Climate Growth at Risk in the Global South

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Abstract

We examine the effect of climate uncertainty shocks on the growth rate distribution of Latin American and Caribbean countries from 1970 to 2022. We provide novel indicators for second-moment shocks (volatility), third-moment shocks (skewness), and fourth-moment shocks (kurtosis) based on daily temperatures at the country level. Our panel quantile models with fixed effects reveal a significant negative impact of time-varying skewness on the lower quantiles of the growth distribution during negative growth periods. Conversely, volatility and kurtosis do not significantly affect growth rates. These findings emphasize the importance of incorporating time-varying climate skewness in economic climate models and highlight the impacts of climate uncertainty shocks across different growth quantiles beyond the traditional effects of the average change in temperature.

Keywords: Climate Uncertainty, Economic Growth, Quantile Regression, Latin America, Caribbean, Temperature Shocks, Growth at Risk, Panel Data.
JEL Classifications: Q54, O40, C33, E32.

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1. Introduction

Recent macroeconomic studies have revisited the significance of the skewness of economic shocks in explaining key aspects of macroeconomic dynamics in both the short and long term (see McKay and Reis, 2008; Morely and Piger, 2012; Berger et al., 2020; Salgado et al., 2019; Busch et al., 2022; Iseringhausen et al., 2023). Long-tailed distributions of shocks, such as those related to income, technology, productivity, employment, and financial conditions, better explain the asymmetric nature of economic contractions and expansions (McKay and Reis, 2008; Morely and Piger, 2012; Salgado et al., 2019). These distributions also more accurately capture the asymmetric responses to expected and realized measures of macroeconomic uncertainty (Berger et al., 2020). Additionally, revisions in expected skewness lead to business cycle fluctuations that align closely with observed patterns, even when controlling for macroeconomic volatility and a wide range of alternative macroeconomic shocks (Iseringhausen et al., 2023; Iseringhausen 2024). Collectively, these findings highlight the significant role of higher-order moments, especially the skewness of shocks, in explaining business cycle fluctuations.

The asymmetric nature of climate shocks is well acknowledged in climate economics. Natural disasters resulting from climate change are recognized as rare events with catastrophic economic consequences, inherently implying a long-tailed distribution of climate-related shocks. However, empirical studies examining the relationship between climate factors (e.g., temperature or precipitation) and economic activity have almost invariably focused on average effects. These studies typically estimate the impact of average changes in temperature (or average temperature itself[5]) on the growth rates of countries, yielding mixed results. Average increases in temperature have been shown to either increase or decrease economic activity, as discussed in Tol (2024), who provides a recent review of this literature.

One notable recent exception to this trend is Kiley (2023), who uses the “Growth at Risk” framework developed by Giglio et al. (2016) and Adrian et al. (2018, 2019) to measure the impact of average temperature on real growth rates (see also Chuliá et al., 2023). However, this author focused on the average temperature (or some functional form of it, á la Burke et al. (2015, 2019)) across different segments of the growth rate distribution. This approach, a topic recently revisited by Kotz et al. (2024), is somewhat controversial, as it involves regressing a flow variable (growth rate) on a stock variable (temperature). Moreover, Kiley (2023) emphasized the average impact of temperature on the quantiles of the growth conditional distribution rather than other moments of temperature shocks. This emphasis contrasts with theoretical perspectives that highlight the

[5] For a more technical discussion on whether using levels or growth rates is more appropriate, see Kahn et al. (2021) and Tol (2024). Following the advice in these studies, we used growth rates for both temperature and economic output.

importance of the asymmetric distribution of shocks affecting the economy. Our contribution aims to fill this gap in the literature.

By leveraging the different frequencies in the measurements of temperature and real gross domestic product (GDP), we estimate the sensitivity of the annual growth rates of countries at different quantiles of the growth rate distribution to various measures of climate uncertainty shocks. Our indicators of climate uncertainty capture different aspects of this uncertainty, all of which are based on daily temperature measurements at the country level. They represent different moments of the daily variations in temperature distribution: second moment shocks (volatility), third moment shocks (skewness), and fourth moment shocks (kurtosis).

Moreover, by using log-differences of both temperature and GDP, along with realized estimates of different moments of temperature shocks, we avoid the controversy associated with mixing variables expressed in levels with variables expressed in differences, particularly in a panel of countries such as ours. Importantly, our analysis focuses exclusively on Latin American and Caribbean countries. This approach helps mitigate the effects of mixing highly heterogeneous regions in terms of institutional frameworks, productive infrastructure, and exposure to climatic conditions, which is a common issue in previous literature. We employ panel quantile models with fixed effects (Koenker, 2004) to account for country differences that remain within the sample.

Our set of countries remains relatively large, comprising 34 nations (see Tables 1 and 2), which enhances the efficiency of our estimates by significantly increasing the sample size with respect to using individual countries as the unit of analysis. We utilize the Growth at Risk framework (Adrian et al., 2018, 2019), allowing us to identify a significant negative effect of realized (time-varying) skewness on the lower quantiles of the real growth distribution. This effect diminishes across the growth distribution, indicating that asymmetric shocks in daily temperature are particularly relevant during periods of negative growth.

This finding, among other policy implications, underscores the importance of considering time-varying skewness when modeling the effects of temperature on economic activity at the theoretical level. We also present suggestive, though inconclusive, evidence that our results are driven not only by cross-sectional variation across countries but also by the time series dimension of our data. Our dataset spans from 1970 to 2022, covering 53 years, with the time series dimension being larger than the cross-sectional one. To support this view, we provide country-specific quantile regressions in addition to panel quantile regressions. While these country-specific regressions are often nonsignificant due to limited power from the relatively short sample, they consistently show a tendency for greater and more negative effects at the lower end of the GDP growth distribution compared to other segments of the growth distribution.

2. Literature Review

Climate change is the most significant and complex externality, surpassing all other environmental and economic challenges in terms of scale and uncertainty. Heat-trapping gas emissions come from a broad range of sources, as almost every production unit and household produces emissions. The effects are just as widespread, impacting agriculture, energy consumption, health, and numerous natural systems, thereby affecting all areas of life.

The causes and consequences of climate change are diverse and multifaceted. Paradoxically, the nations with the lowest emissions, typically those with lower incomes, are the most susceptible to its adverse effects. Furthermore, this is a long-term issue, as certain greenhouse gases can remain in the atmosphere permanently.

Research on the economic impact of climate change burgeoned notably from the late 20th century onward. This epoch witnessed an escalating focus in scientific research delineating the potential impacts of climate change across diverse domains of human society, prominently encompassing economic frameworks. As scientific consensus consolidated around the tangible and consequential aspects of climate change, there arose a commensurate acknowledgment among economists and policymakers of the imperative to comprehensively assess and quantify its economic dimensions.

Research on the economic impact of climate change can be divided into two main categories. The first category, which includes most early studies, examines the impact of climate—defined as the thirty-year average of weather—on the economy and overall welfare. These studies primarily use cross-sectional variation to identify the effects of climate, but they face significant limitations due to the numerous factors that vary across different regions and the persistence of confounders over time, even when using panel data.

The second category consists of a smaller number of studies that investigate the impact of weather, a more variable and unpredictable factor, on economic performance. This approach is motivated by the relatively slow and minimal changes in climate over the periods for which data are available. Weather, being a random variable, allows for more precise identification of its impact. However, it is crucial to note, as Dell et al. (2014) discuss, that the effects of weather shocks are not directly equivalent to the effects of long-term climate change.

Within this second category, most studies focus on temperature shocks and their influence on economic growth. Some of these studies model economic output growth rates as a function of temperature levels, while others examine the relationship between economic growth rates and changes in temperature. The primary focus across these studies is on mean temperature.

2.1. Studies on the Impact of Climate on Economic Growth and Welfare

Early studies examining the impacts of climate change on welfare focused on the United States (Manne and Richels, 1991; Nordhaus, 1991; Cline, 1992; Jorgenson and Wilcoxen, 1993). Fankhauser (1994) was the first to evaluate the worldwide impacts of climate change on welfare. This paper assesses the global marginal social costs of greenhouse gas emissions using a stochastic greenhouse damage model with random parameters. This study estimates that the social costs of carbon emissions are approximately $20 per metric ton of carbon during the 1991-2000 period, increasing to approximately $28 per metric ton of carbon by 2021-2030.

Other early contributions to understanding the global welfare effects of climate change include those of Tol (1995), Nordhaus and Yang (1996), Mendelsohn, Schlesinger, and Williams (2000), Tol (2002), and Hope (2006). Tol (2009) conducted a systematic review of these initial studies, revealing significant uncertainty in determining the social costs associated with climate change. Although the average estimate across these studies suggests a marginal cost of carbon of approximately $105 per metric ton, the most frequently cited estimate is substantially lower at $13 per metric ton. This discrepancy underscores the disproportionate influence of a few exceptionally high estimates. In fact, the social cost estimate reaches $360 per metric ton at the 95th percentile and increases to $1,500 per metric ton at the 99th percentile. This significant variation can be attributed in part to the differing intertemporal discount rates employed across these studies, as well as to the diversity in countries and sample periods included in their analyses. The results also depend upon the sectors chosen for assessing the welfare impacts of climate change.

Subsequent studies continued to yield notably divergent estimates. The profound uncertainty regarding climate impacts prompted the emergence of meta-analytical studies. Nordhaus and Moffat (2017) conducted a meta-analysis using 31 studies and estimated a potential impact of -2.04% (± 2.21%) of income under 3°C warming and -8.06% (± 2.43%) of income under 6°C warming. The study also explored the possibility of thresholds or pronounced convexities in the damage function but found no evidence of sharp discontinuities or high convexity in the damage estimates.

Recent studies, despite continuing to offer a range of estimates, have revealed even more substantial welfare effects of climate change. Kompas et al. (2018) employ a high-dimensional intertemporal CGE trade model to evaluate the diverse impacts of global warming on GDP growth and levels across 139 countries, both by decade and in the long term. The study revealed that the potential economic benefits of adhering to the Paris Agreement, even under a conservative set of damage scenarios, are substantial. The global economic gains of meeting the 2°C target are projected to reach approximately US$17,489 billion per year by 2100. This study highlights that the relative damages from failing to comply are particularly severe for underdeveloped countries, especially those of Sub-Saharan Africa, India, and Southeast Asia, across all temperature ranges.

Dellink et al. (2019) employ a dynamic computable general equilibrium model encompassing multiple regions and sectors to project that climate change-related damages will increase at twice the rate of global economic growth. According to their findings, annual global GDP losses are expected to range from 1.0% to 3.3% by 2060. However, significant variation exists within and between regions and countries. The economic impacts are expected to be particularly severe in Africa and Asia, where economies are highly vulnerable to a variety of climate effects. Conversely, some higher-latitude countries may experience economic benefits in areas such as tourism, energy, and health. The global analysis also indicates that countries less adversely affected by climate change could gain from increased trade opportunities.

Takakura et al. (2019) contend that the significant disparities in climate change impact assessments stem from uncertainties in three key areas: socioeconomic development pathways, climate change mitigation strategies, and climate responses. Their study employs a comprehensive framework combining global multi-sectoral impact models with an integrated assessment model, enabling the estimation of global economic impacts while accounting for these uncertainties. The results vary based on the assumptions used in the models. In the worst-case scenario, the net economic impact could reach 6.6% (ranging from 3.9% to 8.6%) of the global GDP by the end of the century. However, scenarios involving rigorous mitigation efforts could confine the impact to approximately 1% or even lower.

Kalkuhl and Wenz (2020) use annual panel models, long-difference regressions, and cross-sectional regressions to study the effects of climate change on productivity levels and growth for 1,500 regions across 77 countries. While they do not find evidence of permanent growth rate impacts, the results indicate that temperature significantly affects productivity levels. A projected increase of approximately 3.5°C in global mean surface temperature by the end of the century could reduce global output by 7-14% by 2100, with greater damages expected in tropical and poor regions. Their findings suggest that the social cost of carbon due to temperature-induced productivity losses ranges from $73 to $142 per ton of carbon in 2020, increasing to $92 to $181 per ton of carbon by 2030. These estimates exclude non-market damages as well as damages from extreme weather events or sea-level rise.

Conte et al. (2021) develop a dynamic spatial growth model with two sectors, illustrating the interplay among economic activity, carbon emissions, and temperature. Their findings indicate projected losses of 6% in real GDP and 15% in utility by the year 2200. Increased trade costs escalate the expense of adapting through shifts in sectoral specialization, resulting in reduced geographic concentration in agriculture and greater climate-induced migration.

Newell et al. (2021) explored 800 different specifications of the temperature-GDP relationship and showed that these models produce a diverse spectrum of projected climate change impacts by 2100, highlighting considerable uncertainty. Models that incorporate temperature effects on GDP growth over time exhibit the greatest variability, with the 95% confidence interval across top-performing models spanning from an 84% GDP loss to a 359% gain. Conversely, models focused on GDP levels show a narrower range of impacts, typically centered at approximately 1–3% losses, which aligns closely with established damage functions in major integrated assessment models. Furthermore, models accounting for lagged temperature effects primarily indicate impacts on GDP levels rather than GDP growth.

Cruz and Rossi-Hansberg (2024) presented a dynamic economic assessment model with high spatial resolution to evaluate the global impacts of climate change. Their analysis revealed highly uneven welfare losses, with certain regions in Africa and Latin America experiencing losses of up to 20%, while some northern latitudes seeing gains. This leads to an overall increase in spatial inequality. Although there is significant uncertainty regarding average welfare effects, the relative losses across different regions are more consistently estimated.

Petrović (2023) employs a comprehensive model averaging technique that incorporates numerous significant factors influencing economic growth. According to the study's findings, a 1% increase in CO_2 emissions is associated with an average increase in economic growth of 0.00132 percentage points, while the same increase in CH_4 emissions corresponds to a 0.00537 percentage point increase. Additionally, a one-degree Celsius rise in surface temperature is linked to an average economic growth rate increase of 0.865 percentage points. Furthermore, each additional climate-related disaster is associated with an average growth rate increase of 0.115 percentage points. This study highlights the varied impacts of climate change across different countries.

Kotz et al. (2024) used data from more than 1,600 regions across four decades to project the economic impacts of temperature and precipitation changes, including extremes. They found that global economic output could decrease by 19% over the next 26 years due to climate impacts regardless of future emissions reductions. These damages exceed the costs of limiting global warming to 2°C by sixfold in the short term, with outcomes varying significantly based on future emission trajectories. Most losses result from changes in average temperatures, with additional climate factors increasing by approximately 50% and showing strong regional disparities. Losses are expected in all regions except those at very high latitudes, where reduced temperature variability may be beneficial. Lower-latitude regions with lower historical emissions and current income levels face the greatest projected impacts.

In a recent meta-analysis, Tol (2024) incorporated 69 estimates from all 39 studies conducted to date on the overall economic impact of climate change. He argued that the high variability in estimates of the global economic impact of climate change can be mainly attributed to the diverse empirical methods utilized in these studies. Research on the economic impacts of climate change employs various methodologies, including enumeration, elicitation, econometric analysis, and computable general equilibrium models. Studies follow two different approaches: one where temperature directly influences economic growth and another where changes in temperature affect growth. The first approach is inconsistent with the climate science literature, while the second approach aligns with it, contingent on specific scenarios and models.

This recent meta-analysis yielded three key findings. First, this result consistently indicates a negative economic impact from global warming. Second, compared to earlier meta-analyses, the confidence intervals of these estimates are notably broader. Third, elicitation methods tend to yield more pessimistic results, while econometric studies are more optimistic. Additionally, two findings from previous meta-analyses remain unchanged: there is a skew toward negative surprises in the uncertainty surrounding the impact, and poorer countries have greater vulnerability than wealthier countries.

2.2. Effect of Temperature Shocks on Economic Growth

The pioneering study on the effect of temperature shocks on economic growth was conducted by Dell et al. (2012). The study investigates the impact of temperature fluctuations on economic growth by analyzing historical temperature variations within countries to ascertain their effects on aggregate economic outcomes. Three major findings are identified. Firstly, elevated temperatures significantly hinder economic growth in poorer countries; secondly, higher temperatures may decrease growth rates in addition to reducing output levels; and thirdly, increased temperatures have extensive negative effects, including diminishing agricultural and industrial production and even compromising political stability.

Burke et al. (2015) enhance the existing literature by exploring the non-linear impacts of temperature on macroeconomic productivity. Their research reveals that economic productivity across all countries follows a non-linear pattern, reaching its optimum at an annual average temperature of 13°C and markedly decreasing at higher temperatures. This global relationship has remained consistent since 1960 and applies to both agricultural and non-agricultural activities, both for developed and underdeveloped economies.

In contrast, Henseler and Schumacher (2019) reveal that elevated temperatures have a much stronger adverse effect on poorer countries compared to wealthier ones. Their research explores the effects of weather on GDP and its primary production components, including total factor productivity, capital stock, and employment. Analyzing a panel dataset comprising annual observations from 103 countries between 1961 and 2010, their findings underscore the greater susceptibility of poorer nations to the detrimental impacts of rising temperatures.

Acevedo et al. (2020) also study a broad range of countries and time periods, finding that low-income nations in hotter climates bear the highest costs from weather shocks. In a median low-income country, a 1°C rise in average annual temperature leads to roughly a 2% decline in aggregate output and a 10% drop in investment over seven years. Their research shows that economic development offers protection against temperature shocks, with hot regions in high-income countries suffering less economic damage from rising temperatures than similar regions in low-income countries. Other studies on the effect of temperature on economic growth are Damania et al. (2020) and Kikstra et al. (2021).

A small number of papers have focused on the effect of temperature changes, rather than temperature levels, on economic growth. Letta and Tol (2018) and Kotz et al. (2022) find a linear effect of temperature changes on economic growth. However, while the former identifies this effect for poor countries only, the latter finds that this effect is present for all countries. Kahn et al. (2021) conclude that while all countries experience effects from temperature changes, hot shocks exert a greater impact compared to cold shocks.

Tol (2024) emphasizes that the absolute levels of temperature exert a more pronounced influence on economic growth than the fluctuations in temperature itself.

Empirical research on the relationship between weather shocks and economic activity has traditionally focused on average effects. These studies typically assess how changes in average temperature impact growth rates or output levels, yielding varied findings. A notable departure from this approach is found in Kiley (2023), who adopts the “Growth at Risk” framework developed by Giglio et al. (2016) and Adrian et al. (2018, 2019). This framework measures the influence of average temperature levels on real growth rates across different segments of the growth rate distribution. This methodology has sparked some controversy because it involves regressing growth rates, which are a flow variable, against temperature levels, which are a stock variable, and this topic was recently revisited by Kotz et al. (2024). Furthermore, Kiley (2023) emphasized the impact of temperature averages on growth rate quantiles rather than other aspects of temperature shocks, which contrasts with theoretical viewpoints stressing the asymmetric nature of economic shocks. Our study seeks to address this gap in the literature by exploring these dynamics more comprehensively.

3. Methodology

3.1. Realized Moments

The temperature shock series used to test the effect of climate shocks on economic activity are, by general rule, average values of the series in levels, the average of the increments, or the volatilities of the increments. We expand this traditional analysis by allowing higher moments as our unit of analysis. We estimate yearly realized variances of log temperature Y (see Andersen et al., 2011) as follows:

$$RV = \sum_{j=1}^{n} \left(Y_{t_j} - Y_{t_{j-1}}\right)^2, \tag{1}$$

where $0 = t_0 < t_1 < \cdots < t_n = 1$ are the times at which temperatures are available, in our case on a daily frequency. This approach has proven to be a useful methodology for estimating and forecasting conditional variances for risk management. We also estimate realized skewness and realized kurtosis in our framework as follows:

$$RS = \sum_{j=1}^{n} \left(r_{t_j}\right)^3, \tag{2}$$

$$RK = \sum_{j=1}^{n} \left(r_{t_j}\right)^4, \tag{3}$$

where $r_{t_j} = Y_{t_j} - Y_{t_{j-1}}$.

We estimate all the measures at the country level, omitting country subscripts for simplicity. Therefore, we have a panel with three measures, denoted as RV_{it}, RS_{it} and RK_{it}, for $i = (1, \dots, N)$ countries and $t = (1, \dots, T)$ years. In our case, there were 34 countries spanning across 53 years (1970-2022).

3.2. Climate Growth at Risk with Panel Quantile Fixed Effects

We adopt the framework proposed by Koenker (2004) and Abrevaya et al. (2008), among others, who have extended quantile regression models to longitudinal contexts. In their approach, the dynamics of the τ-quantile of the dependent variable are characterized by the following equation:

$$Q_\tau(growth_{it} | a_i, \beta, growth_{it-1}, climate_{it}) = a_i + \beta_\tau^q growth_{it-1} + \beta_\tau^c climate_{it}, \tag{4}$$

where for a given quantile $\tau \in (0,1)$, β_τ^k, $k \in (g, c)$ summarizes the relationship between the explanatory variables x on the one hand, and the τ-th response quantile of growth on the other hand, for a country whose growth rate baseline level is equal to a_i. x consists of lagged values of GDP growth, as is customary in the Growth at Risk literature, enhanced with climate uncertainty measures, as explained in Section 3.1. The model in Equation 4 is akin to traditional panel data models of economic activity and can be equivalently written as:

$$growth_{it} = a_i + x_{it}'\beta_\tau + \varepsilon_{it}, \tag{5}$$

where $Q_\tau(\varepsilon_{it} \mid b_i, \beta, x_{it}) = 0$.

4. Data

Tables 1 and 2 provide summary statistics for the primary datasets utilized in this study. Table 1 presents summary statistics for the annual economic growth rates from 1970 to 2022 across 34 Latin American and Caribbean countries. The statistics include the number of observations (N), mean growth rate (Mean), standard deviation (St. Dev.), minimum growth rate (Min), and maximum growth rate (Max). The annual growth rates of these countries exhibit significant variability, reflecting diverse economic conditions and performance over the past five decades.

The mean annual growth rate across all countries is 2.70%. This average reflects a moderate overall economic expansion over the period, albeit with variations among individual countries. Countries such as Belize (4.79%), the Dominican Republic (5.28%), and Panama (4.78%) consistently show higher-than-average growth rates, indicating relatively robust economic performance. The minimum annual growth rate observed was -23.51% (Bahamas), while the maximum growth rate recorded was 63.37% (Guyana), which were attributed to exceptional growth spurts influenced by oil booms.

The standard deviation of the growth rates ranged from 2.39% (Guatemala) to 11.21% (Guyana). This variability underscores the economic volatility experienced by these countries, which is influenced by factors such as political stability, natural disasters, commodity prices, and global economic cycles.

Table 1. Summary Statistics Annual Growth Rate 1970-2022

Country	N	Mean	St. Dev.	Min	Max
Antigua and Barbuda	45	3.40	5.87	-18.88	12.71
Argentina	53	2.10	5.51	-10.89	10.72
Bahamas	53	2.00	7.82	-23.51	26.14
Barbados	53	1.22	4.02	-12.74	11.33
Belize	53	4.79	5.34	-13.73	17.86
Bolivia	53	3.13	3.12	-8.74	7.97
Brazil	53	3.56	4.17	-4.35	13.97
Cayman Islands	29	2.29	3.11	-7.20	6.50
Chile	53	3.88	4.96	-12.91	11.74
Colombia	53	3.91	2.85	-7.25	11.02
Costa Rica	53	4.22	3.12	-7.29	9.20
Cuba	52	2.67	5.94	-14.88	19.69
Dominica	45	2.25	5.74	-18.36	13.38
Dominican Republic	53	5.28	4.31	-6.72	18.23
Ecuador	53	3.56	3.57	-7.79	13.95
El Salvador	53	1.95	4.06	-15.84	11.18
Grenada	45	3.05	4.65	-13.76	13.28
Guatemala	53	3.57	2.39	-3.53	8.00
Guyana	53	4.16	11.21	-13.19	63.37
Haiti	53	1.40	3.96	-11.95	9.90
Honduras	53	3.74	3.61	-8.96	12.53
Jamaica	53	1.27	4.48	-9.92	18.01
Mexico	53	3.02	3.87	-8.65	9.70
Nicaragua	53	1.98	5.93	-26.48	14.19
Panama	53	4.78	5.57	-17.67	15.84
Paraguay	53	4.40	3.82	-3.04	12.03
Peru	53	3.23	5.32	-12.31	13.42
Puerto Rico	53	2.36	3.60	-4.36	8.75
St. Kitss and Nevis	45	3.77	4.77	-14.56	11.18
St. Lucia	45	3.34	6.29	-24.36	15.88
Suriname	53	1.49	4.82	-15.98	10.20
Trinidad and Tobago	53	2.74	5.48	-10.30	14.44
Uruguay	53	2.38	4.40	-10.27	8.81
Venezuela	53	-0.54	8.85	-19.62	18.29

Note: The table shows the summary statistics of the annual growth rate of the 34 Latin American and Caribbean countries included in our sample.

Table 2 provides summary statistics for daily temperature measurements from 1970 to 2022 across the same 34 Latin American and Caribbean countries. The statistics included the number of observations (N), mean temperature (Mean), standard deviation (St. Dev.), minimum temperature recorded (Min), and maximum temperature recorded (Max). The data illustrate the variability in daily temperature across different countries and highlight regional climate differences, from tropical to temperate climates, influencing daily temperature ranges and averages.

The mean daily temperatures range from 13.56°C (Chile) to 27.15°C (St. Lucia). These variations reflect the geographic diversity of the region, encompassing tropical climates in the Caribbean islands to more temperate climates in countries such as Chile and Argentina. Such climatic diversity influences agricultural practices, energy consumption patterns, and overall living conditions. Countries such as Dominica and the Barbados exhibit significant temperature variations, with minimum temperatures recorded as low as -25.55°C and 11.50°C, respectively, and maximum temperatures reaching 37.40°C and 32.00°C, respectively.

The standard deviation of the daily temperatures ranged from 1.02°C (Trinidad and Tobago) to 5.56°C (Argentina). Lower deviations indicate more stable temperatures year-round, while higher deviations suggest greater variability, impacting agricultural yields, water resource management, and public health considerations.

Table 2. Summary Statistics Daily Temperature 1970-2022

Country	N	Mean	St. Dev.	Min	Max
Antigua and Barbuda	13,045	26.70	1.37	-9.00	39.40
Argentina	13,827	17.46	5.56	2.55	31.84
Bahamas	13,827	25.25	3.09	6.70	36.70
Belize	13,827	26.35	2.31	13.00	39.00
Barbados	13,002	27.07	1.12	11.50	32.00
Bolivia	13,827	17.71	3.53	3.55	31.50
Brazil	13,827	22.95	2.46	4.64	30.42
Chile	13,827	13.56	4.23	0.77	31.58
Colombia	13,827	20.97	2.19	16.00	28.80
Costa Rica	13,042	22.24	2.16	15.99	35.50
Cuba	13,827	25.36	2.21	14.35	30.66
Cayman Islands	13,827	26.97	2.94	0.79	31.22
Dominica	13,045	26.86	1.37	-25.55	37.40
Dominican Republic	13,827	25.37	1.56	19.63	29.92
Ecuador	13,826	18.65	2.74	8.00	31.00
El Salvador	13,045	24.15	2.92	-1.00	29.52
Grenada	13,035	27.14	1.07	19.64	30.50
Guatemala	13,827	22.29	2.15	15.24	31.08
Guyana	13,045	25.60	1.31	19.50	33.00
Haiti	13,045	25.67	2.53	17.22	34.00
Honduras	13,045	23.95	2.12	12.95	33.20
Jamaica	13,827	26.81	1.80	19.00	37.78
Mexico	13,827	20.45	3.27	10.47	28.06
Nicaragua	13,045	27.02	1.38	20.57	34.50
Panama	13,045	26.52	1.09	20.23	32.50
Paraguay	13,045	22.92	5.39	3.86	36.31
Peru	13,825	20.04	2.22	14.90	32.50
Puerto Rico	13,827	26.23	1.39	21.69	29.69
St. Kitss and Nevis	13,045	26.83	1.35	19.00	32.00
St. Lucia	13,045	27.15	1.16	18.50	32.85
Suriname	13,827	26.51	1.29	22.31	30.13
Trinidad and Tobago	13,045	26.80	1.02	13.50	31.00
Uruguay	13,827	16.97	5.28	1.00	32.33
Venezuela	13,827	25.64	1.42	20.49	29.90

Note: The table shows the summary statistics of the daily temperature of the 34 Latin American and Caribbean countries included in our sample.

5. Results

This study employs a unique approach by exploiting the variability in temperature and real GDP measurements at different frequencies to assess the responsiveness of annual growth rates across various quantiles of the growth rate distribution to climate uncertainty shocks. These uncertainties are captured through multiple indicators based on daily temperature data at the country level, reflecting different statistical moments of temperature variations, volatility (second moment shocks), skewness (third moment shocks), and kurtosis (fourth moment shocks).

To address methodological concerns, we utilize log-differences for both temperature and GDP variables and rely on realized estimates of temperature shock moments. This approach circumvents controversies associated with using variables in levels, particularly in panel data settings such as ours. Notably, our analysis focuses exclusively on countries in Latin America and the Caribbean, thereby reducing confounding factors related to diverse institutional qualities, productive infrastructures, and climatic exposures present in global datasets.

To account for inherent country-specific differences within our dataset, we employ panel quantile models with fixed effects. This modeling approach enables us to control for unobserved heterogeneity across countries while examining how climate uncertainties impact growth rates at different points in the growth rate distribution. The inclusion of fixed effects controls for country-specific heterogeneity and temporal variations enhances the reliability of the findings. Scaling variables to zero mean and unit variance enables meaningful comparisons across quantiles, facilitating a clearer interpretation of the results.

By adopting these methodological strategies, our study contributes to a clearer understanding of how climate uncertainty affects economic growth dynamics in specific regional contexts, offering insights that are robust to variations in institutional and environmental conditions across Latin American and Caribbean nations.

Table 3 presents the main results. Crucially, the findings highlight that the impact of climate shocks on GDP growth is significantly influenced by both the moment order and the specific distribution quantile. Panel A shows the second-moment results. The intercepts for all quantiles (tau=0.1, 0.25, 0.5, 0.75, and 0.9) are statistically significant, indicating baseline growth for each quantile. Across all quantiles, the lag of GDP exhibits consistently positive and statistically significant coefficients, suggesting a robust positive association between past economic performance and current growth rates. Notably, second-moment climate shocks exhibit statistical insignificance across all quantiles except the highest (0.9), where they demonstrate a positive and statistically significant effect on economic growth at the 5% significance level.

Panel B presents the third-moment results. Across different quantiles, intercepts consistently show negative and statistically significant results, suggesting baseline negative growth rates in the absence of other factors. The lag of GDP continues to display positive and significant coefficients across all quantiles, emphasizing its persistent positive impact on growth rates. Regarding skewness, lower quantiles (tau=0.1 and tau=0.25) reveal negative and statistically significant coefficients, indicating that skewness climate shocks adversely affect growth rates. However, these effects diminish in higher quantiles (tau=0.5 to tau=0.9), where skewness coefficients become statistically insignificant, though they are still negative.

Finally, Panel C exhibits the fourth-moment results. Intercepts across all quantiles exhibit statistically significant negative results, indicating baseline negative growth rates when other variables are held constant. Similar to previous panels, the lag of GDP maintains positive and significant coefficients across all quantiles, underscoring its consistent positive association with growth rates. However, the coefficients for kurtosis are consistently statistically insignificant across all quantiles, suggesting that kurtosis climate shocks do not significantly influence growth rates within the analyzed sample.

The findings from the panel quantile model with fixed effects provide valuable insights into how climate shocks influence growth rates across different quantiles at different times. While past economic performance consistently enhances current growth rates, the study reveals that volatility and kurtosis climate shocks do not exert significant effects on growth rates. Conversely, lower quantiles highlight significant negative impacts of skewness on growth rates, indicating that these types of climate shocks considerably affect countries in regions that exhibit low rates of economic growth.

These results contribute to a deeper understanding of the heterogeneous impacts of climate shocks on growth rates, offering insights that can inform policy aimed at promoting sustainable economic growth and resilience across diverse national contexts.

Table 3. Results Panel Quantile with Fixed Effectsperature 1970-2022

Panel A: Volatility

		Effect	Std. Error	T- statistic	P value
tau=0.1	Intercept	-3.65	0.50	-7.24	0.00
	Lag of GDP	0.54	0.09	5.82	0.00
	Volatility	-0.06	0.40	-0.15	0.88
tau=0.25	Intercept	-0.49	0.26	-1.85	0.07
	Lag of GDP	0.47	0.06	7.95	0.00
	Volatility	0.09	0.21	0.44	0.66
tau=0.5	Intercept	2.22	0.15	14.57	0.00
	Lag of GDP	0.36	0.04	9.03	0.00
	Volatility	0.20	0.18	1.10	0.27
tau=0.75	Intercept	4.40	0.22	19.84	0.00
	Lag of GDP	0.28	0.04	6.98	0.00
	Volatility	0.34	0.26	1.33	0.18
tau=0.9	Intercept	7.31	0.30	24.50	0.00
	Lag of GDP	0.15	0.05	3.21	0.00
	Volatility	0.43	0.22	1.99	0.05

Panel B: Skewness

		Effect	Std. Error	T- statistic	P value
tau=0.1	Intercept	-3.79	0.53	-7.22	0.00
	Lag of GDP	0.55	0.10	5.79	0.00
	Skewness	-0.55	0.16	-3.45	0.00
tau=0.25	Intercept	-0.53	0.26	-2.02	0.04
	Lag of GDP	0.47	0.06	8.30	0.00
	Skewness	-0.29	0.11	-2.75	0.01
tau=0.5	Intercept	2.17	0.14	15.20	0.00
	Lag of GDP	0.36	0.04	8.96	0.00
	Skewness	-0.15	0.09	-1.60	0.11
tau=0.75	Intercept	4.37	0.18	24.58	0.00
	Lag of GDP	0.29	0.04	7.25	0.00
	Skewness	-0.04	0.11	-0.33	0.74
tau=0.9	Intercept	7.35	0.30	24.20	0.00
	Lag of GDP	0.15	0.05	2.70	0.01
	Skewness	-0.15	0.08	-1.89	0.06

Note: The table shows the results of the estimation of a panel quantile model with fixed effects by country. The Growth at Risk estimates correspond to the 0.1 quantile (tau=0.1), representing the lowest 10th percentile of annual growth rates in the sample. Panel A presents the results for realized volatility, Panel B for realized skewness, and Panel C for realized kurtosis. All variables, except for GDP and its lag, have been scaled to have zero mean and unit variance to allow for meaningful comparisons.

Table 3. Results Panel Quantile with Fixed Effectsperature 1970-2022

Panel C: Kurtosis

		Effect	Std. Error	T- statistic	P value
tau=0.1	Intercept	-3.71	0.48	-7.68	0.00
	Lag of GDP	0.54	0.09	5.77	0.00
	Kurtosis	-0.28	0.47	-0.58	0.56
tau=0.25	Intercept	-0.59	0.27	-2.19	0.03
	Lag of GDP	0.47	0.06	7.96	0.00
	Kurtosis	-0.38	0.46	-0.82	0.41
tau=0.5	Intercept	2.13	0.17	12.22	0.00
	Lag of GDP	0.36	0.04	8.34	0.00
	Kurtosis	-0.45	0.56	-0.80	0.42
tau=0.75	Intercept	4.37	0.22	19.49	0.00
	Lag of GDP	0.28	0.04	6.76	0.00
	Kurtosis	-0.08	0.63	-0.13	0.90
tau=0.9	Intercept	7.31	0.30	24.01	0.00
	Lag of GDP	0.15	0.06	2.68	0.01
	Kurtosis	-0.24	0.88	-0.27	0.78

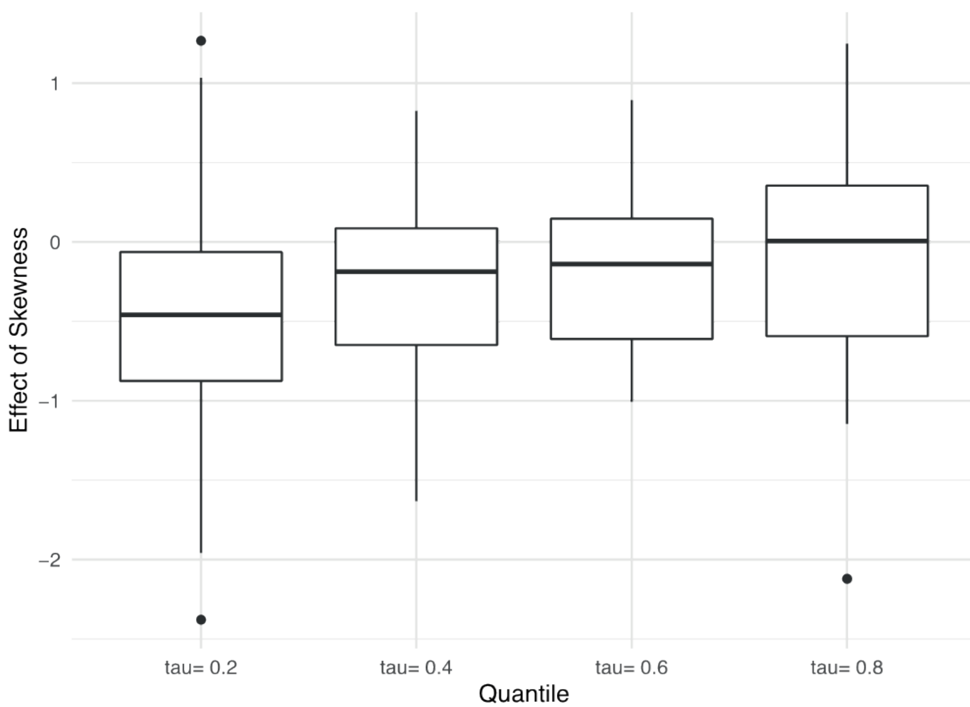
Note: The table shows the results of the estimation of a panel quantile model with fixed effects by country. The Growth at Risk estimates correspond to the 0.1 quantile (tau=0.1), representing the lowest 10th percentile of annual growth rates in the sample. Panel A presents the results for realized volatility, Panel B for realized skewness, and Panel C for realized kurtosis. All variables, except for GDP and its lag, have been scaled to have zero mean and unit variance to allow for meaningful comparisons.

Figure 1 displays box plots depicting point estimates for skewness at various quantiles across individual countries. Each quantile (tau) has its own box plot. The box itself represents the interquartile range (IQR), which contains 50% of the data points. The bottom of the box marks the 25th percentile (Q1), while the top of the box marks the 75th percentile (Q3). Therefore, the height of each box represents the spread of the data within the middle 50%. The solid line inside each box represents the median point estimate for that quantile. The median is the middle value when the data points are ordered from lowest to highest. Lines extending vertically from the top and bottom of each box (whiskers) show the range of the data outside the interquartile range. They can represent minimum and maximum values within a certain range or a certain number of standard deviations from the mean, depending on the specific plot.

By examining the box plots at different quantiles, it can be observed how the point estimates vary across different parts of the distribution. Differences in the heights, widths, and positions of the boxes and medians between quantiles indicate how the relationship between variables (climate shocks and GDP growth) changes depending on the level of the growth rate distribution being analyzed. The box plots in Figure 1 illustrate how the effect of skewness climate shocks on GDP growth rates varies over time across different quantiles of the growth distribution for individual countries. This temporal variation depicted in Figure 1 highlights the dynamic nature of these effects, emphasizing that changes over time are significant alongside the variations observed across countries.

This discovery underscores the significance of incorporating time-varying skewness into theoretical models examining the impact of temperature on economic activity, as our findings suggest that the observed effects are influenced not only by cross-sectional differences among countries but also by changes in these relationships over time.

Figure 1. Box Plot of Point Estimates at Different Quantiles for Individual Countries



Note: The figure presents box plots at various quantiles (τ = 0.2, 0.4, 0.6, 0.8) for individual quantile regressions at the country level. Each box represents the interquartile range, encompassing 50% of the data, with the solid line indicating the median.

6. Conclusions and Policy Implications

This paper studies the effect of climate uncertainty shocks on the growth rate distribution for Latin American and Caribbean countries between 1970 and 2022. Our indicators, derived from daily country-level temperature measurements, encompass second-moment shocks (volatility), third-moment shocks (skewness), and fourth-moment shocks (kurtosis). By employing log-differences of both temperature and GDP, along with realized estimates of different moments of temperature shocks, we circumvent the controversy associated with using variables in levels, especially within a panel structure.

Focusing on Latin American and Caribbean countries, our analysis mitigates the effects of mixing disparate regions with varying institutional qualities, productive infrastructures, and exposure to climatic conditions, which is a common issue in the prior literature. We utilize panel quantile models with fixed effects to account for country-specific differences within the sample. This approach enhances the efficiency of our estimates by significantly increasing the sample size, as it includes 34 nations.

Our application of the Growth at Risk framework (Adrian et al., 2018, 2019) reveals a significant negative effect of realized (time-varying) skewness on the lower quantiles of the real growth distribution. This effect diminishes across the growth distribution, indicating that asymmetric shocks in daily temperature are particularly impactful during periods of negative growth. This underscores the importance of considering time-varying skewness in theoretical models of the effects of temperature on economic activity.

The findings from our panel quantile model with fixed effects offer valuable insights into how different moments of climate shocks influence growth rates across various quantiles. Past economic performance consistently enhances current growth rates. However, the study reveals that volatility and kurtosis climate shocks do not exert significant effects on growth rates. In contrast, significant negative impacts of skewness on growth rates are evident at lower quantiles, indicating that these climate shocks more substantially affect countries with low rates of economic growth in the region.

We also present suggestive, though inconclusive, evidence that our results are driven not only by cross-sectional variation across countries but also by the time series dimension. Our dataset, spanning across 53 years from 1970 to 2022, has a larger time series dimension than that of cross-sectional studies. Supporting this view, country-specific quantile regressions, although often nonsignificant due to limited power from the short sample, consistently show a tendency for greater and more negative effects at the lower end of the GDP growth distribution compared to other segments.

Our results contribute to a deeper understanding of the heterogeneous impacts of climate shocks on growth rates, providing insights that can inform policies to promote sustainable economic growth and resilience across diverse national contexts. This study emphasizes the significance of incorporating time-varying skewness in economic models and highlights the various ways in which different types of climate uncertainty shocks can influence economic outcomes.

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