES
<i>v</i>	YES	YES	YES	YES
R ²	0.805	0.864	0.852	0.773
Obs	2944	3450	3193	3190

Standard errors in parentheses; * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

risks. In response, urban infrastructure and machinery are often adapted to these climatic conditions—for instance, through the installation of cooling systems and the use of heat-resilient equipment. Consequently, TFP in these areas tends to demonstrate greater resilience to high temperatures, with a relatively higher estimated threshold. Hsiang and Narita (2012) provide empirical evidence that countries frequently exposed to intense tropical cyclones incur lower marginal damages during such events, highlighting their adaptive capacity in the face of climate risk. Compared with northern China, southern regions tend to have higher levels of economic development, which may also help explain their lower sensitivity to temperature variations. Prior studies suggest that the marginal impact of weather shocks tends to be lower in colder climates or wealthier countries (Kahn et al. 2021). The combination of adaptive capacity and economic resources provides an effective means of reducing the damages associated with climate change. In neighbouring Southeast Asia, India—one of the largest emerging economies—experiences higher average temperatures than China, and faces a pronounced negative effect of rising temperatures on TFP, particularly within the services sector (Dua and Garg 2024). In tropical economies such as Indonesia, the absence of climate adaptation finance may reduce economic competitiveness under global warming, particularly in the agricultural sector (Nugroho et al. 2023).

5.2 Sectoral heterogeneity analysis

A growing body of research has demonstrated the climate sensitivity and vulnerability of the primary sector, particularly agriculture, to climate change (Furtak and Wolińska 2023; Nguyen and Scrimgeour 2022). Agricultural activities are typically characterised by high climate exposure and strong dependence on climatic factors such as sunlight and humidity. Abrupt climatic fluctuations may therefore exert stronger adverse effects on agriculture, which can subsequently affect urban-level

TFP. This study adopts the share of primary sector output in regional GDP as a proxy for industrial structure. The sample is then split into two groups—low and high primary industry share—according to whether the sector's contribution lies below or above the sample median. An empirical analysis is undertaken to assess the heterogeneity in the temperature-TFP relationship across different industrial structures (Table 9, Columns 3–4). The findings indicate that cities with a higher proportion of primary industry exhibit a stronger marginal sensitivity of TFP to temperature, relative to cities where the primary sector plays a lesser role. This suggests that cities with greater reliance on the primary sector are more sensitive to climate variation, and that moderate increases in temperature may improve agricultural, pastoral, and fishery output, thereby contributing to short-term gains in TFP. However, once temperature levels exceed a certain threshold, the land, water, and labour resources on which agriculture depends become increasingly strained, and given that such cities often lack robust climate adaptation strategies and technological buffers, productivity tends to decline rapidly. These findings are supported by Chamma (2024), who emphasises that the impacts of climate change on cities are primarily channelled through their effects on agriculture, whereas industrial, manufacturing and service sectors exhibit comparatively lower sensitivity to climatic fluctuations.

5.3 Heterogeneity analysis by income level

Income levels influence both living standards and the capacity to adapt to climate change. This study adopts per capita income as a proxy for local income levels. Cities with income levels above the sample median are classified as high-income, while those below are categorised as low-income. Regression results are presented in Columns (1) and (2) of Table 10. The results suggest that TFP appears relatively insensitive to climate variation in high-income cities, with temperature effects statistically insignificant. In contrast, TFP in low-income cities demonstrates greater

Table 10 Heterogeneity analysis by income level and resource endowment

	(1) High income lnTFP	(2) Low income lnTFP	(3) Resource-based cities lnTFP	(4) Non-resource-based cities lnTFP
Tem	0.0144 (0.9242)	0.0601*** (4.9325)	0.0821*** (4.1356)	0.0708*** (3.6377)
Tem ²	− 0.0007 (− 1.1814)	− 0.0012*** (− 2.8003)	− 0.0039*** (− 4.4049)	− 0.0023*** (− 2.8343)
C.V	YES	YES	YES	YES
<i>u</i>	YES	YES	YES	YES
<i>v</i>	YES	YES	YES	YES
<i>R</i> ²	0.9248	0.8338	0.7816	0.8527
<i>Obs</i>	3198	3196	2553	3841

Standard errors in parentheses; * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$

sensitivity to climatic conditions. Letta and Tol (2019) observe that the effects of climate change on affluent countries are nearly negligible, whereas dynamic effects in poorer countries, extrapolated from weather patterns, raise growing concerns over the unequal distribution of future climate-related impacts. This supports this paper's conclusion that TFP is more vulnerable in lower-income areas, where exposure to climate risk is more pronounced.

5.4 Analysis based on resource endowment

To investigate heterogeneity arising from differences in resource endowment, this study builds on Yang et al. (2023a) and adopts the official classification from the National Plan for the Sustainable Development of Resource-Based Cities, dividing the sample into 111 resource-based and 167 non-resource-based cities. The regression results (Table 10, Columns 3–4) show that temperature exhibits a significant inverted U-shaped effect on TFP across both city types. However, the marginal effects and critical temperature thresholds differ notably. TFP is markedly more sensitive to temperature fluctuations in resource-based cities, partly due to their concentrated industrial structures and high dependence on energy resources. Many coal-dependent cities face resource depletion, ecological inefficiency, high unemployment, and inflexible economic systems, making them more susceptible to external environmental shocks (Yang et al. 2023b). Under high-temperature conditions, energy-intensive industries such as coal, electricity, and non-ferrous metals suffer from rising cooling costs, infrastructure deterioration, and efficiency losses, resulting in sharp productivity declines. In contrast, non-resource-based cities—characterised by greater industrial diversification, stronger technological capability, and enhanced environmental adaptability—demonstrate more stable responses to climate change and exhibit greater overall resilience.

6 Conclusion, policy implications, and research limitations

6.1 Conclusions

This study provides a framework for understanding economic growth under the influence of temperature changes. Following the causal identification framework proposed by Hsiang (2016), the empirical design of this study satisfies three key assumptions required for credible identification. First, temperature is primarily driven by exogenous large-scale climatic systems, which mitigates endogeneity concerns. Second, including city and year fixed effects enables the model to account for unobservable heterogeneity across both spatial and temporal dimensions. Third, key covariates—such as economic structure and urbanisation—are included to control for potential confounders that may jointly influence temperature and TFP. To further strengthen the robustness of the identification strategy, this study adopts the modelling approach proposed by Burke et al. (2015), incorporating a quadratic temperature term into the baseline specification and comparing estimates under alternative

modelling strategies. The results indicate that the temperature threshold and non-linear form identified in this study closely align with those reported in Burke et al. (2015), thereby supporting the robustness and generalisability of the findings. Henseler and Schumacher (2019) also identified this nonlinear effect of temperature on TFP. Considering the mechanisms of impact and adaptive behaviours, the average temperature in China indirectly influences TFP by affecting capital productivity. However, the inverted U-shaped relationship between average temperature and labour productivity is not statistically significant. This may be due to the varying degrees of labour productivity loss associated with high temperatures across different regions (Zhao et al. 2024). Furthermore, air pollution, energy consumption, and ecosystem services serve as key mediating mechanisms through which temperature affects TFP. Within the study sample, heterogeneity in geographic location, industrial structure, income level, and resource endowment gives rise to divergent TFP responses to temperature variation across cities. These underlying differences highlight the importance of considering both environmental channels and city-specific characteristics when evaluating the economic consequences of climate change.

To unify the climate change economic growth model and the TFP accounting framework, this study employs the Cobb–Douglas production function to calculate TFP. Based on the principle that output equals productivity multiplied by inputs, a TFP accounting framework satisfying constant returns to scale is derived, revealing that TFP is the geometric weighted average of labour productivity and capital productivity. Due to limitations in statistical data sources, this study standardises the selection of urban-scale labour input data, estimates labour input, and aligns the accounting standards for input and output data, integrating city-level and provincial-level research comparably. This study does not account for the non-market losses induced by climate change, including negative impacts on human health, mortality rates, and biodiversity. When non-market impacts are considered, the resulting damage estimates are likely to exceed those presented in this study. This highlights the urgent need for substantial climate finance to support effective adaptation and mitigation strategies, foster green innovation, and advance the transition towards cleaner and renewable energy sources (Adebayo and Olanrewaju 2025; Jin and Chen 2024; Özkan and Adebayo 2024).

6.2 Policy implications

Drawing on the empirical findings, this study proposes the following policy recommendations.

First, infrastructure resilience should be strengthened, particularly in regions with average temperatures close to or above the estimated threshold. When temperatures exceed this point, they accelerate the depreciation of physical capital, increase energy system loads, and raise the likelihood of transport disruption, resulting in reduced urban productivity. Governments should prioritise retrofitting urban infrastructure to withstand high-temperature stress in areas such as the Pearl River Delta, the Jiangsu–Zhejiang corridor, and parts of Central China. In manufacturing and logistics hubs, this includes adopting heat-resistant paving materials

and temperature-stable rail systems. Urban buildings should be equipped with green roofs, shading structures, and mist-based cooling systems to help mitigate urban heat island effects. Northern cities should also proactively prepare for extreme summer heatwaves by expanding green space systems and emergency cooling facilities, thereby buffering the short-term impact of heat on capital efficiency. Sector-specific adaptations are equally important: construction sites should install shaded rest areas and mobile cooling units, while the logistics industry should develop cold-chain protection mechanisms and maintain redundant summer transport capacity to reduce the risk of heat-related service disruptions. A zoned, industry-targeted infrastructure strategy would help mitigate the adverse effects of extreme temperatures on core production and supply chains.

Second, labour market adaptability must be enhanced. This study finds that deviations from optimal temperature levels increase labour demand, particularly in heat-exposed sectors such as construction, frontline manufacturing, and outdoor services. Governments should enforce occupational safety regulations for high-temperature work, including time restrictions, mandatory heat protection facilities, financial subsidies, and access to emergency medical services, to minimise climate-related labour losses. Furthermore, labour mobility should be encouraged toward climate-resilient industries. The digital economy, financial services, information technology, and R&D sectors exhibit lower climate sensitivity and offer flexible or remote work arrangements. By implementing vocational training schemes and skill transition subsidies, especially in southern cities or those nearing high critical temperatures, policymakers can promote the reallocation of labour towards these low-sensitivity industries, improving labour efficiency and strengthening the workforce's overall resilience to climate shocks.

Third, promoting sector-specific adaptive technologies and innovation is essential given the uneven temperature impacts across different industries. Automated and intelligent production lines should be prioritised in manufacturing to reduce dependence on manual labour and ensure operational continuity during extreme weather events. The adoption of high-efficiency electromechanical systems and energy-saving cooling technologies can also help mitigate heat-induced losses in productivity. In the construction sector, the use of heat-resistant materials, such as high-reflectivity coatings and thermal insulation panels, should be encouraged, alongside the enforcement of energy-efficient design standards. Building plans should further incorporate passive cooling and natural ventilation strategies to strengthen resilience during the use phase. In agriculture, where temperature sensitivity is particularly high, the development of heat- and drought-resistant crop varieties should be accelerated, supported by smart farming technologies such as precision irrigation, weather-based monitoring, and microclimate management to ensure yield stability. For the service sector, especially in retail, hospitality, and tourism, adaptive strategies should include energy-efficient retrofitting of premises, flexible scheduling, and integration of online and offline services to reduce the risk of climate-related operational disruptions.

Fourth, green investment should be strategically guided to support not only carbon mitigation but also climate adaptation. A dedicated climate adaptation fund should prioritise investment in heat-resilient infrastructure, energy-efficient systems,

high-performance cold chains, and intelligent environmental monitoring networks. Financial institutions—including banks, insurers, and investment funds—should be encouraged to develop climate-adaptive financial products such as targeted loans for heat-resistant assets, temperature-indexed insurance schemes, and green bonds. These mechanisms can help reduce the financing costs and risk premiums associated with adaptive investment, particularly for firms and local governments. At the sectoral level, green retrofitting loans should be extended to manufacturing and construction, while climate-adaptive agricultural insurance can buffer producers against heat-related yield losses. Together, these initiatives would foster a multi-sectoral climate adaptation investment framework, enhancing the capacity of the economic system to adjust and recover under climate stress.

6.3 Research limitations

While the proposed TFP measurement approach has been benchmarked against DEA-based estimates, potential sources of error merit further scrutiny. In addition, the use of ERA5-Land climate data introduces uncertainty, owing to factors such as changes in observational instruments, measurement protocols, calculation methods, station relocation, alterations in local environments, and the influence of urban heat islands—all of which may affect the precision of surface climate indicators. Beyond economic productivity effects, climate change also results in substantial non-market losses. Hogan et al. (2024) report that increased warming and declining precipitation have led to severe reductions in forest productivity across the western United States, highlighting the fragility of global forest carbon sinks. In domains where losses are less readily quantified, such as public health, differences in exposure, sensitivity, and adaptive capacity have generated significant human costs. Moreover, food insecurity resulting from climate-related shocks further compounds the adverse consequences for human well-being (van Daalen et al. 2024). Future research could integrate both market-based and non-market dimensions of climate impact to expand the TFP estimation framework and provide more accurate and comprehensive assessments of climate risks.

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