Impact of Temperature Changes on Economic Growth

A comparative Analysis of Wealthy and Poor Countries

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Abstract

This paper investigates the impact of temperature changes on economic growth, with a focus on differential effects between high-income and low-income countries. Building on the work of Dell et al. (2012), we extend the analysis period to 2014 and update the dataset using revised and corrected GDP figures from the World Bank. Our findings largely reaffirm earlier results: rising temperatures reduce economic growth in poor countries, while no significant effects are observed in wealthy nations. Although the effects appear weaker in terms of magnitude and statistical significance when using the latest GDP data, this attenuation does not apply to the newly added time period. Importantly, we uncover new evidence of lagged temperature effects: warming in the previous year is associated with a temporary positive impact on current-year growth—though the overall cumulative effect remains negative. These results underscore the persistent vulnerability of low-income economies to climate change.

JEL Classification: Q54, O44, O47

Keywords: Climate change, Temperature, Economic growth, Developing countries

1 Introduction

Climate change is among the greatest challenges of the 21st century. While its ecological consequences are becoming increasingly visible, its economic implications are receiving growing attention in both academic and policy debates. A growing body of economic research on climate impacts is focused on the question of how rising temperatures affect economic activity.

A significant branch of this literature lies in microeconomic evidence. Numerous studies examine the relationship between short-term temperature variations and economic outcomes in specific domains. For instance, Deschênes and Greenstone (2007) as well as Schlenker and Roberts (2009) analyze the impact of heat on agricultural yields, while Deschênes and Greenstone (2011) investigate the effects on human health. Other works, such as Burke et al. (2015) and Heilmann et al. (2021), explore links between rising temperatures, crime, and violent conflict. This micro-based approach allows for the identification of concrete causal relationships and the analysis of detailed transmission channels.

Such analyses are often embedded in integrated assessment models (IAMs), which are widely used in the climate impact literature. These models aim to simulate the complex interactions between climate and economy and form the basis for many policy recommendations regarding greenhouse gas emissions. However, this approach faces significant methodological challenges. One key challenge is the multitude of potential impact channels — from labor productivity and infrastructure strain to migration — which makes it difficult to capture their individual effects comprehensively.

An alternative approach focuses on macroeconomic evidence. These studies aim to capture the aggregate economic effects of climate change and identify broader patterns across regions and over longer time horizons. For instance, Dang et al. (2023) use global data to show that rising temperatures can lead to increased poverty and inequality, particularly in low-income countries.

In line with this macroeconomic perspective, our study investigates how temperature changes affect economic growth and whether these effects systematically differ between rich and poor countries. An influential contribution in this field is the study by Dell, Jones, and Olken (2012), who analyze a panel of countries from 1960 to 2003. They find evidence that higher temperatures significantly reduce economic growth in poor nations, while wealthy economies appear largely unaffected.

Our project builds directly on the empirical framework developed by Dell et al. (2012) and pursues two main objectives. First, given the scientific relevance of their findings, we reassess whether the identified effects persist in the most recent years. To this end, we extend the analysis period through 2014. Second, the original study used economic data from 2007, which has since been revised and corrected multiple times by the World Bank.

To ensure our analysis reflects the most accurate information, we re-estimate the effects using the latest available macroeconomic data.

The remainder of this paper is structured as follows: We begin by describing the data, followed by a presentation of our empirical model. Next, we report the results and assess their robustness. Finally, we summarize and discuss the findings.

Our updated analysis largely confirms the original results: Temperature increases negatively affect economic growth in poor countries, while no significant effects are detected in wealthy ones. However, the strength and statistical significance of these effects are somewhat reduced when using the most recent GDP data. Additionally, our model with lagged variables reveals new, significant evidence of delayed temperature effects: specifically, a temperature increase in the previous year appears to have a positive impact on current-year growth — though the overall cumulative effect of rising temperatures remains negative.

2 Data and descriptive statistics

Data source

The temperature data used in this analysis are derived from the Terrestrial Air Temperature: 1900-2014 Gridded Monthly Time Series, Version 4.01 Matsuura and for Atmospheric Research Staff (2023). These data are based on monthly mean air temperatures from various sources, including GHCN-Monthly, GHCN-Daily, Environment Canada, and several other regional archives. The station-based observations were interpolated onto a $0.5^\circ \times 0.5^\circ$ grid (approximately 56 km $\times$ 56 km at the equator) using a combination of spatial interpolation techniques, such as digital elevation model (DEM)-assisted interpolation and climatologically aided interpolation (CAI). To account for spatial interpolation errors, station-by-station cross-validation was employed.

The temperature data were aggregated at the country level using Esri (2024) (ArcGIS Pro). Missing grid cells, which mainly occur in coastal regions, were filled using focal statistics. The temperature data were then resampled to match the resolution of the population data (30 arc seconds, approximately 1 km at the equator) in order to compute population-weighted annual temperatures for each country. These population data, from the Global Rural-Urban Mapping Project Balk et al. (2004), are based on 1990 population figures. The same source also provides the country boundary data.

Economic data - specifically GDP per capita (constant LCU) and GDP per capita (PPP, constant 2021 international dollars) - are obtained from the World Bank (2024a) World Development Indicators and are available up to 2014.

Comparison with Dell et al. (2012)

Since this paper closely follows the methodology and data sources of Dell et al. (2012), we begin by comparing the underlying datasets. As they did not publish details on how they calculated population-weighted annual temperatures, we constructed our own estimates to extend the analysis period. This led to slightly different temperature values.

Overall, the correlation between our temperature data and those by Dell et al. (2012) is high, at 0.96. However, the correlation is noticeably lower in countries with large coastal areas, such as Australia (0.85), Ghana (0.88), Uruguay (0.86), and Bangladesh (0.83). This suggests that differences likely come from how missing coastal grid cells were treated. While we experimented with several interpolation techniques to align the data as closely as possible, the best match was achieved using focal statistics. Nonetheless, these updated temperature data have only a minor impact on our regression results.

In contrast, the differences between the GDP per capita data used in the original paper and the most recent World Bank data are more substantial. These discrepancies are due to various corrections and revisions made by the World Bank over time. A detailed documentation of these changes is provided in Appendix A. We discuss the implications of these revisions for the regression analysis in the results section.

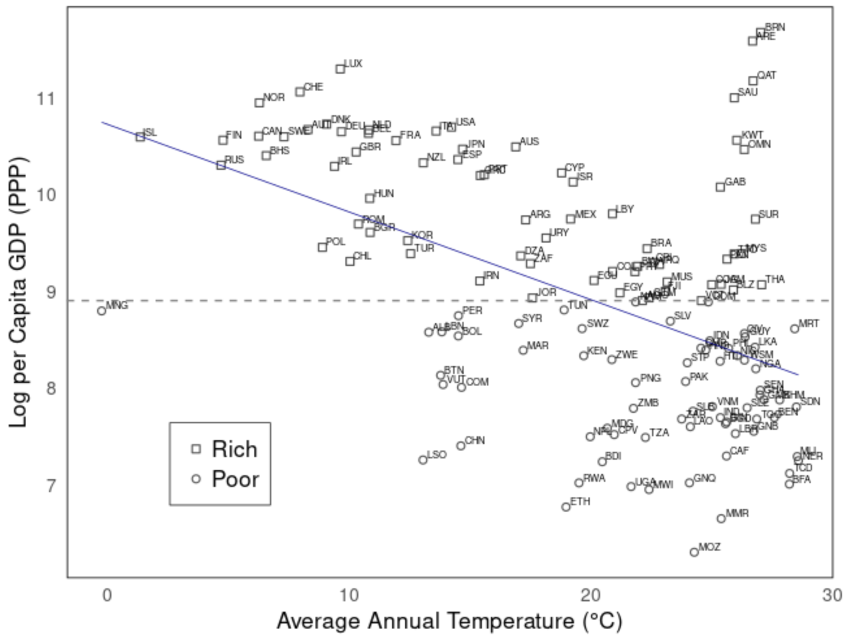
Descriptive statistics

The original dataset contains temperature and GDP per capita data for 157 countries. After applying various filters, 137 countries remain for the main regression analysis. The earliest available data on economic growth begins in 1961 for most countries; accordingly, the regression focuses on the period from 1961 to 2014. Data on GDP per capita in PPP terms — used to classify countries as rich or poor - are available for most countries beginning in 1990. This year therefore serves as the basis for categorizing countries into income groups.

Figure 1 displays the distribution of countries by income level. Even at this cross-sectional level, a clear pattern can be observed: warmer countries tend to be poorer on average. A one-degree Celsius increase in average annual temperature is associated with an approximate 9.2 percentage point decrease in GDP per capita. Notable exceptions to this negative relationship are oil-rich Gulf states such as Saudi Arabia, Qatar, and the United Arab Emirates, whose high levels of wealth are largely driven by resource exports.

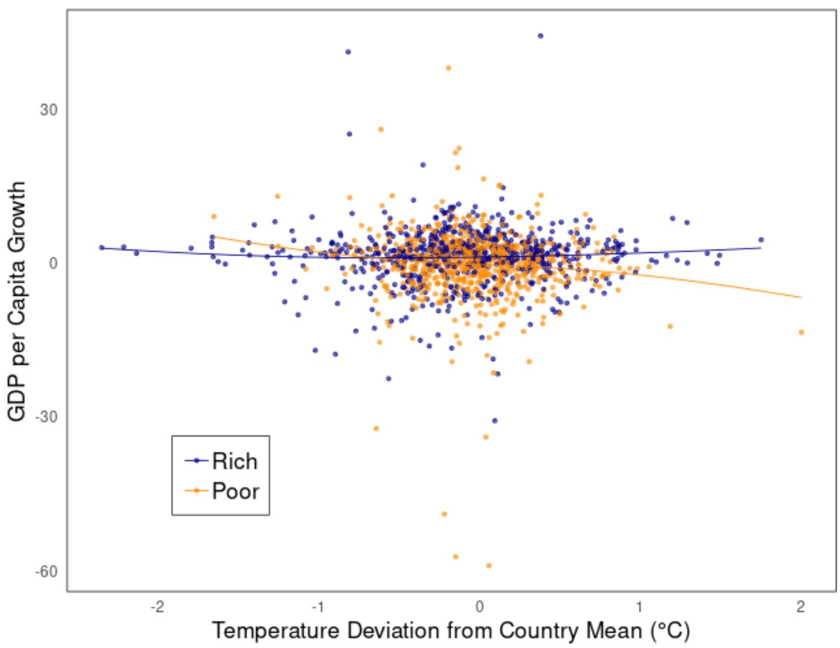
Figure 2 plots the deviation from the country-specific mean temperature against GDP growth for the years 1983 to 1992, the midpoint of the dataset. This visual provides an initial impression of the key research question: whether the effect of rising temperatures differs systematically between rich and poor countries.

Figure 1: Temperature and Income Levels in 1990



Notes: The figure shows the relationship between average annual temperature and log GDP per capita (PPP) in 1990. Countries are classified as rich or poor based on 1990 GDP data. A negative correlation is visible, with warmer countries tending to be poorer.

Figure 2: GDP Growth and Temperature Anomalies



Notes: The figure shows deviations from country-specific mean temperature against GDP growth for 1983–1992, the midpoint of the dataset. The visual suggests a negative relation between high temperatures and growth in poor countries, while no clear pattern appears for rich countries. The period also shows higher temperature variability in rich countries and more volatile GDP growth in poor countries.

The pattern suggests that in low-income countries, positive deviations from the temperature mean are often associated with lower growth rates. For high-income countries, no such relationship is evident; both positive and negative temperature anomalies appear alongside positive growth figures.
When comparing the variance of these variables between rich and poor countries, the following patterns emerge: rich countries show greater variation in temperature deviations from their country-specific mean, with standard deviations of 7.20 during the selected period and 7.24 over the full dataset. In contrast, low-income countries show lower variability, with standard deviations of 5.28 and 5.33, respectively.
Regarding GDP growth, the opposite pattern holds: rich countries experience less volatile growth, with standard deviations of 5.60 (1983–1992) and 5.96 (overall), whereas poor countries show higher volatility, with standard deviations of 6.89 and 6.46.

3 Empirical Specifications

To empirically analyze the relationship between temperature and economic growth, we begin with a linear specification, assuming a constant marginal effect of temperature on growth. Later in the analysis, we explore potential nonlinear effects.
We estimate the economic growth rate $\text{growth}_{i,t}$ of country i in year t as a function of the annual average temperature $\text{temp}_{i,t}$. Our baseline regression model is:

$$\text{M1: } \text{growth}_{i,t} = \beta_1 \text{temp}_{i,t} + \mu_i + \lambda_{r,t} + \gamma_t^{\text{poor}} + \varepsilon_{i,t}$$

where μ_i denotes country fixed effects, capturing time-invariant, country-specific unobserved characteristics, $\lambda_{r,t}$ represents region-year fixed effects, accounting for regional shocks or trends within a specific year, γ_t^{poor} includes year fixed effects for poor countries, controlling for events that specifically affect low-income countries over time, and $\varepsilon_{i,t}$ is the error term.

In M1, we estimate the effect of temperature on economic growth without further modifications. In model M2, we extend the specification by including an interaction term between temperature and a poverty indicator dummy (*poor_ dummy*):

$$\text{M2: } \text{growth}_{i,t} = \beta_1 \text{temp}_{i,t} + \beta_2(\text{poor\_dummy}_i \times \text{temp}_{i,t}) + \mu_i + \lambda_{r,t} + \gamma_t^{\text{poor}} + \varepsilon_{i,t}$$

This interaction term allows us to capture temperature effects across income groups. A significant coefficient β_2 would indicate that the impact of temperature varies systematically between poor and rich countries.

Since the effects of temperature may not only occur in the same year but also with a delay, we expand the model in M3 by including lagged temperature values ($\text{temp}_{i,t-\ell}$ for $\ell = 1, \ldots, 5$). This allows us to capture both immediate and delayed impacts of temperature changes on economic growth:

$$\text{M3: growth}_{i,t} = \sum_{\ell=0}^{5} \left[\beta_{1\ell}\, \text{temp}_{i,t-\ell} + \beta_{2\ell}(\text{poor\_dummy}_i \times \text{temp}_{i,t-\ell})\right] + \mu_i + \lambda_{r,t} + \gamma_t^{\text{poor}} + \varepsilon_{i,t}$$

To account for potential autocorrelation and heteroskedasticity, we use cluster-robust standard errors. The standard errors are clustered at both the country level and the region-year level (Region×Year) - following the multi-way clustering approach by Cameron et al. (2006).

Accordingly, we begin by testing the null hypothesis that temperature has no effect on economic growth:

$$H_0^{(1)} : \beta_1 = 0$$

Next, we test the hypothesis that temperature does not affect growth, neither annually nor with a delay, in rich and poor countries, respectively:

$$H_0^{(2a)} : \beta_{1\ell} = 0 \quad \text{for all } \ell = 0, \ldots, 5$$

$$H_0^{(2b)} : \beta_{2\ell} + \beta_{2\ell} = 0 \quad \text{for all } \ell = 0, \ldots, 5$$

Finally, we examine whether temperature has no cumulated effect on growth in rich and poor countries, respectively:

$$H_0^{(3a)} : \sum_{\ell=0}^{5} \beta_{1\ell} = 0$$

$$H_0^{(3b)} : \sum_{\ell=0}^{5} \beta_{1\ell} + \beta_{2\ell} = 0$$

4 Results

This chapter presents the empirical findings of our regression analysis. As the model by Dell et al. (2012) serves as the foundation, we began by replicating their original results. Given subsequent data revisions and corrections by the World Bank's WDI (see Appendix A for details), we then reassessed the findings using the updated dataset, focusing in particular on M2. Notably, the coefficient decreased by 0.351. A 1°C increase in temperature now leads to a 1.043% decline in economic growth. While the level of statistical significance has slightly diminished, the result remains highly significant.

Table 1: Replication Results

Growth	(1)	(2)
Temperature x Poor	-1.394***	-1.043**
	(0.387)	(0.465)
Temperature x Rich	0.261	0.25
	(0.295)	(0.274)
Observations	4924	5236
R-squared	0.22	0.2

Notes: (1) replicates the results of Dell et al. (2012) using the same dataset as they did.
(2) uses the same temperature data but the most recent GDP data.
Both consider the period from 1960 to 2003.
Significance levels: *p<0.1, **p<0.05, ***p<0.01.

Table 2 presents the main results derived from our regression analysis covering the period 1960–2014, using newly computed temperature data alongside the updated GDP figures. A simple regression (M1), with temperature as the sole explanatory variable, yields no statistically significant result (coefficient: –0.258, SE: 0.263). This changes in M2 and M3. Model 2 distinguishes between the effects of temperature on low-income and high-income countries. While high-income countries experience a positive growth response to rising temperatures, this result is not statistically significant. In contrast, for low-income countries, a 1°C increase in temperature leads to a 1.169% decline in economic growth. This finding suggests that the adverse temperature effect observed in earlier periods persists in the more recent timeframe (2004–2014) and has even slightly intensified.

Model 3 extends the analysis by including temperature lags as control variables. Here, Current-year temperature increases continue to have a significantly negative impact on economic growth in poor countries — an effect that is in fact somewhat stronger. Interestingly, the one-year lagged temperature variable (L1) shows a positive and statistically significant relationship with growth. This pattern may indicate short-term adaptation or recovery effects: following a temperature-induced shock in the previous year, economic activity may rebound, potentially supported by governmental or international relief efforts. However, this interpretation remains speculative and warrants further investigation.
Nonetheless, the cumulative effect of temperature on low-income countries remains negative and statistically significant, suggesting that higher temperatures lead to medium-term growth losses when effects are aggregated over several years.

Table 2: Main Results

Dependent Variable: Growth	M2 (1)	M3 - 1 lag (2)	M3 - 3 lags (3)	M3 - 5 lags (4)
Temperature x Poor	-1.169**	-1.544***	-1.406***	-1.394***
	(0.467)	(0.519)	(0.529)	(0.521)
L1: Temperature x Poor		0.948**	1.111**	1.114**
		(0.43)	(0.446)	(0.467)
L2: Temperature x Poor			-0.089	-0.067
			(0.422)	(0.45)
L3: Temperature x Poor			-0.562	-0.568*
			(0.363)	(0.327)
Temperature x Rich	0.298	0.193	0.177	0.18
	(0.282)	(0.265)	(0.257)	(0.268)
L1: Temperature x Rich		0.358	0.352	0.369
		(0.239)	(0.23)	(0.257)
L2: Temperature x Rich			0.198	0.227
			(0.22)	(0.221)
L3: Temperature x Rich			0.273	0.389
			(0.32)	(0.319)
Observations	6709	6709	6510	6306
R-squared	0.19	0.19	0.2	0.2

Notes: (1) shows results for Model 2.
(2)–(4) show results for Model 3 with 1, 3, and 5 lags, respectively. Coefficients for lags 4 and 5 are not shown for better visual clarity.
Significance levels: *p<0.1, **p<0.05, ***p<0.01.

Our robustness checks, conducted for Model 2, further support our main results. Specifically, we tested a quadratic model but found no statistically significant effects, reinforcing the assumption of a linear relationship. Additionally, we re-estimated Model 2 using various different data filtering and processing techniques, detailed in Appendix B, all of which yielded consistent results.

5 Summary and Discussion

The results of this study confirm that rising temperatures negatively affect economic growth - but only in poor countries. While wealthy economies show no significant temperature related effects, poor countries are clearly more vulnerable. These findings are highly relevant in the context of the global climate crisis. They provide empirical evidence that rising temperatures are already causing measurable economic damage, especially in low-income countries that have historically contributed little to global warming. This analysis therefore offers an important contribution to quantifying the economic costs of

climate change and highlights the unequal distribution of these costs.
While climate policy debates often focus on long-term, hard-to-measure risks — such as rising sea levels or extreme weather events, this study adds a crucial dimension: temperature increases also have direct short- and medium-term economic consequences. And these effects are not a distant future concern, but they are already observable today. Economic growth, in this context, is not merely an abstract indicator; it is closely linked to employment, public finances, poverty reduction, and social stability.

Despite the insightful findings, this analysis has several limitations that should be taken into account when interpreting the results. First, the study relies on aggregated national level data, which masks important within-country differences—such as disparities between rural and urban areas or across economic sectors. Future research should increasingly make use of subnational data to better capture regional vulnerabilities and develop more targeted adaptation strategies.
Moreover, future studies could broaden the scope by examining alternative indicators beyond GDP growth, such as employment rates, health outcomes, or inequality measures. Finally, models aimed at assessing the long-term effects of temperature on growth should incorporate our findings into their frameworks.

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Appendix A: Data Description

When examining the correlation between the most recent growth data and those from Dell et al. (2012), we could observe substantial differences for some countries:

Country: United Arab Emirates - Code: ARE - Correlation: 0.899025797451015
Country: Australia - Code: AUS - Correlation: 0.210473418497964
Country: Botswana - Code: BWA - Correlation: 0.879055902857263
Country: Bolivia - Code: BOL - Correlation: 0.528890021577065
Country: Solomon Islands - Code: SLB - Correlation: 0.620429248879391
Country: Bhutan - Code: BTN - Correlation: 0.864611762586601
Country: Bulgaria - Code: BGR - Correlation: 0.704920428018334
Country: Sri Lanka - Code: LKA - Correlation: 0.568501962629127
Country: Egypt - Code: EGY - Correlation: 0.788193581161434
Country: Honduras - Code: HND - Correlation: 0.827088950416631
Country: Hungary - Code: HUN - Correlation: 0.456351517290168
Country: Japan - Code: JPN - Correlation: 0.895370858253069
Country: Jordan - Code: JOR - Correlation: 0.784943948006024
Country: Libya - Code: LBY - Correlation: 0.799300768569777
Country: Mongolia - Code: MNG - Correlation: 0.782086134711119
Country: Oman - Code: OMN - Correlation: -0.0288621446033243
Country: Panama - Code: PAN - Correlation: 0.881735821215248
Country: Saudi Arabia - Code: SAU - Correlation: 0.807442130207894
Country: Senegal - Code: SEN - Correlation: 0.709943617601391
Country: Somalia - Code: SOM - Correlation: 0.700047589423032
Country: Tunisia - Code: TUN - Correlation: 0.549679015245557

To gain a better understanding of the differences in the economic data, we reviewed data revisions in the World Bank's World Development Indicators (WDI) and present some key changes here. Unfortunately, specific changes to individual countries or years are rarely addressed; instead, revisions are typically described in more general terms. All of the following information is taken from the same source.[1]

December 2010: "The December 2010 update of the World Development Indicators database contained an error for Zimbabwe's data for the following indicators: GDP per capita, PPP

[1] World Bank. *World Development Indicators Data Updates and Errata.* December 2024. Retrieved April 12, 2025, from https://datahelpdesk.worldbank.org/knowledgebase/articles/906522-data-updates-and-errata

(constant 2005 international \$); GDP per capita, PPP (current international \$); GDP, PPP (constant 2005 international \$); GDP, PPP (current international \$); GNI per capita, PPP (current international \$); GNI, PPP (current international \$); Household final consumption expenditure, PPP (constant 2005 international \$);"

July 2011: "2010 data (plus revised historical data, where necessary) for all countries and groups for population-, GDP- and GNI-related indicators are released."

September 2011: "Population related indicators have been revised based on the United Nations World Population Prospects 2010. These population revisions also affect per capita series, such as GNI per capita and GDP per capita."

April 2012: "National accounts growth rates and shares data published in December 2011 for some Sub-Saharan Africa countries (most notably Lesotho, Mauritania and Zimbabwe) were not properly aligned with base data. These inconsistencies have been corrected in this release. Constant price GNI and GNI per capita data have also been corrected to reflect the proper application of deflated factor income values."

July 2013: "2012 data (plus revised historical data, where necessary) for all countries and groups for population-, GDP- and GNI-related indicators have been released. National accounts constant U.S. dollar data are now based to the year 2005."

April 2014: "The April 2014 WDI database features a full update of development data to coincide with publication of the World Development Indicators 2014 book. National accounts data for Nigeria are based on official government statistics as of 1 February 2014.

New estimates of nominal and constant GDP released by the Nigeria Bureau of Statistics on 6 April 2014 will be included in future editions of the WDI database."

March 2015: "National accounts data have been corrected and revised for Bahrain, Israel, Kuwait, and Oman (local currency values, all years; with minor adjustments to purchasing power parity values); Kenya (constant values and growth rates, 1960-61); Mauritania (constant values and growth rates, 1960-93; and services value added)"

December 2016: "The release on December 16 features new external debt data from the International Debt Statistics database, and revised data for national accounts, PPP series, balance of payments, FDI inflows, remittances, and monetary indicators."

Appendix B: Robustness

Table B1: Robustness Tests

	No filter for countries with < 25 growth data (1)	Poor defintion in year 2010 (2)	Balanced sample 1990 - 2014 (3)
Temperature x Poor	-1.14**	-0.892**	-1.872**
	(0.455)	(0.408)	0.897
Temperature x Rich	0.325	0.14	-0.334
	(0.275)	(0.341)	0.333
Observations	6879	6732	3334
R-squared	0.2	0.19	0.23

Notes: Significance levels: *p<0.1, **p<0.05, ***p<0.01.