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Regional Heterogeneity in Temperature Effects on China's Economic Seasonality: Evidence from 30 Provinces

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Abstract. This paper studies the heterogeneous temperature effect on provincial GDP growth fluctuations in China from Q1 2005 to Q2 2021. The temperature effect is divided into two parameters, i.e., the inter-quarter changes of average temperature and the intra-quarter highest-lowest temperature difference. The GDP fluctuations are represented by the quarterly GDP residual seasonality. A mixed-effect panel regression model with random coefficients of the two temperature parameters is compared to the baseline model with fixed coefficients of temperature variables. The result demonstrates strong regional heterogeneous relationships between the temperature variables and quarterly GDP fluctuations. Provinces in the Northern-China plain, such as Shangdong, Henan, and Anhui, exhibit positive GDP seasonality associated with both warmer average temperatures and higher intra-quarter temperature deviations, which benefit the agricultural production. Southwestern provinces (e.g., Guangxi, Yunnan, and Chongqing) experience a negative impact from rising inter-quarter average temperatures and larger intra-period temperature fluctuations, partly due to the hot summer's adverse effect on both industries and tourism. Northwestern and Southeastern provinces get mixed temperature-economic effects, with the former benefiting from higher average temperature and the latter suffering, while the former suffers from large intra-period climate fluctuations and the latter benefits, also due to their agricultural and industrial patterns and their respective geographical locations. The heterogeneity of the provincial temperature-economic effects reinforces the necessity for region-specific climate adaptation strategies, especially the development of green energy and coordinated efforts to integrate local climate risk assessments into national central economic planning.

Keywords: Climate Economics, Regional Heterogeneity, GDP Seasonality, Temperature Shocks, China

1. Introduction

Global climate change has been increasingly recognized as a significant driver of worldwide macroeconomic development. Temperature is the key indicator of climate, and the fluctuations of temperature have become major shocks to worldwide economic growth rates and their seasonality patterns. On the other hand, the seasonality of economic indicators, especially gross domestic product (GDP), is a key disturbance factor affecting public perceptions of economic trends. Statistical authorities worldwide have introduced various methods for seasonal adjustment.

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However, residual seasonality remains an issue, with a notable pattern being the systematically lower GDP growth in Q1—partly due to seasonal temperature fluctuations [1]. And China, a vast country with diverse geographic patterns and very different climates, demostrates heterogeneous GDP seasonality across its provinces, municipalities, and autonomous regions (hereafter referred to as 'provinces'). Temperature impact is a key factor of the variant seasonal patterns of China's provincial GDP growth rates. While the temperature-economy linkage is established in the literature, its manifestation within large, climatically diverse economies like China is less understood.

China presents a compelling case study of temperature-economy linkage due to its vast territory and economic scale, spanning from the frigid province of Heilongjiang (January mean -18 °C) to the tropical province of Hainan (January mean +21°C). In the meantime, the provincial idiosyncrasy of seasonal GDP fluctuations calls for special policy attention [2]. Yet, existing research on China rarely studies the influence of temperature fluctuations on GDP seasonality at the provincial level, creating a gap in both climate economics and regional business cycle analysis. This study, therefore, brings together two issues—temperature fluctuations and China's provincial GDP seasonality—to ask two questions: 1) Do Chinese provinces exhibit temperature-driven residual seasonality similar to the global pattern? 2) Does accounting for it improve the assessment of the economic fluctuations across different provinces? By addressing these questions, this study aims to uncover the spatially heterogeneous impact of temperature on China's economic seasonality—a critical step toward designing region-specific climate adaptation policies.

2. Literature review

2.1. Temperature as a driver of macroeconomic seasonality

Temperature fluctuations across different seasons and within the season are very important factors affecting economic activities, thus creating GDP seasonality. Multiple studies analyze these interlinkages across worldwide economies. Wilson adopts a dynamic panel regression at the U.S. county level and finds that weather shocks can be useful in explaining and predicting movements in aggregate payroll employment as well as asset price responses to payroll employment releases [3]. Colacito, Hoffman, and Phan reveal nonlinearities in U.S. state-level growth. Summer warming reduces annualized growth (−0.15 to -0.25 pp per °F), whereas autumn warming weakly boosts economic growth [4]. Linsenmeier introduces a novel "seasonal differencing" method across 80 countries and finds that a 10°C seasonal temperature gap corresponds to about 4% GDP divergence [5].

2.2. Residual seasonality in economic data: the temperature debate

The U.S. statistical community has made many studies on the residual seasonality in GDP and the impact of temperature. Gilbert et al. first noted that by introducing January–March temperature anomalies as controlled variables, the otherwise significant Q1 dummy in GDP growth becomes statistically insignificant from zero, suggesting that temperature, rather than calendar effects, drives GDP growth [6]. The U.S. Bureau of Economic Analysis (BEA) then introduced a three-stage action plan that lengthened revision windows and began seasonally adjusting monthly source data before aggregation, which was implemented in 2018 [7,8]. Nevertheless, Consolvo & Lunsford argued that even after the 2018 overhaul, Q1 GDP growth rate still showed 0.6 pp weaker and Q2 0.5 pp stronger at an annual rate. To address the problem, Barrett introduced three tests, i.e., MBF, VS, and ROOT, and confirmed that colder winters did not correspond to the Q1 GDP shortfall, and created

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tools accordingly to validate the misalignment between monthly and quarterly seasonal adjustments [9].

2.3. Climate-economy linkages in China: existing evidence

A burgeoning literature has recently examined the impact of temperature on the Chinese economy, and many scholars have utilized provincial-level data, which generates important findings. However, their work has predominantly focused on its effects on long-term growth patterns, with little attention paid to the implications for economic seasonality. Peng, She, and Huang examine the effects of temperature on China's urban economies and reveal an asymmetric impact—warmer winters boost growth (+0.19% per °C), while hotter summers suppress it (−0.20% per °C) [10]. Zhang & Masron employ ARDL-ECM models to document regional divergence and find that the impact of temperature mainly occurs in underdeveloped regions in western China [11]. Feng et al. deploy a panel Ricardian model with the Hsiao two-step estimator to quantify how temperature and precipitation affect per-mu crop net revenue across seasons, crops, and regions, and their CMIP6 simulations show that rising temperatures and more variable rainfall will depress China's net farming revenue up to 2100 [12]. These studies focus on growth patterns rather than seasonality.

Building on the established temperature-economy literature (2.1), the methodological insights from heated academic debates over residual GDP seasonality and the underlying temperature effect (2.2), as well as the nascent findings on China's climate-economy linkage (2.3), this study bridges these strands by conducting a systematic, province-level analysis of the heterogeneous impact of temperature fluctuations on residual GDP seasonality in China. It directly addresses the identified gap concerning high-frequency, climate-induced economic volatility within a regionally diverse national context.

3. Data and model set-up

3.1. Data sources and variable definitions

The dataset comprises quarterly constant-price GDP (in 100 million CNY) for 30 Chinese provinces (excluding Tibet, Taiwan, Hong Kong, and Macau), covering the time period of Q1 2005 to Q2 2021. In addition, quarterly sectoral GDP shares (primary, secondary, and tertiary industries) for each province are also collected. All data are sourced from the Wind database, which aggregates official statistics from provincial statistical bureaus.

3.2. Construction of the residual seasonality component

Further calculations are made to fit the model settings. First, quarter-on-quarter economic growth rates ($y_{i,t}$) are seasonally adjusted according to the Chinese holiday calendar using the X13-ARIMA method [13]. Second, the STL method is applied to generate the residual seasonality [14]. Seasonally adjusted quarter-on-quarter GDP growth rates ($y^{s}_{i,t}$) of 30 provinces are modeled to include three components: business-cycle component ($c_{i,t}$); a seasonal component ($s_{i,t}$), which is the residual seasonality because the original GDP series is seasonally adjusted; and an irregular residual component ($r_{i,t}$). These components sum to give GDP growth as follows:

$$y^{s}_{i,t} = c_{i,t} + s_{i,t} + r_{i,t} \tag{1}$$

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Where i denotes the numerical counting of the 30 provinces, and t denotes the time periods. For each province's seasonally adjusted GDP growth rate($y^s_{i,t}$), the STL (period=4 quarters) method is applied to generate $c_{i,t}$, $s_{i,t}$, and $r_{i,t}$. In order to confine the seasonal component ($s_{i,t}$) within an economically reasonable level, an algorithm named constrain seasonality is created, which compares the mean absolute magnitude of $s_{i,t}$ to $y^s_{i,t}$, and if $s_{i,t}$ dominates, it is scaled down proportionally. As a result, the mean adjustment factor is 0.394. The descriptive statistics of GDP growth rates across the 30 provinces after data processing are presented in Table 1, and a representative graph of Beijing is shown in Figure 1.

The $s_{i,t}$ time series data reveal substantial heterogeneity in seasonal GDP growth patterns across Chinese provinces. Economic growth rates, both level and variation, of almost all provinces decrease in amplitude after 2015, which represents the structural economic transformation from over-industrial capacity toward services. In addition, all provinces exhibited COVID-19 disruptions in Q1 2020, with residual seasonality exceeding pre-pandemic extremes by 20-50%, and tourism-dependent regions, such as Hainan and Yunnan, suffered the most severe loss. As a result, seasonal patterns vary across geographical areas, with coastal service-driven economies demonstrating greater stability than resource-dependent inland provinces.

1) Traditional manufacturing bases: Hebei and Shandong display strong Q2 rebounds of +15-25% after Q1 contractions;

2) Resource-rich provinces: Inner Mongolia and Shanxi show extreme Q4 peaks and Q1 troughs;

3) Southern modernized economies: Guangdong and Fujian demonstrate moderate seasonality under ±10%;

4) Northeastern rustbelt provinces: Liaoning and Heilongjiang maintained persistent Q4-Q1 differentials exceeding 30 percentage points, reflecting enduring heavy industrial seasonality.

Table 1. The descriptive statistics of GDP growth rates

Parameter	Descriptive statistics				
	Count	Mean (%)	Std (%)	Max (%)	Min (%)
$y_{i,t}$	1950	7.22	28.09	170.39	-67.87
$y^s_{i,t}$	1950	7.11	20.19	143.01	-73.36
$c_{i,t}$	1950	6.44	4.97	34.27	-11.54
$s_{i,t}$	1950	0.10	9.80	39.71	-41.03
$r_{i,t}$	1950	0.67	19.97	144.34	-75.75
$primary_{i,t}$	1950	0.10	0.06	0.33	0.00
$secondary_{i,t}$	1950	0.45	0.09	0.65	0.12
$tertiary_{i,t}$	1950	0.45	0.10	0.88	0.27

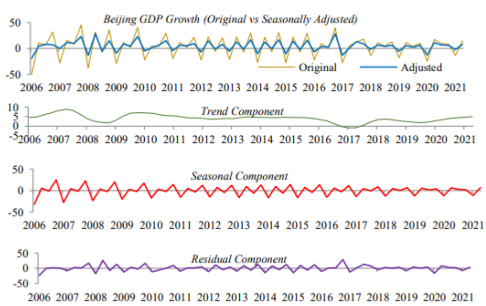

Figure 1. STL decomposition of seasonality-adjusted GDP (Beijing)

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3.3. Temperature data processing

Temperature data are obtained from monthly meteorological station records across China, including mean, maximum, and minimum temperatures. The data span January 2005 to April 2021 and are collected from the Wind database, which sources official data from the China Meteorological Administration. The paper processes the temperature data as follows: for provinces with multiple meteorological stations, mean temperatures are averaged across stations, maximum temperatures are set to the highest recorded across stations, and minimum temperatures are set to the lowest recorded across stations. Monthly temperature data are then aggregated into quarterly data (Q1 2005–Q2 2021). Quarterly mean temperature is calculated as the average of monthly means; Quarterly maximum temperature is picked from the highest monthly maximum; Quarterly minimum temperature is derived from the lowest monthly minimum. The descriptive statistics of the parameters modeled in this paper are illustrated in Table 2. In addition, all the temperature parameters are stationary and passed the ADF test. The ADF tests are conducted with an optimal lag length selected by the AIC criterion, including both intercept and trend terms where appropriate. All temperature variables are confirmed to be stationary at the 5% significance level.

Table 2. The descriptive statistics of temperature parameters

Parameter	Descriptive statistics				
	Count	Mean (%)	Std (%)	Max (%)	Min (%)
$temp\_avg_{i,t}$	1949	13.72	10.13	29.33	-16.54
$temp\_min^{s}_{i,t}$	1950	5.20	12.75	25.60	-42.50
$temp\_max_{i,t}$	1950	32.63	6.02	49.00	9.00

3.4. Model set-up

The baseline fixed-effect model. The residual seasonality of Chinese provinces ($s_{i,t}$) is modeled into the panel data setting, which includes both temperature and economic structure parameters with fixed coefficients. Following Peng, She & Huang (2020), the baseline specification is:

$$s_{i,t} = \beta_0 + \beta_1 temp\_avg_{i,t} + \beta_2 temp\_diff_{i,t} + \beta_3 secondary_{i,t} + \beta_4 tertiary_{i,t} + \beta_5 s_{i,t-1}$$
$$+\beta_6 crisis08_t + \beta_7 covid19_t + \sum_{k=1,2,3} \gamma_k q_k + \varepsilon_{it} \tag{2}$$

In addition to the GDP and temperature parameters, the lag term of residual seasonality ($s_{i,t-1}$) and the share of secondary and tertiary industries is introduced as a control variable. In addition, two periodic dummies of the 2008 crisis (2008q4 to 2009q2) and the Covid-19(2020q1 to 2021q2) are included, and three quarterly dummies of the 1st to 3rd quarters are applied (Q4 is not included because the summary of q1 to q4 dummies equals 1).

The mixed-effect model with random coefficients. In addition, a model with random coefficients for the temperature variables is introduced to capture the different weather effects of the 30 provinces. $b_{1,i}$ denotes the influence of fluctuation of temperature across time on the residual GDP seasonality, and $b_{2,i}$ represents the effect of temperature fluctuation within the quarter. The other settings are the same as the baseline model.

$$s_{i,t} = \beta_0 + \alpha_i + b_{1,i} temp\_avg_{i,t} + b_{2,i} temp\_diff_{i,t} + \beta_1^{FE} secondary_{i,t} + \beta_2^{FE} tertiary_{i,t} +$$

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$$\beta_3^{FE} s_{i,t-1} + \beta_4^{FE} crisis08_t + \beta_5^{FE} covid19_t + \sum_{k=1,2,3} \gamma_k^{FE} q_k + \varepsilon_{it} \tag{3}$$

4. Results

4.1. Overall model performance and key coefficients

Applying pooled OLS regression on the Q1 2005 to Q2 2021 sample period, the regression results of the baseline model and the mixed-effect model are illustrated in Table 3. The lagged dependent variable coefficient strengthens from -0.40 (Model (2)) to -0.54 (Model (3)), implying faster mean-reversion when accounting for provincial heterogeneity.

4.2. Average effects of temperature on residual seasonality

The fixed-effect baseline model shows uniformly significant temperature effects, with the coefficient of $\mathrm{temp\_avg}_{i,t}$ at 0.24 (significant at 1%), and $\mathrm{temp\_diff}_{i,t}$ at 0.09 (significant at 10%). The random coefficients model reveals substantial province-level heterogeneity, making aggregate coefficients insignificant.

4.3. Dynamics of quarterly residual seasonality

Both models confirm strong quarterly patterns with Q1 showing the largest negative impact (-16.16 and -16.31). The baseline model shows a stronger Q3 effect than the mixed-effect model (6.76 vs -6.76), indicating provincial adaptation moderates late-year seasonality.

Table 3. The regression results of the two models

Parameter	Baseline model (2)		Mixed-effect model (3)	
	Coef.	S.E.	Coef.	S.E.
β_0	24.54***	5.22	22.97***	5.45
$\mathrm{temp\_avg}_{i,t}$	0.24***	0.04	-0.06	1.37
$\mathrm{temp\_diff}_{i,t}$	0.09*	0.04	0.06	1.37
$\mathrm{secondary}_{i,t}$	-25.00***	5.73	-17.96***	4.54
$\mathrm{tertiary}_{i,t}$	-25.18***	5.70	-16.79***	4.42
$s_{i,t-1}$	-0.40***	0.03	-0.54***	0.02
q_1	-16.16***	0.48	-16.31***	0.50
q_2	-7.68***	0.62	-7.56***	0.88
q_3	-6.76***	0.77	-2.65*	1.25
$\mathrm{crisis08}_t$	-0.09	0.43	-0.09	0.32
$\mathrm{covid19}_t$	1.24***	0.39	0.86*	0.43
Model performance	R^2=0.71 (within)		Group Var=359.7, χ^2 p<0.001	

*, **, and *** represents significance level at 10%, 5% and 1%, respectively.

4.4. Provincial heterogeneity in temperature sensitivity

Significant random variances justify the mixed model approach (Group Var = 359.7; χ^2, $p < 0.001$). The coefficients are denoted by $b_{1,i}$ and $b_{2,i}$ are illustrated in Table 4, which can be divided into five distinct quadrants, driven by different geographical and climate characteristics, as well as economic structures:

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Quadrant 1 (Northern provinces): the six provinces at the Northern-China plain, led by Shangdong and Henan, have both positive and statistically significant $b_{1,i}$ and $b_{2,i}$. Their production benefits both from average temperature increase and larger intra-quarter temperature variance, which means warmer winters and cooler summers. This can be explained by the fact that most of these provinces have a larger agricultural sector than other areas. The outlying province of Sichuan is also a large agricultural base in China, although it is at the northwest area.

Quadrant 2 (Northwestern provinces): the four northwestern provinces, led by Gansu and Ningxia, have positive $b_{1,i}$ while negative $b_{2,i}$ (for some of them $b_{2,i}$ is negative but not statistically significant from 0). They benefit from higher average temperatures, but suffer from large variations in intra-quarter temperature, which may lead to severe climate events such as drought or flood. This can also be explained by their agricultural patterns, which heavily rely on irrigation and a stable climate. There are two outlier provinces of Hubei and Jiangxi falling into this group, both of which are at the mid-stream of the Yangtze River, and have a long history of flood experiences, which means they also need stable weather to keep their economy at a healthy state.

Quadrant 3 (Southwestern provinces): the three southwestern provinces, led by Guangxi, Yunnan, and Chongqing, have both negative $b_{1,i}$ and $b_{2,i}$. These provinces are in the tropical or sub-tropical area, and may suffer from extreme summer heat if the average temperature rises. They are also vulnerable to larger intra-quarter temperature variations, as these may also lead to floods, which will dampen their agricultural production, or larger cooling expenses in the summer months, which may cause adverse effects to their industries and tourism. There are two northeastern outliers, i.e., Heilongjiang and Inner Mongolia, in this group. They should have benefited from warmer climates. Further studies are needed to get more detailed explanations of them.

Quadrant 4 (Southeastern provinces): the three southeastern provinces of Shanghai, Zhejiang, and Jiangsu are the most developed areas in China, and they benefit from larger intra-quarter temperature variations and suffer from higher average temperature because they already have hot summers and mild winters, and their industries and services have already been adapted well to the current climate pattern. The outliner Hainan is a typical tourism destination, which may also benefit from the current climate.

Quadrant 5 (other provinces): These provinces show no distinct temperature-economic patterns, and further studies are needed.

Table 4. Regional heterogeneity as evidenced $b_{1,i}$ and $b_{2,i}$

Quadrant	Province	b1,t	b2,t	Identity	Quadrant	Province	b1,t	b2,t	Identity
Q1: N	Shandong	1.16	1.48	$b_{1,t}>0.2,b_{2,t}>0.2$	Q3:SW	Chongqing	-0.13	-0.82	$b_{1,t}<0,b_{2,t}<-0.3$
	Henan	0.63	0.6			Heilongjiang*	-0.47	-0.39	
	Anhui	0.42	0.54			InnerMongolia*	-0.04	-0.36	
	Liaoning	0.35	0.21		Q4:SE	Shanghai	-0.27	0.08	$b_{1,t}<0,b_{2,t}>0$
	Tianjin	0.27	0.33			Zhejiang	-0.14	0.05	
	Hebei	0.23	0.29			Jiangsu	-0.03	0.37	
	Sichuan*	0.76	0.78			Hainan*	-0.38	0.34	
Q2: NW	Gansu	0.52	-0.33	$b_{1,t}>0,b_{2,t}<0,\text{or } b_{2,t}\approx 0$	Others	Jilin	-0.29	-0.23	No distinct identity
	Ningxia	0.15	-0.34			Beijing	-0.19	-0.2	
	Xinjiang	0.4	0.14			Shanxi	-0.18	-0.07	
	Qinghai	0.29	0.07			Shaanxi	-0.34	-0.23	
	Jiangxi*	0.14	-0.06			Guizhou	0.07	0.2	
	Hubei*	0.12	-0.22			Hunan	-0.17	-0.05	

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Table 4. (continued)

Q3: SW	Guangxi	-1.19	-0.95	$b_{1,t}<0, b_{2,t}<-0.3$	Fujian	-0.42	-0.1
	Yunnan	-0.95	-0.88		Guangdong	-0.29	-0.23

*: outliers that do not belong to the geographical region

5. Implications for the chinese economy

China's vast and economically diverse provinces exhibit distinct GDP seasonality responding to temperature fluctuations, but there is a clear geographic logic behind this relationship. Therefore, region-specific climate adaptation strategies are in sincere need. Northern China provinces, such as Shandong and Henan, should focus on promoting climate-smart farming technologies, investing in resilient infrastructure, and adopting adaptive industrial practices to capitalize on the favorable seasonal temperature effects identified in this study. In contrast, Southwestern tropical and sub-tropical provinces like Guangxi, Yunnan, and Chongqing require innovative heat-mitigation measures, such as green architecture, flexible work hours, and seasonally adjusted tourism policies to stabilize demand. Northwestern provinces, including Gansu, Ningxia, Xinjiang, and Qinghai, should prioritize green electricity infrastructure to counter the ever-increasing intra-period temperature fluctuations. Southeastern provinces of Shanghai, Zhejiang, and Jiangsu should develop energy-efficient technologies to counter the global warming trend. In addition, the complexity of the above actions necessitates strong central government leadership to coordinate efforts effectively. Central authorities should integrate local climate risk assessments into national economic planning,

To ensure adaptive policy formulation, a cross-country institutional framework should be established. The government should make periodic impact assessments, so as to update policies accordingly. The academia should conduct robust empirical research in climate economics, so as to provide data-driven policy recommendations and enforcement measures. For the industrial sector, it is critical to accelerate the research and deployment of climate adaptation and mitigation technologies.

6. Conclusion

This paper investigates two questions: whether Chinses provinces exhibit heterogeneous temperature-driven GDP residual seasonality, and whether accounting for the above heterogeneity improves the assessment of economic fluctuations of these provinces. The model analysis provides clear affirmative answers to both. The mixed-effect panel regression model identifies significant and heterogeneous temperature-economic effect of different geographical regions in China, fundamentally driven by their respective climate-patterns and regional economic structures. Provinces in the Northern-China plain, such as Shangdong, Henan, and Anhui, exhibit positive GDP seasonality associated with both warmer average temperatures and higher intra-quarter temperature deviations, which benefit the agricultural production. Southwestern provinces (e.g., Guangxi, Yunnan, and Chongqing) experience a negative impact from rising inter-quarter average temperatures and larger intra-period temperature fluctuations, partly due to the hot summer's adverse effect on both industries and tourism. Northwestern and Southeastern provinces get mixed temperature-economic effects, with the former benefiting from higher average temperature and the latter suffering, while the former suffers from large intra-period climate fluctuations and the latter benefits, also due to their agricultural and industrial patterns and their respective geographical locations. Accordingly, region-specific adaptation policies are critical—Northern provinces should

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invest in climate-smart agriculture, Southwestern regions require innovative heat-mitigation measures, and all the provinces will benefit from green energy. Importantly, the study stresses the need for centralized coordination to align localized climate adaptation with national economic planning.

The methodology and results of this study carry substantial business and social value. This paper is among the rare academic studies on the relationship between temperature and short-term economic fluctuations across vast China. The two econometric models provide insight into residual GDP seasonality and the temperature variations behind it, which provides insight to both the government, academia, and the industrial sector.

The value of this paper is limited by the fact that the temperature data stops at Q2 2021, so the two models cannot reveal the relationship based on the most up-to-date information. Additionally, the analysis focuses solely on temperature effects, without accounting for climate factors such as precipitation. Future research should integrate the most recent data and more comprehensive climate data to refine causal mechanisms.

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