

Examining the Effects of Labor Productivity on Air Pollution in a Changing Climate

Hsiao-I Kuo¹, Shu-Chen Chang^{2*}

¹Department of Golden-Ager Industry Management, Chaoyang University of Technology, Taichung

²Department of Business Administration, National Formosa University, Yunlin

Email: *shu-chen@nfu.edu.tw

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Abstract

This paper investigates the nonlinear effects of labor productivity on air pollution in the context of climate change, using a dataset of 52 countries over the period 1971-2015. The analysis reveals a threshold effect on CO₂ emissions, indicating that the influence of labor productivity and income on emissions varies based on temperature regimes. Our findings show that in the non-high temperature regime, the coefficient for labor productivity is significant and negative at the 5% significance level, suggesting that CO₂ emissions decrease as labor productivity increases. This emphasizes the role of labor productivity in reducing emissions in cooler climate conditions. Additionally, the coefficients for GDP and its squared term are both positive and significant at the 5% level, indicating that higher GDP is associated with increased CO₂ emissions. The positive and significant coefficient for lagged CO₂ emissions further suggests a persistence in emissions over time, reinforcing the cumulative impact of economic activity on environmental degradation.

Keywords

CO₂ Emissions, Labor Productivity, Climate Change, Income

1. Introduction

The anthropogenic rise in global temperatures has led to significant climate changes, characterized by more frequent and severe instances of extreme weather, including intense heatwaves, heavy precipitation, and prolonged droughts. These climatic extremes have substantial impacts, causing environmental degradation and considerable economic losses on a global scale.

Research has consistently highlighted the differential effects of climate change on agriculture, showing that rising temperatures may benefit crop yields in

temperate regions while adversely affecting agricultural income in tropical areas (Deressa, 2007; Seo & Mendelsohn, 2008a, 2008b). Additionally, high temperatures have been found to reduce the yield of various crops (Lobell, Schlenker, & Costa-Roberts, 2011; Schlenker & Roberts, 2009; Auffhammer, Ramanathan, & Vincent, 2006). Dell, Jones, and Olken (2012) further demonstrated that elevated temperatures notably hinder economic growth in low-income countries.

Beyond agriculture, rising global temperatures can directly impact labor productivity. A 2015 report by the UK-based risk analysis agency Verisk Maplecroft warned that a 2°C rise in global average temperature by 2045 could exacerbate heat stress, potentially reducing labor productivity in Southeast Asia by up to 16% over the following 30 years. Chang, Graff Zivin, Gross, and Neidell (2019) explored the effects of temperature and air pollution on labor productivity, finding that productivity increases with temperature up to a certain threshold before declining. In another study, Gibson and Heutel (2020) used a Dynamic Stochastic General Equilibrium (DSGE) model to examine how pollution, technological advancements in abatement, and labor allocation between production and “green technology” sectors interact. Their findings suggest that temperature increases influence both labor productivity and CO₂ emissions, underlining the interconnection between environmental stressors and economic productivity.

This study seeks to analyze the economic implications of climate-induced temperature changes on labor productivity and pollution emissions, focusing on the broader economic effects. Climate change may exacerbate health risks for workers—particularly those in agriculture and construction, including older workers—whose productivity is crucial to economic development and who often face prolonged exposure to extreme temperatures.

To incorporate temperature dynamics into a model that assesses labor productivity, scale effects, and CO₂ emissions, this paper employs a threshold model with temperature as the threshold variable. The objective is to identify threshold values and assess the impacts of labor productivity and scale effects on CO₂ emissions across different regimes. This approach minimizes the sum of squared errors to determine the optimal threshold value and applies one-step and two-step System-GMM methods to evaluate the differential effects of labor productivity and scale between regimes on CO₂ emissions.

The remainder of the study is structured as follows: Section 2 outlines the theoretical framework and specifies the empirical model. Section 3 describes the data sources and methodology used for the analysis. Section 4 presents the results, including robustness checks and discussions of the findings. Section 5 offers policy implications derived from the analysis, and Section 6 concludes with key insights.

2. Literature Review

The impact of climate change on agricultural productivity and economic activities has been a significant focus of scholarly inquiry in recent years, with research revealing the nuanced and heterogeneous effects of temperature variations across

regions and sectors. Empirical studies, including those by [Deressa \(2007\)](#) and [Seo and Mendelsohn \(2008a, 2008b\)](#), have identified a contrasting impact of rising global temperatures on agricultural outcomes: while temperate regions have experienced enhanced agricultural yields due to moderate warming, tropical regions have suffered significant declines in agricultural income, exacerbating socioeconomic disparities. [Lobell, Schlenker, and Costa-Roberts \(2011\)](#) and [Schlenker and Roberts \(2009\)](#) further emphasize the vulnerability of agricultural systems, reporting substantial reductions in crop yields under high-temperature conditions. Similarly, [Auffhammer, Ramanathan, and Vincent \(2006\)](#) provide evidence of compounding effects of atmospheric brown clouds and greenhouse gases on rice yields in India, underscoring the complex interactions between anthropogenic pollutants and climatic factors. These findings align with [Dell, Jones, and Olken's \(2012\)](#) analysis, which demonstrates the disproportionately adverse economic consequences of higher temperatures in low-income countries, illustrating the unequal distribution of climate risks globally.

The implications of climate change extend beyond agriculture, notably affecting labor productivity in thermally stressful environments. Research by [Ye, Chen, and Lian \(2010\)](#), [Maughan, Otani, and Watson \(2012\)](#), and [Shi, Zhu, and Zheng \(2013\)](#) have established a statistically significant relationship between indoor environmental conditions and workforce output, particularly under conditions of elevated temperatures and humidity. [Kjellstrom et al. \(2009\)](#) corroborate these findings, highlighting that increased heat exposure significantly impairs productivity, particularly among workers engaged in physically demanding tasks or those in regions with limited access to adaptive infrastructure. These studies collectively highlight the adverse physiological and cognitive effects of extreme heat and humidity, which constrain workforce efficiency, especially in economically and climatically vulnerable regions.

Optimal workplace productivity is generally observed within a narrow range of thermal comfort; deviations beyond this range—especially under excessive heat—trigger heat stress and physiological disruptions, including elevated heart rates, increased perspiration, and enhanced skin blood flow. [Graff et al. \(2012, 2014\)](#) further substantiate this notion, demonstrating that higher temperatures systematically reduce labor productivity, particularly in outdoor and labor-intensive industries. This growing body of evidence emphasizes the urgent need for targeted adaptation strategies and equitable climate policies to mitigate the multifaceted socioeconomic challenges posed by global warming.

3. Empirical Models

3.1. Empirical Model

This paper hypothesizes a nonlinear relationship between temperature and labor productivity, where productivity increases up to an optimal temperature level and declines thereafter. This nonlinear relationship can be modeled as follows:

$$E_{it} = \mu + \alpha_1 B_{it}(\gamma) + \alpha_2 E_{it-1} + u_{it} \quad (1)$$

$$B_{it}(\gamma) = \begin{bmatrix} B_{it}I(T_{it} \leq \gamma) \\ B_{it}I(T_{it} > \gamma) \end{bmatrix}, \alpha_1 = (\alpha'_{11}, \alpha'_{12})'$$

The subscripts i and t represent countries and years, respectively. E_{it} denotes environmental degradation, while B_{it} represents labor productivity, with data obtained from the World Development Indicators. CO₂ emissions per capita serve as the proxy for environmental degradation, as emissions predominantly stem from energy-related activities. The model incorporates the impact of economic growth on environmental quality within the framework of the Environmental Kuznets Curve (EKC) theory. This theory posits that economic development initially exacerbates pollution levels but, after surpassing a certain income threshold, leads to a decline in pollution due to increased environmental awareness and the adoption of cleaner production technologies. Guided by this theoretical foundation, the model is specified as follows:

$$E_{it} = \mu + \alpha_1 B_{it}(\gamma) + \alpha_2 E_{it-1} + \alpha_3 \text{GDP}_{it} + \alpha_4 \text{GDP}_{it}^2 + \alpha_5 B_{it-1} + \alpha_6 \text{GDP}_{it}(\gamma) + e_{it} \quad (2)$$

$$\text{GDP}(\gamma) = \begin{bmatrix} \text{GDP}_{it}I(T_{it} \leq \gamma) \\ \text{GDP}_{it}I(T_{it} > \gamma) \end{bmatrix}, \alpha_6 = (\alpha'_{61}, \alpha'_{62})'$$

The control variables include economic development (GDP_{it}), and the lagged environmental degradation (E_{it-1}) and lagged labor productivity (B_{it-1}).¹ γ is the threshold value. u_{it} and e_{it} are an error term.

According to Kjellstrom et al.'s (2009) study, this paper assumes that labor productivity is influenced by working hours, temperature, and lagged productivity, which can be expressed as:

$$B_{it} = \beta_0 + \beta_1 \text{HR}_{it} + \beta_2 T_{it} + \phi_{ij} \sum_{j=1}^p B_{it-j} + v_{it} \quad (3)$$

where HR_{it} is worked hours, T_{it} is temperature, and B_{it-j} is lagged labor productivity. v_{it} is an error term. p is the lag length, and ϕ_{ij} are the estimated coefficient of labor productivity.

3.2. Empirical Approach

This paper addresses the endogenous nature of labor productivity and income within an environmental pollution model, aiming to estimate the nonlinear effects of labor productivity on environmental pollution. Economic development and temperature, the primary drivers of environmental degradation, are treated as exogenous variables. This approach enables an estimation of the relationship between environmental pollution and labor productivity within distinct temperature regimes.

Following Chang and Li's (2019) recommendation, this study avoids using OLS and 2SLS estimators, as they lack efficiency in this context. Instead, it employs the threshold model with instrumental variables proposed by Caner and Hansen

¹Explanatory variables of environmental degradation do not consider square and cubic terms of real income per capita because its coefficient is not statistically significant in our linear or nonlinear regressions.

(2004) to capture the effects of labor productivity on environmental pollution across different temperature regimes.

4. Description of Variables

This study excludes countries for which complete climate data are unavailable, resulting in an unbalanced panel dataset² spanning 45 years (1971–2015)³ and covering 52 countries (see **Appendix Table A**). Temperature and precipitation data are sourced from the Climate Change Knowledge Portal (CCKP) of the World Bank, a platform providing global climate data and reports on climate change. Data on pollutant emissions is sourced from the World Development Indicators (WDI), while other economic variables are obtained from the Penn World Table. Definitions of all variables are provided in **Table 1**, and their descriptive statistics are presented in **Appendix Table B**.

Table 1. Data definitions.

Symbol	Variables	Definitions
E_{it}	Environmental pollution	Total CO ₂ emissions divided by population.
HR_{it}	Average annual hours worked	Average annual hours worked by employed individuals.
B_{it}	Labor productivity	GDP per hour worked, adjusted to 2011 international dollars.
GDP_{it}	Economic development	Real GDP per capita at constant 2011 national prices (in millions, 2011 US\$).
T_{it}	Annual average temperature	Annual average temperature in degrees Celsius.

5. Estimated Results

5.1. Empirical Results of Nonlinear Regression with a Cross-Term

This paper extends the analysis by considering a nonlinear model of CO₂ emissions to examine whether temperature variations influence the impact of labor productivity and scale effects on CO₂ emissions. The estimated results are presented in **Table 2**. According to the Breusch–Godfrey LM test for serial correlation, all models show no evidence of serial correlation in the residuals at the 5% significance level.

The coefficient of labor productivity is statistically significant across all models, indicating that higher labor productivity positively correlates with CO₂ emissions. The linear GDP term is positive and significant, suggesting that as GDP increases, CO₂ emissions rise. The estimated coefficient on GDP_{it}^2 is not statistically significant at the 5% level. The coefficients of interaction terms involving temperature

²Missing data points were not replaced or imputed to preserve the dataset's integrity and avoid biases that could distort variable relationships, ensuring reliable and robust findings.

³Data post-2015, especially after 2020, is influenced by factors like the COVID-19 pandemic, which temporarily reduced emissions. The Paris Agreement in 2015 marked a global shift in climate policies. Using data from 1971–2015 provides a clear view of historical emissions and trends before these major changes.

are statistically insignificant. This implies that the inclusion of temperature as a modifying factor does not substantially influence the relationship between labor productivity, GDP, and CO₂ emissions.

Table 2. Results of nonlinear model with cross-terms.

Independent Variables	Model (1)	Model (2)	Model (3)
B_{it-1}	0.015** (0.000)	0.015** (0.000)	0.014** (0.000)
GDP_{it}	0.115** (0.024)	0.193** (0.018)	0.220** (0.011)
$(GDP_{it})^2$	-0.005 (0.162)	-0.007 (0.088)	-0.007 (0.070)
E_{it-1}	0.915** (0.000)	0.911** (0.000)	0.908** (0.000)
$B_{it} \times T_{it}$	0.107×10^2 (0.911)		0.243×10^2 (0.279)
$GDP_{it} \times T_{it}$		-0.006 (0.218)	-0.008 (0.130)
constant	0.114 (0.182)	0.160 (0.068)	0.148 (0.095)
R-squared	0.918	0.918	0.917
Breusch-Godfrey LM test for serial correlation test	0.592 (0.441)	1.46 (0.225)	1.727 (0.188)

Notes: p -values are shown in parentheses. **denotes statistical significance at the 5% level.

5.2. Results of Panel Threshold Test

To investigate potential threshold effects in the relationship between labor productivity, GDP per capita, and lagged CO₂ emissions, this paper employs 999 bootstrap replications. The results of these threshold tests are presented in **Table 3**.

In **Table 3**, the null hypothesis of “no threshold effect” is rejected ($p < 0.05$), confirming the existence of two distinct regimes: “high temperature” and “non-high temperature.” In the non-high temperature regime, the coefficient for lagged labor productivity is negative and significant (-0.013) at the 5% level, indicating that increasing lagged labor productivity reduces CO₂ emissions. Specifically, a 1% increase in lagged labor productivity is associated with a 0.013% reduction in CO₂ emissions. However, in the high temperature regime, the coefficient is positive but not statistically significant, suggesting no clear effect. This finding underscores the influence of labor productivity on emissions under non-high temperature conditions.

Additionally, the coefficients for GDP and its squared term are both positive and significant at the 5% level, suggesting that increases in GDP lead to higher

CO₂ emissions regardless of the temperature regime. The positive and significant coefficient for lagged CO₂ emissions indicates persistence in emission levels over time, suggesting that past emissions strongly influence current levels.

Table 3. Threshold effects of labor productivity and income on CO₂ emissions.

Independent variables	The dependent variable: CO ₂ emissions per capita	
B_{it-1}	−1.109** [−0.039, −0.017]	
GDP_{it}		0.062** [2.700, 7.141]
$(GDP_{it})^2$	0.014** [0.007, 0.018]	0.072** [0.026, 0.073]
E_{it-1}	0.072** [0.052, 0.070]	0.010** [−0.268, −0.093]
$B_{it} I(T_{it} \leq \gamma)$		−0.013** [−0.040, −0.001]
$B_{it} I(T_{it} > \gamma)$		0.014 [−0.020, 0.027]
$GDP_{it} I(T_{it} \leq \gamma)$	−0.127** [0.172, 0.737]	
$GDP_{it} I(T_{it} > \gamma)$	0.087** [0.038, 0.440]	
regime constant	0.664** [−8.399, −1.437]	−0.170 [−2.511, 0.077]
Tests of threshold effects		
Null hypothesis: no threshold effect		
LM test (<i>p</i> -value)	418.530(0.000)	79.595 (0.000)

Notes: Bootstrap *p*-values were calculated based on 999 iterations. **denotes statistical significance at the 5% level. The numbers in brackets are 0.95 confidence interval.

Comparing the panel threshold regression with a nonlinear regression model reveals that the threshold model effectively captures regime-specific differences, highlighting the nuanced influence of labor productivity and GDP on emissions under varying temperature conditions. This indicates that the effect of labor productivity may be underestimated in models with interaction terms⁴. Moreover, the estimated impacts of GDP and lagged CO₂ emissions remain consistent across both the panel threshold and traditional nonlinear regression models.

⁴While the primary focus of the analysis was on temperature, future robustness checks could incorporate humidity, precipitation, or indicators of extreme weather (e.g., storms, floods) to capture additional climatic effects. Humidity, in particular, may interact with temperature to influence labor productivity and emissions. Sudarshan and Tewari (2014) controlled for both high humidity and heat stress in their analysis of Indian manufacturing, confirming that their results were robust even when humidity was included as an additional variable. Parsons et al. (2022) incorporated “humid heat” metrics such as wet bulb globe temperature (WBGT), a combination of temperature and humidity, to better represent the labor productivity effects in hot and humid climates.

6. Policy Implication

In high-temperature regimes, the study identifies diminished benefits of labor productivity in reducing CO₂ emissions, potentially due to increased energy demands for cooling. Governments should introduce mandatory occupational heat standards, such as limiting working hours during peak heat or requiring adequate cooling measures in workplaces, such as, Malaysia, Singapore, and Thailand, provide adequate protection for the workers as their occupational exposure to heat and hot environment standard.

The positive association between GDP growth and CO₂ emissions highlights the need for integrating climate considerations into economic policies. Governments should prioritize green growth strategies, such as supporting low-carbon industries and renewable energy transitions, to decouple economic development from environmental degradation.

The persistence of CO₂ emissions across time emphasizes the importance of long-term monitoring and mitigation. Governments should strengthen emissions trading schemes, carbon taxes, and other market-based mechanisms to incentivize reductions in CO₂ emissions across industries. Governments should invest in climate and labor productivity research to better understand regime-specific dynamics and their long-term implications.

7. Conclusion

While prior research has explored the effects of climate change on agricultural output, the nonlinear relationships between labor productivity, GDP, and climate change remain less studied. This study investigates the marginal effects of labor productivity and income on climate change through the following methods: 1) assessing the impact of labor productivity and GDP on CO₂ emissions using panel linear regression; 2) identifying threshold effects by using climate levels as a threshold variable; and 3) estimating the marginal effects of labor productivity and income on pollution through a nonlinear model with interaction terms and a threshold regression model.

Several key findings and economic implications emerge from this study. First, labor productivity and income exhibit a threshold effect on CO₂ emissions. Second, CO₂ emissions per capita decline with increased labor productivity, particularly in non-high temperature countries, where this effect is more pronounced. Finally, regardless of temperature regime, CO₂ emissions per capita continue to increase with rising income per capita. This research contributes to the understanding of how labor productivity and economic growth interact with climate variables to influence emissions, providing insights for policies aimed at balancing economic development and environmental sustainability.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Appendix Table A. Sample countries.

Argentina, Australia, Austria, Belgium, Bulgaria, Canada, Switzerland, Chile, China, Colombia, Costa Rica, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Jamaica, Japan, Cambodia, Republic of Korea, Sri Lanka, Lithuania, Luxembourg, Latvia, Mexico, Malta, Netherlands, Norway, New Zealand, Pakistan, Poland, Portugal, Russian Federation, Singapore, Trinidad and Tobago, Türkiye, United States, Venezuela (Bolivarian Republic of), Viet Nam, South Africa.

Appendix Table B. Descriptive statistics.

Statistics	Labor Productivity	Annual Average Temperature	Environmental Pollution	Economic Development	Average Annual Hours Worked
Mean	28.6	13.03	7.83	984121.32	1897.35
Maximum	83.91	28.24	36.07	17059526.00	2910.73
Minimum	0.89	−8.95	0.14	3233.23	1362.70
Std. Dev.	17.78	8.35	5.47	2086471.19	266.5
Observations	1824.00	1824.00	1824.00	1824.00	1824.00