Heterogenous Impacts of Climate Change on China's Green Total Factor Efficiency

Yi Li, Zhengfei Guan; Food and Resource Economics Department, University of Florida; yi.li1@ufl.edu, guanz@ufl.edu

Selected Poster prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC: July 23- 25, 2023

Heterogenous Impacts of Climate Change on China's Green Total Factor Efficiency

Yi Li, Zhengfei Guan

UF IFAS UNIVERSITY of FLORIDA
FOOD & RESOURCE ECONOMICS DEPARTMENT

INTRODUCTION

- The increase in average temperature negatively affects most economic variables, including agriculture, industrial output, economic growth, etc. Extreme cold or hot weather can hinder people's ability to focus on their tasks, leading to decreased productivity. But its impact on green economic efficiency is less discussed.
- Adaptive behaviors in response to climate change may lead to considerable energy consumption and pollution emission costs, reducing the efficiency of the green economy.
- Whether it favors the poor or the rich, the consequence of climate change remains unclear. While undeveloped areas face substantial negative effects from climate change, the environmental costs of wealthy regions' adaptation strategies, like high energy consumption and pollution emissions, are often overlooked.
- "Cracking the code" of when, where, and why adaptation is successful or unsuccessful holds promise for major green growth benefits. These sources of heterogeneity may include difficult access to technology, perverse political incentives, climate mitigation policies and high adaptation costs.
- China's net-zero emission goal makes it a challenge to coordinate economic growth and emission reduction. While paying more attention to climate governance, China pursues green development rather than high-speed growth. Limited efforts have been made to discuss China's green development efficiency.

Objectives

- This paper evaluates the heterogeneous impacts of climate change on China's green total factor efficiency (GTFE) by focusing on sources of regional adaptation gaps.

METHODS

- Fixed effect model (FE). According to Deryugina and Hsiang (2014), the identification strategy is to build the following fixed effect model:

$$Gtfe_{it} = \alpha + \beta^k Temperature_{it}^k + \phi Weather_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Temperature_{it}^k$ refers to the total number of days the average temperature falls within bin k for city i in year t. The temperature is divided into 9 indicator bins at 6 °C intervals, with [6°C, 12°C) serving as the baseline bin. β^k implies the change in $Gtfe_{it}$ per additional day in a specific temperature bin (relative to the 6 to 12°C range). $Weather_{it}$ represents other climate variables including precipitation, sunshine time, dew point temperature, vapor pressure, and average wind speed. X_{it} denotes economic variables affecting GTFE, including per capita GDP, environmental regulation level, industrial structure, the ratio of FDI to GDP, fiscal autonomy, and population density. u_i signifies city fixed effects. λ_t represents year fixed effects, and ε_{it} is robust standard errors clustered at the city level.

- Long difference regression (LD). Referring to Zivin et al.(2018), we also set a LD model for assessing the long-run impact of climate change on GTFE:

$$Gtfe_{it} - Gtfe_{it-m} = \tilde{\beta}^{LD,k}\left[\ln\left(1 - Temperature_{it}^k\right) - \ln\left(1 - Temperature_{it-m}^k\right)\right] + \tilde{\phi}\,[Weather_{it} - Weather_{it-m}] + \tilde{\delta}[X_{it} - X_{it-m}] + \tilde{\lambda}_t + \tilde{\varepsilon}_{it} \quad (2)$$

where $\tilde{\beta}^{LD,k}$ is the long-difference estimator. The interpretation of other variables is the same as equation (1).

DATA

- GTFE data: The Undesired SBM method is used to calculate GTFE, with inputs including labor, capital, and energy, and outputs including GDP and pollution emissions. It contains 3,903 observations across 284 cities.
- Temperature indicator bins are constructed based on average daily temperatures, calculating the number of days in a year that falls within each bin. Weather data comes from the ERA-Interim database. Economic variable data are sourced from the China Urban Statistical Yearbook, China Statistical Yearbook, etc.

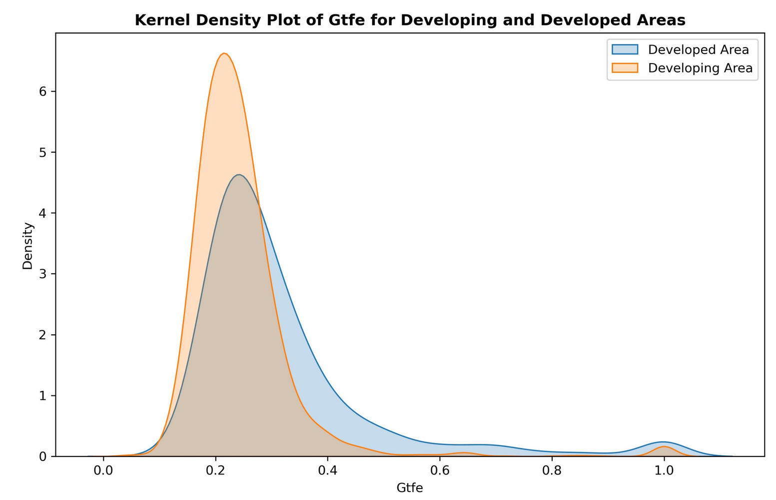

Figure 1. Kernel Density of GTFE.

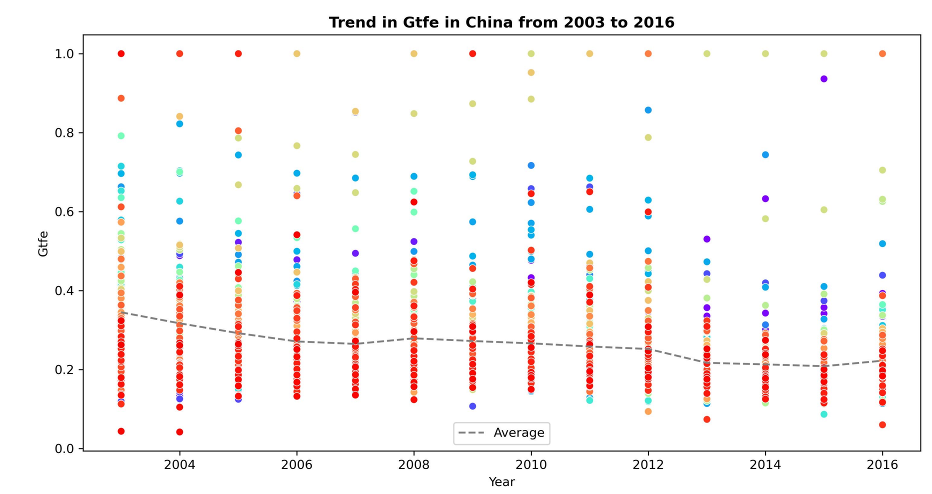

Figure 2. Recent Trends in GTFE in China.

RESULTS

- There is an inverted U shape between temperature and GTFE: taking the 6 to12 °C bin as the baseline, both decreases and increases in temperature negatively affect GTFE.
- LD analysis indicates that with each additional day in the 12 to 18°C bin, GTFE is reduced by 0.0003 units in the long run. However, this effect is no longer significant when the temperature rises or falls beyond one bin. Heterogeneous adaptability could contribute to the results.

Table 1. The impact of temperature change on GTFE: FE and LD estimates.

Variable	FE		LD	
	(1)	(2)	(3)	(4)
<-12°C	-0.000	-0.000	-0.000	-0.000
	(-0.48)	(-0.58)	(-0.59)	(-0.50)
[-12°C, -6°C)	-0.001**	-0.001**	-0.001	-0.000
	(-2.34)	(-2.01)	(-1.25)	(-0.84)
[-6°C, 0°C)	-0.000	-0.000	0.000	0.000
	(-1.22)	(-1.00)	(0.10)	(0.05)
[0°C, 6°C)	-0.001**	-0.000**	-0.000*	-0.000
	(-2.41)	(-2.00)	(-1.70)	(-1.31)
[12°C, 18°C)	-0.000	-0.000	-0.000	-0.000*
	(-0.91)	(-1.14)	(-1.53)	(-1.84)
[18°C, 24°C)	-0.001*	-0.001**	-0.000	-0.000
	(-1.72)	(-1.97)	(-1.15)	(-1.60)
[24°C, 30°C)	-0.000	-0.001	-0.000	-0.000
	(-1.10)	(-1.29)	(-0.18)	(-0.73)
>30 °C	-0.001	-0.001	-0.000	-0.000
	(-1.26)	(-1.50)	(-0.17)	(-0.76)
Wind speed	-0.015	-0.010	-0.018	-0.012
	(-0.88)	(-0.60)	(-0.70)	(-0.46)
Sunshine	0.024	0.027	-0.010	-0.010
	(0.71)	(0.78)	(-1.04)	(-1.09)
Precipitation	-0.023	-0.030	-0.086	-0.056
	(-1.18)	(-1.47)	(-1.64)	(-1.09)
Vapor pressure	-0.167**	-0.161**	0.000	0.002
	(-2.48)	(-2.50)	(0.03)	(0.54)
Dewpoint temperature	-0.004	-0.002	0.003	0.009
	(-0.80)	(-0.32)	(0.24)	(0.69)
Constant	16.546**	15.801**	-0.032***	-0.034***
	(2.53)	(2.52)	(-4.44)	(-4.80)
Economic Controls	No	Yes	No	Yes
City fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	3903	3849	3621	3566
R^2	0.612	0.636	0.095	0.146

Notes: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

RESULTS

- The negative impact is more pronounced for developed areas and areas with high degrees of environmental regulation where the labor is concentrated and the cost of adaptation is higher, following an inverted U-shaped relationship.

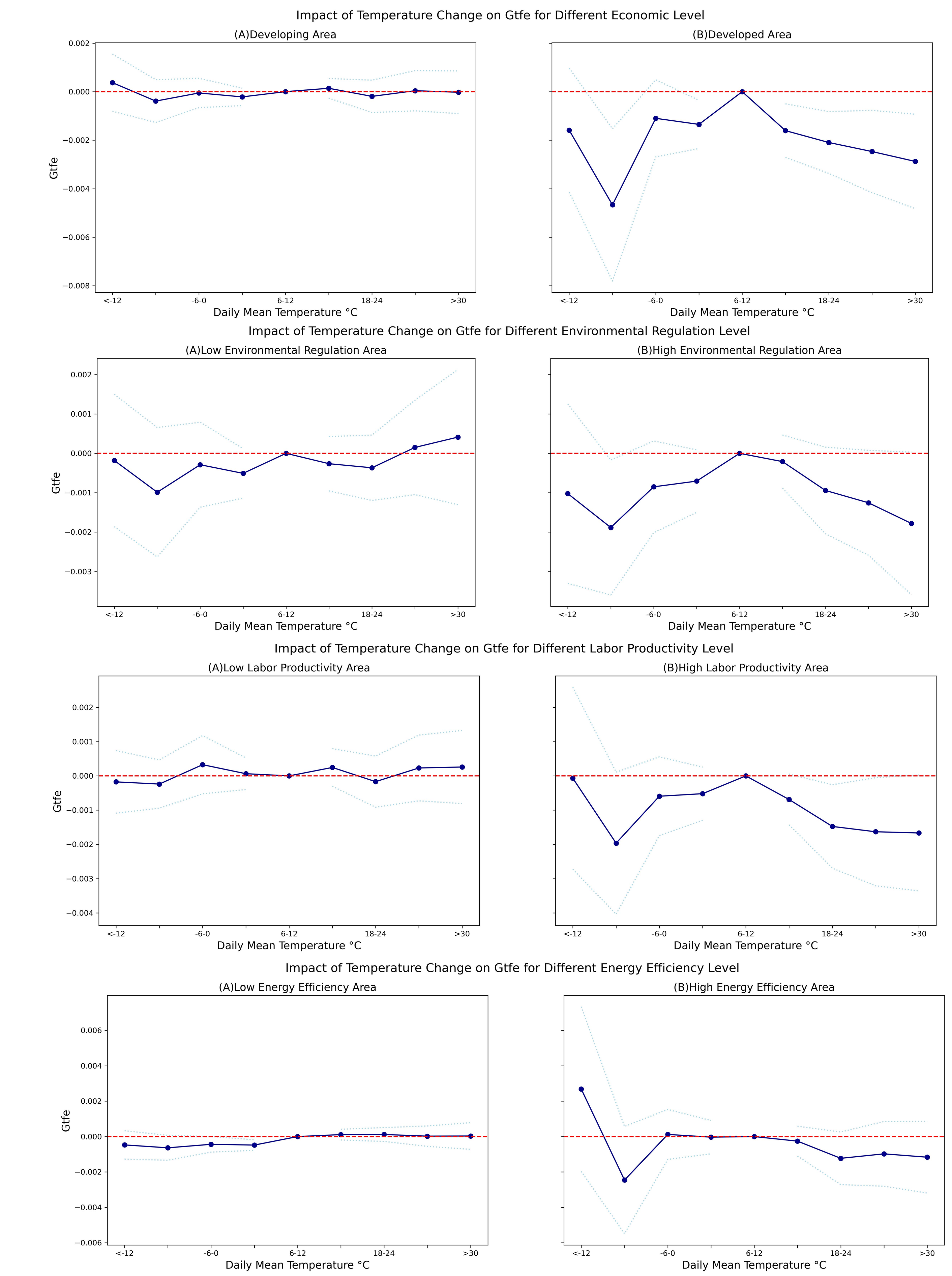

Figure 3. The Heterogeneity impacts of temperature change on GTFE in China.

- It is also more significant for areas with high levels of labor productivity, where the higher the temperature, the greater the negative impact on GTFE. With each additional day in the above 30°C bin, the GTFE decreases by 0.0017 units. A decrease in temperature significantly reduces the GTFE for areas with low energy efficiency, which is insignificant after the temperature drops below -12°C. Temperature changes do not have a significant impact on areas with high energy efficiency.

CONCLUSIONS

- We find an inverted U-shaped relationship between temperature and GTFE in China by introducing FE and LD models. This relationship is more pronounced in developed areas and areas with high environmental regulation levels due to a higher cost of adaptation. Given the limited adaptability of the labor to temperature changes, the negative impact of climate change on GTFE is greater in areas with high labor productivity. Low energy efficiency area suffers from the decrease in temperature. Our research offers valuable insights for the optimization of climate policy design towards green growth by leveraging various sources of adaptation.