Climate change and economic growth: evidence from a growth at risk model of Indonesia

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Paresh Kumar Narayan
Monash University, Melbourne, Australia

Seema Narayan
Asia-Pacific Applied Economics Association, Berwick, Australia

Yoga Affandi
Bank Indonesia, Jakarta, Indonesia, and

Danny Hermawan
Bank Indonesia BI Institute, Central Jakarta, Indonesia

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Abstract

Purpose – This study aims to examine how climate change affects economic growth in Indonesia – the world's largest Muslim-majority country with a dual banking system – by analyzing the distribution of future growth risks rather than average outcomes.

Design/methodology/approach – The paper employs a Growth at Risk (GaR) framework, integrating climate variables into ordinary least sqaures and Quantile Regression models using quarterly data from 2008Q1 to 2023Q3. This approach allows the assessment of climate impacts across different states of the economic cycle and forecasting horizons.

Findings – The results reveal a nonlinear and state-dependent relationship between climate change and economic growth. Climate change has its strongest and statistically significant effects at the lower tail of the growth distribution, where climate-induced fiscal stimulus supports economic recovery during downturns.

Research limitations/implications – The analysis is conducted at the national level and does not explicitly model differential transmission channels between Islamic and conventional banks, which could be explored in future research.

Practical implications – The findings suggest that climate-responsive fiscal policy can play a stabilizing role during periods of economic weakness, particularly in dual-banking systems where risk-sharing financial structures may enhance resilience to climate shocks.

Social implications – By highlighting the role of fiscal responses and inclusive financial systems in mitigating climate-related downturns, the study informs policy strategies aimed at protecting livelihoods and supporting sustainable growth in climate-vulnerable, Muslim-majority economies.

Originality/value – This study extends the GaR literature by incorporating climate change as a key predictor of growth risk and by contextualizing the analysis within a Muslim-majority, dual-banking economy, offering new insights into the interaction between climate shocks, fiscal policy and financial system structure.

Keywords Growth at risk, Indonesia, Climate, Economic growth

Paper type Research paper

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1. Introduction

Indonesia ranks among the top third of countries globally in terms of climate risk, with significant vulnerability to various forms of flooding and extreme heat, according to the World Bank. As climate change intensifies, these hazards are expected to become more severe, leading to increased exposure for the population unless effective adaptation measures are implemented. The report highlights that temperature and rainfall forecasts for Indonesia by 2050 are projected to be below global averages. However, it also points out limitations in these forecasts, particularly in accounting for spatial and temporal variations (World Bank, 2023).

Temperature and precipitation projections differ significantly depending on emissions scenarios. Persistently high greenhouse gas emissions could result in substantially greater warming, whereas moderate emission reductions are projected to lead to a global temperature rise exceeding 1.5°C above preindustrial levels by 2050. Under a high-emissions scenario, warming may reach between 4.5°C and 5°C by the end of the century; however, by 2050, the increase would be less pronounced but still significant [1]. Elevated temperatures are expected to intensify the hydrological cycle, resulting in more frequent extreme rainfall events, flooding in certain regions and droughts in others.

In Indonesia, mean annual temperatures increased by approximately 0.8°C from the 1951 to 1980 baseline during the period 2010–2017 [2]. While average annual precipitation has declined, regional variations persist across the country [3]. By 2050, Indonesia's temperature is anticipated to rise by 0.8°C–1.4°C, with potentially higher increases inland. Rainfall projections indicate an increase in the western and southern regions and a decrease in the southern islands, accompanied by heightened intensity of extreme rainfall events [4].

Given the uncertainties in global climate models, especially concerning Indonesia, there is a pressing need to better understand the economic implications of climate change factors such as temperature and rainfall. A deeper understanding of these impacts is crucial for designing and implementing policies that effectively address the challenges posed by climate change. Accurate economic assessments can guide Indonesia in developing targeted adaptation strategies to mitigate the adverse effects of climate change, ensuring sustainable economic growth and resilience for its population.

To evaluate the effects of climate change on Indonesia's economic growth, we propose a Growth at Risk (GaR) analysis, which will allow us to assess how climate factors like temperature and rainfall impact economic growth across different states of the economy. Drawing from the extensive literature on the subject, our central hypothesis posits that the influence of climate change on economic growth is conditional, meaning that the effects vary depending on the current state of economic growth – essentially, they are quantile-dependent.

Our GaR approach is inspired by Adrian *et al.* (2019), who modeled economic growth in relation to financial conditions. However, we innovate by extending their first-order growth model to include climate change-related variables. Specifically, we will incorporate data on temperature, rainfall and floods to capture the broad effects of climate change. To ensure that our model robustly represents the multifaceted nature of climate change, we create a principal component that aggregates these climate variables.

This methodology not only allows for a nuanced analysis of how climate factors affect economic growth at different points in the economic cycle but also provides a comprehensive understanding by using a broad proxy for climate change. By incorporating these climate variables into our model, we aim to produce insights that can inform policy design and implementation, helping Indonesia better manage the economic risks associated with climate change.

Our work contributes to the literature in two significant ways. First, we extend the existing GaR literature by introducing climate change as a critical predictor of economic growth. Traditionally, GaR-based studies have concentrated on various financial and economic predictors. For example, researchers have explored the impact of credit growth to households on economic risk (Duprey and Ueberfeldt, 2020; Gächter *et al.*, 2023), while others have examined broader indicators like the Composite Indicator of Systemic Stress (Figueres and Jarociński, 2020) or narrower ones such as the volatility of the S&P 500 index (Brownlees and Souza, 2021). There are also studies that have employed global indicators of economic conditions and financial-specific factors (Plagborg-Møller *et al.*, 2020), economic policy uncertainty (Gu *et al.*, 2021), bank capitalization (Aikman *et al.*, 2019) and macro-prudential policies (Franta and Gambacorta, 2020).

By incorporating climate change variables – such as temperature, rainfall and flood data – into the GaR framework, our research not only adds a new dimension to the analysis but also demonstrates that climate change can be a powerful predictor of future economic growth. This approach is novel in that it considers how environmental factors, increasingly relevant due to global climate change, can influence the economic outlook comparably to traditional financial indicators.

The second contribution of our work is offering a new perspective on the relationship between climate change and economic growth, which extends beyond studies such as Dong *et al.* (2024) who focus on income inequality; Kong *et al.* (2024), who focus on employment; Lee *et al.* (2024), who take issue with agricultural effects; and Behera *et al.* (2025) who focus on environment. Specifically, we hypothesize and empirically demonstrate that climate change can positively impact economic growth, particularly when the economy is underperforming. The rationale is that during periods of economic downturn, climate-related events often lead to government intervention through fiscal stimulus aimed at mitigating the adverse effects of these events. This stimulus typically involves increased public spending on disaster recovery, infrastructure rebuilding and other climate adaptation measures, which, in turn, can boost consumption and investment.

Our empirical analysis confirms this proposition by showing that the positive effects of climate-induced fiscal stimulus are most pronounced at lower quantiles of economic growth, where the economy is struggling. For example, in the aftermath of a severe climate event, government spending on recovery efforts can stimulate economic activity, leading to a rebound in growth. This finding is particularly important as it challenges the conventional view that climate change is solely a negative factor for economic performance. Instead, our research suggests that under certain conditions, climate change can act as a catalyst for economic recovery, particularly in times of economic distress.

Our findings also join the broader climate change-economic growth literature (see Desbordes and Eberhardt, 2024). Traditionally, this literature has focused on the marginal effects of climate change on economic growth, often highlighting its negative impacts. Theoretical studies have supported these negative effects, particularly in developing countries (Fankhauser and Tol, 2005; Cai *et al.*, 2023). However, there is also evidence of positive (Petrović, 2023) or statistically insignificant effects (Abidoye and Odusola, 2015). We add to this literature by showing that the state of economic growth plays a crucial role in determining the impact of climate change. When economic growth is depressed, climate change is likely to have a positive effect due to the stimulus aimed at recovery, which also aids economic growth recovery.

Overall, our study contributes to the broader GaR literature by introducing climate change as a new predictor and providing evidence that the relationship between climate change and economic growth is more complex and context-dependent than previously understood. By highlighting the potential for climate change to positively influence economic growth during downturns, our work offers new insights for policymakers and researchers interested in the intersections of environmental and economic policy.

The remainder of this paper is structured as follows: Section 2 presents the Gar framework and details the incorporation of the climate change variable into this model. Section 3 offers an empirical analysis accompanied by a discussion of principal findings, and Section 4 concludes with final observations.

2. The gar framework and climate change

2.1 The Growth at Risk framework

The GaR model was originally developed by Cecchetti (2008) and Cecchetti and Li (2008), and later expanded and popularized by the work of (Adrian *et al.*, 2018, 2019). These models have since become valuable tools for forecasting economic growth, particularly in assessing downside risks by utilizing financial conditions (Brownlees and Souza, 2021). The GaR model is an extension of the Value-at-Risk model, which is widely used in risk management to assess systematic risks.

While Value-at-Risk models focus on expected investment losses based on financial market conditions, GaR models extend this concept to predict the distribution of gross domestic product (GDP) growth, conditioned on macroeconomic and financial conditions – collectively known as macro-financial conditions (Adrian *et al.*, 2019; Prasad *et al.*, 2019; Busch *et al.*, 2022). This extension makes GaR models particularly useful for evaluating and designing macro-prudential policies (Suarez, 2022).

Institutions like the International Monetary Fund and the European Central Bank regularly publish GaR estimates for major economies, highlighting the model's relevance and applicability (Brownlees and Souza, 2021). In essence, the GaR concept corresponds to the probability that future real GDP growth will fall below a prespecified threshold, providing a risk-focused perspective on economic forecasts (Prasad *et al.*, 2019; Adrian *et al.*, 2018).

Following the methodologies established by (Adrian *et al.*, 2018, 2019), we define GaR as a tool to quantify the potential downside risks to economic growth, making it an essential component in understanding and mitigating the impacts of adverse macro-financial conditions. The model has the following form:

$$Probability\left(growth_{Indonesia,h}\right) \leq GaR_{Indonesia,h}\left(\alpha \mid \varphi_t\right) = \alpha \tag{1}$$

where $GaR_{Indonesia,h}\ (\alpha|\varphi_t)$ is GaR for Indonesia i*n h* quarters in the future at a*n* α probability with φ_t, which represents the information set available at time *t*. The probability density is constructed using a two-step procedure. First, the quantile regression of Koenker and Bassett (1978) is used to establish the relationship of the predictors (climate change) to the quantiles of *h*-steps ahead GDP growth, allowing for a shift of focus from the dependent variable's conditional mean to its conditional quantiles (Suarez, 2022). Second, to develop the whole conditional distribution of the dependent variable, or more precisely, the skewed *t*-distribution is used to smoothen (or string together) the estimated quantile distribution every quarter together by interpolating between the estimated quantiles, the skewed *t*-distribution is used, which completes the construction of the *h*-steps ahead GDP growth probability density (Adrian *et al.*, 2019).

The key advantage of the GaR framework is that contrary to point forecasting methods, it assesses financial and macroeconomic risks to assess the entire distribution of future growth (Prasad *et al.*, 2019). Moreover, the GaR framework allows policymakers to focus on downside risks to growth (Adrian *et al.*, 2019).[5] Apart from monitoring the evolution of downside risks to economic activity over time, the GaR approach allows policymakers to quantify the likelihood of risk scenarios, which serves as a basis for pre-emptive action (Prasad *et al.*, 2019).

The GaR framework has become a key tool for examining the conditional distribution of GDP growth influenced by macro-financial variables. Adrian *et al.* (2019) focus on the role of the National Financial Conditions Index, demonstrating that tighter financial conditions significantly increase downside risks to future US output growth. This method's strength lies in its ability to capture the full distribution of growth outcomes, not just the mean, allowing policymakers to better understand and mitigate economic risks.

Duprey and Ueberfeldt (2020) extend this analysis to Canada, finding that increased household credit growth correlates with greater downside risks to economic growth. Similarly, Gächter *et al.* (2023) use a historical analysis over 130 years, revealing a shift in risk factors: while financial stress has become less relevant for downside risks, the impact of credit growth has risen, suggesting a critical trade-off for policymakers between fostering credit growth and managing long-term economic stability.

Further broadening the scope, Figueres and Jarociński (2020) show that a Composite Indicator of Systemic Stress is more effective for predicting euro area growth risks than simpler financial market indicators. Brownlees and Souza (2021) perform out-of-sample back-testing across organisation for economic co-operation and development countries, comparing quantile regression and generalized autoregressive conditional heteroskedasticity (GARCH) models for GaR predictions. They find that while both methods are effective, GARCH offers superior predictive accuracy, particularly under the marginal GaR framework commonly used in risk management.

Innovative approaches include Ferrara *et al.* (2022) and Xu *et al.* (2023), who integrate high-frequency data into the GaR framework using Bayesian mixed-data sampling (MIDAS) quantile regressions. This allows real-time monitoring of economic risks, providing early warnings of potential downturns based on daily financial stress indicators.

Despite its flexibility, the GaR framework has primarily focused on financial and economic variables. It has been used to study other aspects, such as output gaps and inflation (Adrian *et al.*, 2020), and to examine the effects of economic policy uncertainty, bank capitalization and macro-prudential policies (Gu *et al.*, 2021; Aikman *et al.*, 2019; Franta and Gambacorta, 2020). However, a notable gap exists in its application to climate change's impact on economic growth. Addressing this gap could provide valuable insights into how climate risks influence economic outcomes, especially as these risks become increasingly relevant in the global policy agenda.

2.2 Climate change effects on economic growth

Several researchers have explored the relationship between economic growth and climate change, laying the groundwork for empirical studies in this area. Fankhauser and Tol (2005) present a theoretical model suggesting that even developed nations, which may be only moderately impacted by climate change, should be concerned about its dynamic effects. Their study emphasizes that with constant saving, reduced output due to climate change leads to lower investment and future consumption. When saving is endogenous, forward-looking agents adjust their saving behavior to prepare for future climate impacts, which can further suppress current output both in absolute and per capita terms. These effects are amplified in an endogenous growth model through changes in labor productivity and the rate of productivity growth.

Cai *et al.* (2023) introduce a theoretical model to assess the impact of climate change on economic growth under scenarios of regional cooperation and noncooperation. By integrating a novel climate module, they calculate the regional social cost of carbon when climate change affects regional GDP growth. Their findings indicate that climate damage significantly raises the social cost of carbon, suggesting the necessity for stringent climate policies. The study also reveals that noncooperation among regions leads to greater GDP reductions, especially for developing countries. The absence of compensation transfers from wealthier, high-emission regions exacerbates welfare losses for developing nations, highlighting the unequal burden of climate change and the importance of global cooperation and equitable policy measures.

Empirical studies in this area evaluate the effects of climate change on economic growth by extending the traditional economic growth model to climate change variables:

$$y_t = \alpha_1 + \beta_1 Climate_t + \beta_2 control_t + \varepsilon_t \tag{2}$$

where, y_t is economic growth at time t and controls are some of the key determinants of real GDP growth. $Climate_t$ is a climate related variable that signifies short term, long term and/or extreme variations in temperature and/or precipitation. It is featured as long-term climate change phenomena, referred to as an average temperature anomaly, and calculated as a deviation from 20-year temperature average (Barrios *et al.*, 2010; Abidoye and Odusola, 2015). Long-term variation in climate is also captured as a $t - n$ moving average of temperature where $n = 20$ (Abidoye and Odusola, 2015) or $n = 5$ (Barrios *et al.*, 2010). Short-term weather patterns in terms of average temperature over the quarter or year are taken to show the short-term variations of weather conditions. Extreme weather patterns in terms of temperature and precipitation are depicted using the maximum or minimum of the two weather conditions (Khan and Rashid, 2022).

Abidoye and Odusola (2015) analyzed 34 African countries and found that a one-degree increase in temperature results in a 0.67% decline in economic activity. The study also notes that long-term changes in temperature patterns negatively influence economic growth, with temperature anomalies showing a greater impact than moving averages. However, despite these findings, the study concludes that both climate change variables and extreme events have an overall insignificant effect on economic growth in the African context.

In contrast, Petrović (2023) examined a panel of 23 developing and developed countries and found that a one-degree Celsius rise in temperature could lead to an average increase in economic growth by 0.865 percentage points. In addition, an increase in climate-related disasters is associated with a slight increase in economic growth. This study suggests that the effects of climate change on economic growth are heterogeneous and do not uniformly result in negative outcomes.

Elshennawy *et al.* (2016) focused on Egypt, projecting that without significant policy-led adaptation investments, such as coastal protection and improvements in agricultural and irrigation practices, climate change could reduce real GDP by 6.5% by 2050. This study emphasizes the critical role of adaptation strategies in mitigating the negative economic impacts of climate change.

Arndt *et al.* (2014) used integrated models combining climate, biophysical and economic factors to assess the impact of climate change on Malawi's economy. Their findings indicate that while climate change may not significantly hinder economic growth in the short term, its effects could become more pronounced over time, particularly if global emissions remain high.

Sequeira *et al.* (2018) explored the impacts of temperature and precipitation on economic growth across different climate regimes. The study found that rising temperatures and precipitation have a neutral effect on long-term growth, with precipitation even showing a marginally positive effect in the short run. However, these effects vary by region, with poorer countries experiencing negative impacts from rising temperatures and positive impacts from increased precipitation, especially in hot and temperate regions.

Tebaldi and Beaudin (2016) examined the effects of rainfall variability on Brazil's GDP, finding that droughts and floods exacerbate economic inequality, particularly in the poorer northwestern regions. This highlights the disproportionate impact of climate variability on economically vulnerable areas.

Alagidede *et al.* (2016) studied Sub-Saharan Africa and found that precipitation impacts economic growth in the long run, while temperature effects are more immediate. The study also suggests a nonlinear relationship between temperature and GDP, with temperatures above 24.9 degrees Celsius significantly reducing economic growth.

Finally, Duan *et al.* (2022) focused on China, finding that a one-degree Celsius increase in temperature decreases output by 0.78%, while increased rainfall has a positive impact, particularly in more developed regions. The study projects that climate change could reduce China's GDP by up to 4.23% by 2100.

Overall, these studies underscore the complex and varied effects of climate change on economic growth, with significant regional differences and the potential for both negative and positive outcomes depending on the context and adaptation measures in place.

3. Empirical analysis

3.1 Data

We use quarterly national-level data on climate change-related variables, specifically mean temperature, rainfall and floods alongside annualized real GDP growth. These data are sourced from Climate Engine and the National Agency for Disaster Countermeasure (abbreviated as BNPB). The data are quarterly and span the period 2008 quarter 1–2023 quarter 3; see Appendix, Table A1.

In Figure 1, we present the evolution of these climate change variables over time (Panels A and B) and their seasonal variations (Panel C). Two key observations stand out. First, there has been a noticeable intensification of floods in recent years. Second, while mean temperature and precipitation appear relatively stable over time, seasonal variations reveal a different story. Specifically, during the Q3 and Q4 seasons, precipitation reaches its lowest levels, while temperature peaks more than once during these periods, indicating significant seasonal fluctuations.

In this study, we focus on the combined effects of climate change by extracting an aggregate measure of climate change based on the Principal Component Analysis (PCA), which we refer to as *CLIMATE*. The PCA based CLIMATE component is a linear combination of our key variables, including, temperature, rainfall and floods, capturing unique information from each series and avoiding any redundant information in the process (Abdi and Williams, 2010). As shown in Table 1, the contribution of floods, precipitation and temperature (all in log form) to the climate change partition is 59%, 32% and 8%, respectively.

Figure 2 illustrates the evolution of *CLIMATE* alongside real GDP growth. However, at this stage, it remains difficult to draw definitive conclusions about the relationship between the two variables.

In Table 2, we present the common statistics on the variables. The main focus is on the climate change variables – namely, *CLIMATE*, temperature, precipitation and floods. There is a story. Those four climate variables reveal distinct patterns of variability and distribution. *CLIMATE*, for instance, shows low average values but high variability and significant left-

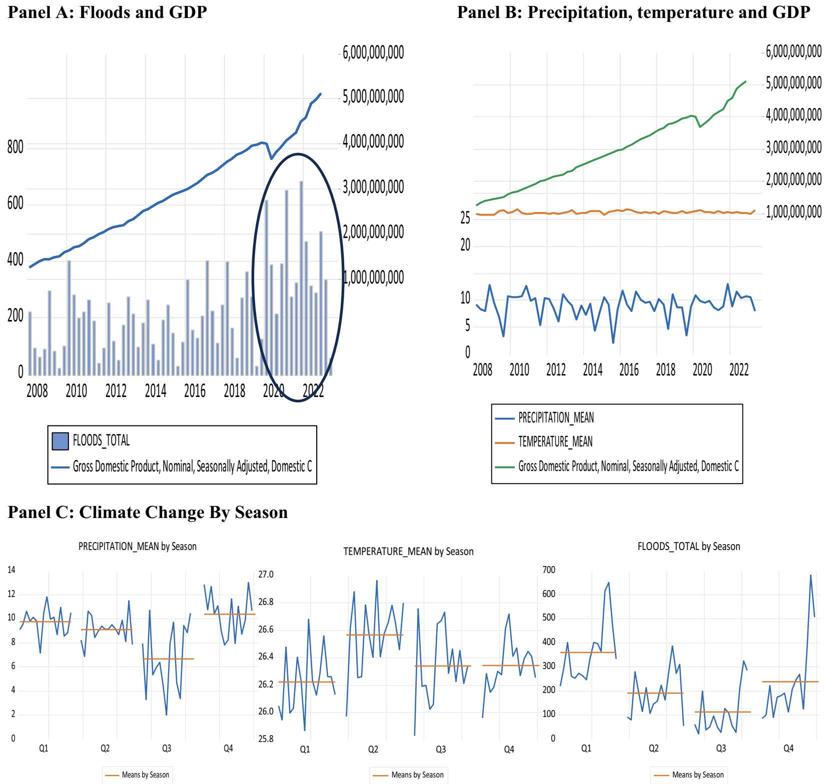

Figure 1. Climate and GDP

Note(s): This figure depicts Indonesia's GDP and climate change variables: floods (total frequency) and mean temperature and precipitation over time (Charts 1 and 2) and by season (Chart 3)

Table 1. Climate partition

Partitions and their components	Proportion
Log floods (total)	0.5917
Log precipitation (mean)	0.3247
Log temperature (mean)	0.0836

Note(s): This table presents the principal components of the climate change variable. The original climate series used include total frequency of floods, and mean precipitation and temperature, all expressed in their logarithmic forms

skewness, indicating sensitivity to extreme climate changes. In contrast, mean temperature is stable with low variability and a nearly normal distribution, suggesting minimal extreme temperature events. Mean precipitation displays moderate variability and slight left-skewness, with high kurtosis, indicating frequent extreme precipitation events. Similarly, floods (total) have high average values and substantial variability, with a slightly right

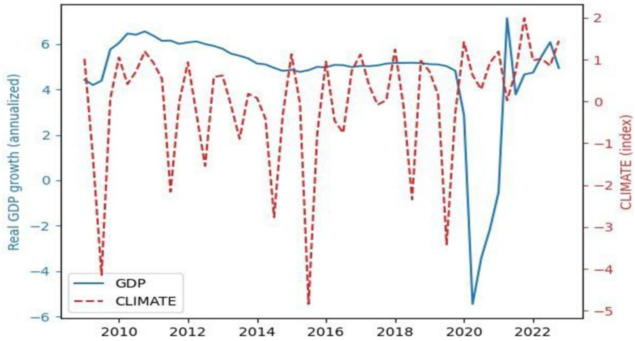

Figure 2. Climate change partition and real GDP growth

Note(s): This figure shows the growth rate of real GDP and the principal component of Climate

Table 2. Descriptive statistics

Key indicators	PC climate	Real GDP growth	Floods total	Precipitation mean	Temperature mean
Mean	0.013	1.170	227.532	9.005	26.368
Median	0.386	1.267	213.000	9.265	26.318
Maximum	1.989	3.350	683.000	13.038	26.963
Minimum	−4.839	−6.944	21.000	2.018	25.831
Std. dev.	1.372	1.220	152.583	2.260	0.266
Skewness	−1.721	−4.981	0.990	−1.025	0.137
Kurtosis	5.931	34.787	3.889	4.230	2.322
CV	10,553	104.27	67.060	25.097	1.009
Jarque–Bera	48.526	2727.9	12.174	14.768	1.382
Probability	0.000	0.000	0.002	0.001	0.501
Observations	57	59	62	62	62

Note(s): This table reports selected descriptive statistics of key variables

skewed and moderately peaked distribution, reflecting significant extreme flooding events. These findings suggest that while temperature remains relatively stable, precipitation and flooding are more susceptible to extreme events, emphasizing the varying impacts of climate change on different environmental factors. It follows that an aggregate measure of climate change, as measured by *CLIMATE* is ideal for our purpose.

3.2 Ordinary least sqaures (OLS) and quantile regression estimations

Quantile regression (QR) estimation is the first step toward estimating the predictive conditional distributions of real GDP. Here, we digress slightly to first check the link between the annualized real GDP growth (y_t), and *CLIMATE*. This QR model takes the following form with the parameters, α and βs, and innovations, ε_t:

$$y_t = \alpha + \beta_1 y_{t-1} + B_2 CLIMATE_t + \varepsilon_t \tag{3}$$

The results estimated using the OLS and QR methods are presented in Table 3. These results indicate that the OLS-estimated contemporaneous effects between economic growth and *CLIMATE* are negative but insignificant. The QR analysis further reveals that the

Table 3. Current RGDP growth (annualised) and climate change

Dependent variable		y_t	
Variable		Coef.	Prob.
Panel A: OLS estimates			
C		1.298	0.012
y_{t-1}		0.726	0.000
Climate		−0.080	0.616
$\overline{R}^2$			0.517
Panel B: Quantile regression estimates			
	Quantile	Coef.	Prob.
y_{t-1}	0.1	0.776	0.000
	0.2	0.837	0.000
	0.3	0.846	0.000
	0.4	0.809	0.000
	0.5	0.811	0.000
	0.6	0.812	0.000
	0.7	0.792	0.000
	0.8	0.815	0.000
	0.9	0.268	0.809
Climate	0.1	−0.111	0.387
	0.2	−0.009	0.633
	0.3	0.009	0.686
	0.4	−0.004	0.875
	0.5	0.000	0.989
	0.6	0.004	0.871
	0.7	0.021	0.273
	0.8	0.045	0.108
	0.9	0.141	0.525

Note(s): This table reports results for equation (3) where $y_t = f(y_{t-1}, Climate)$ estimated using the OLS and Quantile Regression methods. Climate is Principal Component of climate change variables, log of floods, log of temperature and log of precipitation

relationship between economic growth and climate change can be either positive or negative across different quantiles, although these effects are not yet significant. These findings suggest an asymmetric response of economic growth to climate change effects depending on the quantile, highlighting the complexity of the relationship.

Next, we examine the predictive QR model under several forecasting horizons ($h = 1, 4, 8, 12$). This takes the following form:

$$y_{t+h} = \alpha + \beta_1 y_t + B_2 CLIMATE_t + \varepsilon_t \tag{4}$$

In this analysis, we forecast real GDP growth rates y_{t+h} for periods ranging from one quarter ahead to three years ahead. The model includes the current real GDP growth rate y_t and an aggregate measure of climate as explained earlier. Equation (4) allows us to explore how climate change might influence future economic growth.

The results, presented in Table 4, reveal several key insights. First, the OLS estimates show a negative relationship between future economic growth and *CLIMATE* for short-term forecasting horizons ($h = 1, 12$). However, for longer forecasting horizons, this relationship turns positive. Despite these directional shifts, the effects of *CLIMATE* on future economic

Table 4. Future real GDP growth (annualised) and climate change

Horizons		1-qtr-ahead Coef.	1-qtr-ahead Prob.	2-qtr-ahead Coef.	2-qtr-ahead Prob.	3-qtr-ahead Coef.	3-qtr-ahead Prob.	4-qtr-ahead Coef.	4-qtr-ahead Prob.	8-qtr-ahead Coef.	8-qtr-ahead Prob.	12-qtr-ahead Coef.	12-qtr-ahead Prob.
Panel A: OLS estimates													
C		1.304	0.012	2.386	0.001	3.453	0.000	4.510	0.000	4.894	0.000	0.244	0.947
yt		0.725	0.000	0.501	0.000	0.279	0.046	0.048	0.740	−0.063	0.686	0.764	0.259
PC_CLIMATE		−0.079	0.621	0.020	0.923	0.275	0.238	0.178	0.469	0.067	0.797	−0.374	0.186
$\bar{R}^2$			0.51711		0.21865		0.0563		−0.0283		−0.0386		−0.045
Panel B: Quantile regression estimates													
	Quantile	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
y_t	0.1	*0.811*	*0.000*	*0.646*	*0.000*	0.776	0.653	1.251	0.489	−0.233	0.224	4.230	0.027
	0.2	*0.837*	*0.000*	*0.673*	*0.000*	*0.521*	*0.000*	*0.136*	*0.050*	−0.014	0.791	0.008	0.975
	0.3	*0.846*	*0.000*	*0.680*	*0.000*	*0.529*	*0.000*	*0.147*	*0.057*	−0.008	0.902	−0.046	0.855
	0.4	*0.809*	*0.000*	*0.684*	*0.000*	*0.526*	*0.000*	*0.152*	*0.060*	−0.043	0.414	−0.003	0.988
	0.5	*0.811*	*0.000*	*0.663*	*0.000*	0.316	0.807	0.075	0.404	−0.034	0.529	−0.034	0.875
	0.6	*0.812*	*0.000*	*0.670*	*0.000*	*0.212*	*0.073*	0.099	0.216	−0.029	0.581	−0.012	0.951
	0.7	*0.810*	*0.000*	0.541	0.272	*0.197*	*0.082*	*0.137*	*0.050*	−0.005	0.921	−0.016	0.927
	0.8	*0.806*	*0.000*	0.335	0.017	0.178	0.237	−0.028	0.967	−0.029	0.675	0.076	0.758
	0.9	0.256	0.880	−0.090	0.403	−0.097	0.192	−0.084	0.116	0.000	0.995	−0.172	0.278
Climate	0.1	−0.032	0.724	*0.432*	*0.017*	*1.759*	*0.067*	*1.636*	*0.025*	−0.190	0.612	−0.386	0.568
	0.2	0.015	0.640	0.037	0.698	0.093	0.482	0.035	0.688	0.015	0.881	−0.089	0.280
	0.3	0.018	0.586	0.015	0.777	0.059	0.558	0.014	0.887	−0.031	0.787	−0.063	0.475
	0.4	0.002	0.945	0.002	0.969	0.043	0.610	0.025	0.815	−0.008	0.948	−0.037	0.687
	0.5	0.001	0.970	−0.001	0.981	0.023	0.865	0.041	0.734	0.009	0.940	−0.027	0.779
	0.6	−0.007	0.798	0.009	0.862	0.032	0.758	0.034	0.757	0.019	0.872	−0.011	0.903
	0.7	−0.001	0.970	0.062	0.390	0.106	0.269	0.096	0.336	0.065	0.546	−0.002	0.984
	0.8	0.022	0.504	−0.016	0.914	−0.014	0.951	0.006	0.978	0.133	0.159	−0.138	0.254
	0.9	0.009	0.982	0.099	0.415	−0.019	0.866	−0.021	0.868	−0.015	0.892	−0.025	0.758

Note(s): This table reports results for equation (3) where $y_{t+h} = f(y_t, CLIMATE)$ estimated using the OLS and Quantile Regression methods. CLIMATE is Principal Component of climate change variables, log of floods, log of temperature and log of precipitation growth remain statistically insignificant across all forecasting horizons, suggesting that the overall impact is not robustly captured by the OLS method.

In contrast, the QR analysis provides a more nuanced view, emphasizing that the effects of climate change on economic growth vary not only across different forecasting horizons but also across different quantiles of economic performance. Notably, the analysis identifies a positive and significant impact of *CLIMATE* on economic growth at the lowest quantile (0.1), particularly for forecasting horizons of 2–4 quarters ahead ($h = 2, 3, 4$). This finding suggests that when the economy is underperforming, climate change might actually stimulate growth, possibly through mechanisms like increased fiscal stimulus in response to climate-related challenges.

These findings highlight the asymmetric nature of climate change's impact on economic growth, reinforcing the relevance of the GaR framework. The results also suggest that QR is a more appropriate method than OLS for capturing these complex dynamics, as it better accounts for the variability in climate change effects across different economic conditions and forecasting horizons.

3.3 Quantile regression *versus* OLS

Continuing in the spirit of Adrian *et al.* (2019), we further examine the significance of the QR analysis by comparing the univariate regression slopes estimated for the 5th, 50th and 95th quantiles with those from the OLS regression line. Figure 3 presents the outcomes using

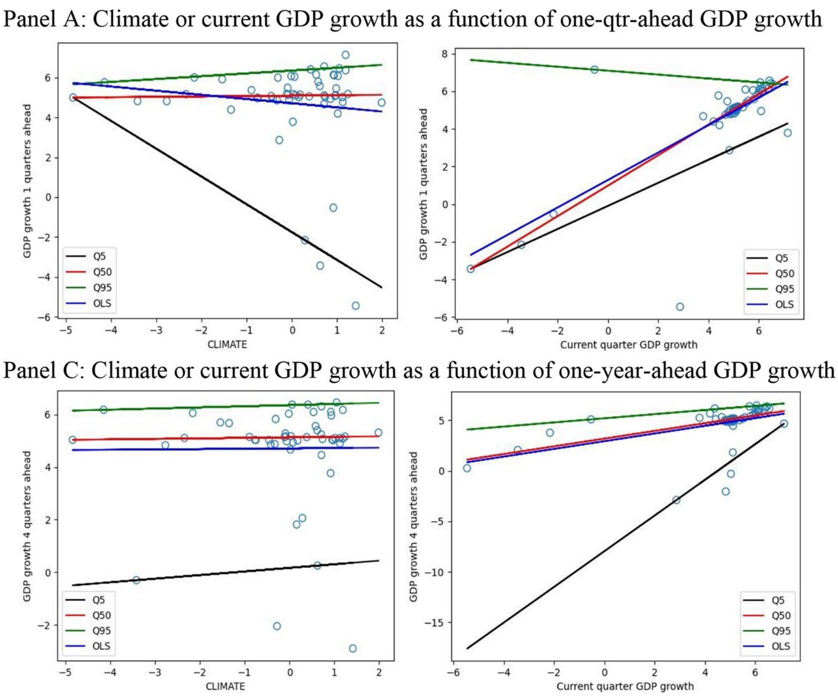

Figure 3. Quantile regression versus OLS

Note(s): The figure shows the univariate quantile and OLS regression of one-quarter-ahead and one-year-ahead real GDP on current real GDP and Climate either current GDP growth (y) or *CLIMATE* as the regressor for forecasting horizons of 1 quarter and 4 quarters.

When *CLIMATE* is used as the regressor, the slope varies significantly across the quantiles and differs from the OLS estimate for one-quarter-ahead GDP growth. However, for one-year-ahead GDP growth, the slopes for the OLS regression line and the 50th and 95th quantiles are similar, while the slope for the 5th quantile differs. This finding aligns with our earlier results, which indicated asymmetric effects across quantiles, with significance observed only at the lower quantile (0.1).

In the case where current GDP is the regressor, the slope also varies significantly across the quantiles and from the OLS estimate for both one-quarter-ahead and one-year-ahead GDP growth. These findings suggest that the QR model is a valuable tool for analyzing the impacts of both *CLIMATE* and economic factors, providing a more detailed understanding of how these variables influence future GDP growth across different economic conditions.

Figure 4 illustrates the estimated QR coefficients alongside the confidence bounds for testing the null hypothesis that the true data process follows an OLS relationship. In this analysis, quantile coefficient estimates that fall outside the confidence bounds suggest a nonlinear relationship between the predictors (*CLIMATE* and real GDP growth) and the predicted variable (one-quarter and one-year ahead real GDP growth).

Interestingly, the results show that *CLIMATE* remains within the confidence bounds and exhibits stability across both forecasting horizons. This stability implies that no nonlinear relationship is detected, suggesting that climate – measured as a principal component of floods, temperature and rainfall – is not contributing to the downside risk of growth. However, there is a tendency for *CLIMATE* to deviate at the lower quantiles, indicating that further deterioration in climatic conditions could potentially exacerbate growth tail risk.

In addition, the quantile regressions in Table 4 reveal the presence of an asymmetric effect of *CLIMATE* when the forecasting horizon (h) is 2, 3 or 4 quarters ahead. This further underscores the importance of considering different quantiles when assessing the impact of climate change on economic growth, as the effects may vary significantly depending on the state of the economy.

GDP growth on the other hand is unstable at the upper tail for one-quarter-ahead GDP growth and lower tail for the one-year-ahead GDP growth, which implied nonlinearity in the relationship between future economic growth and current economic conditions.

3.4 The estimated conditional distribution

To develop the conditional distribution of future economic growth, we use the skewed t-distribution to smooth and connect the estimated quantile distribution for each quarter by interpolating between the estimated quantiles, as described by Adrian *et al.* (2019).

Figure 5 presents the estimated conditional quantile distribution alongside the fitted inverse cumulative skewed t-distribution, conditional on either real GDP and *CLIMATE* or real GDP only. A particularly noteworthy observation is from 2015 (Q4), a period marked by extreme climatic conditions, including the lowest quarterly precipitation recorded for Q3 and Q4, above-average temperatures reaching their highest levels in Q4, and some of the lowest incidences of floods in Q3 and Q4. During this period, the distribution conditional on current GDP and *CLIMATE* shows a substantial deviation from the distribution conditional on economic conditions alone. This indicates that extreme climate events can significantly alter the conditional distribution of future economic growth, highlighting the importance of including climate variables in such analyses.

Figure 6 presents the estimated conditional distribution of future real GDP. For the one-quarter-ahead distributions, both the right and left tails appear equally unstable over time.

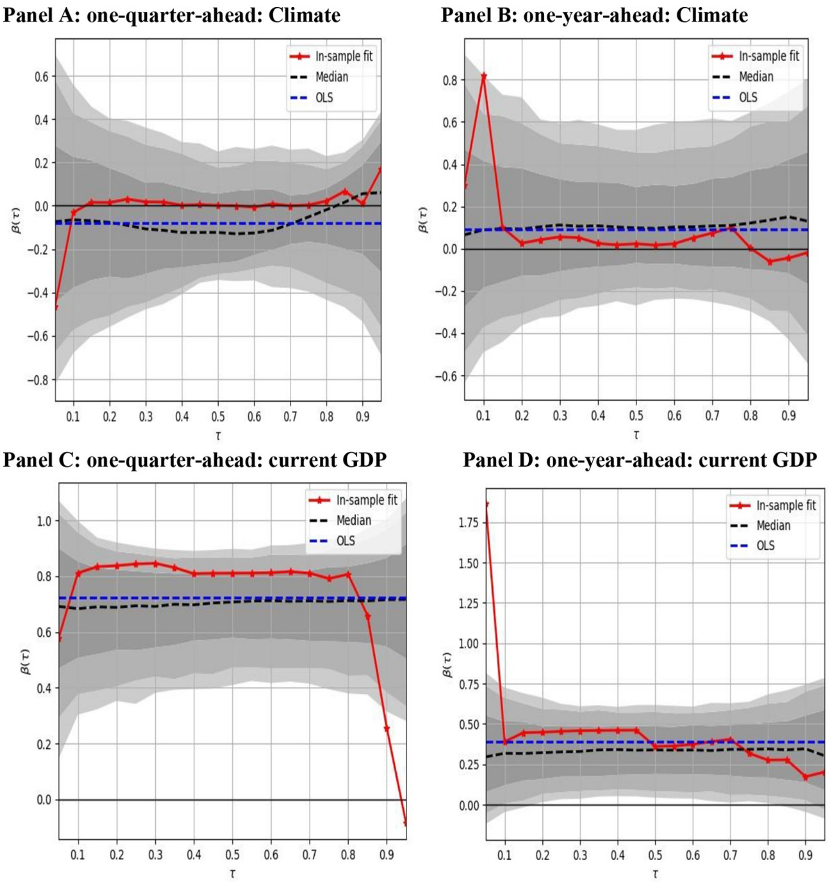

Figure 4. Do the estimated quantile regression coefficients align with a flexible and general linear model [that is, a VAR(4)]?

Note(s): This figure displayed estimated quantile coefficients of one-quarter-ahead and one-year-ahead. Following Adrian *et al*. (2019), we present the 95 % confidence bounds for the null hypothesis that the true data-generating process is a general, flexible linear model for growth and Climate, represented as a vector-auto regression (VAR) with four lags. Gaussian innovations and a constant using Climate and real GDP growth over the full sample. Bounds are computed using 1.000 bootstrapped samples

However, when examining the one-year-ahead distributions, there is a noticeable difference: the left tail and the median exhibit relatively more instability compared to the right tail. This finding suggests that the downside risks to economic growth are more variable over time than the upside risks, indicating a stronger fluctuation in potential negative outcomes.

3.5 Vulnerability of the forecasts to unexpected shocks

Next, we quantify the vulnerability of the predicted path of GDP growth to unexpected shocks. To do this, we use two alternative approaches of upside and downside entropy and expected shortfall and longrise, as in Adrian *et al*. (2019) [6].

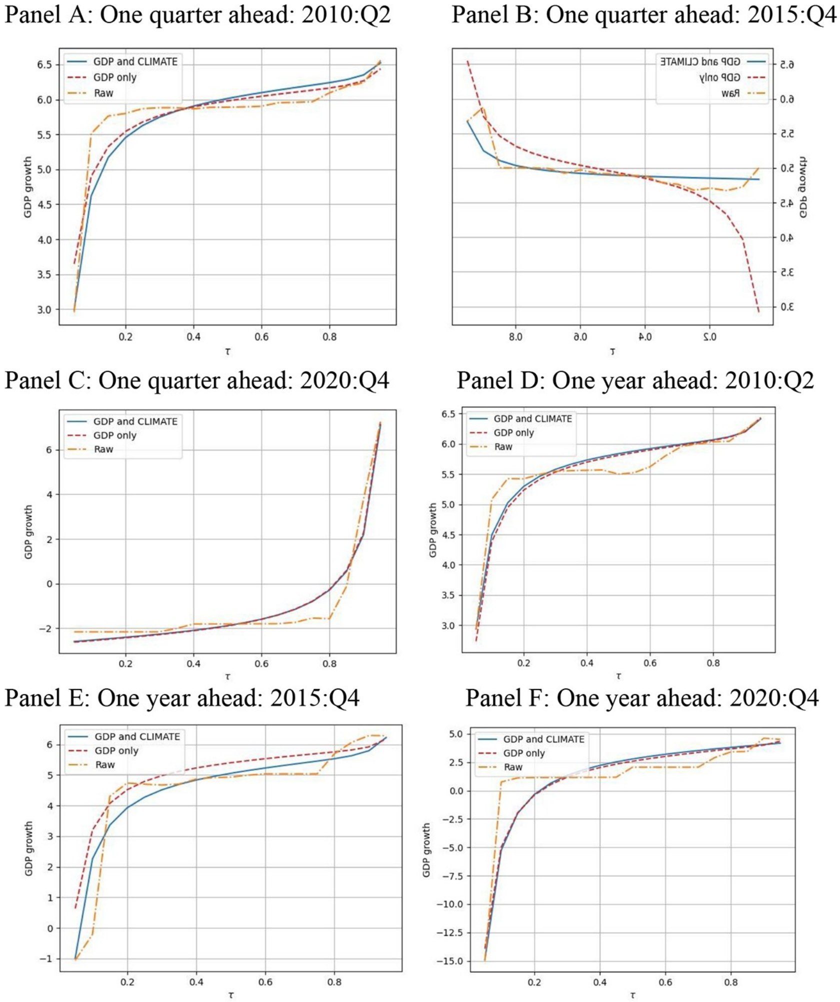

Figure 5. The conditional quantile and skewed *t*-distribution

Note(s): This figure plots the estimated conditional quantile distribution (raw) and two variations of the fitted inverse cumulative skewed *t*-distribution, one conditional on both GDP growth and Climate and the other conditional on GDP growth only, for three sample dates: 2010:Q2 – which depicts the start of recovery from an extreme point in climate condition; 2015:Q4 – which depicts presence of extreme climate condition; and 2020:Q4 – which depicts full recovery from the deepest dip in real GDP growth rate (annualised)

The entropy measure in our analysis compares the probabilities assigned to extreme outcomes by the conditional and unconditional densities. Specifically, downside entropy measures the divergence below the median of the conditional density, while upside entropy measures it above the median. When these entropy measures are high, it indicates that the conditional density assigns a positive probability to more extreme outcomes in the left (for downside entropy) or right (for upside entropy) tails than the unconditional density.

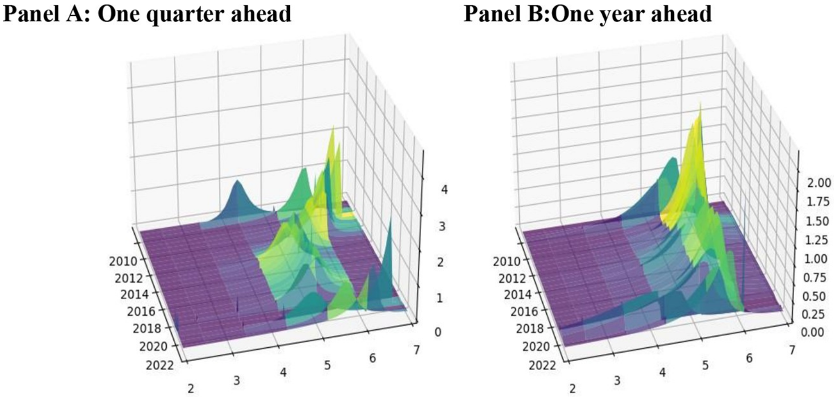

Figure 6. Estimated conditional distribution

Note(s): This figure displays the one-quarter-ahead and one-year-ahead predictive conditional distributions for real GDP growth over the period 2009:Q1 to 2022:Q1. These are based on quantile regression with current real GDP growth and CLIMATE as conditioning variables

Unlike entropy measures, which capture the excess tail behavior of the conditional distribution relative to the unconditional distribution, expected shortfall and longrise (related to the upper tail) provide an absolute measure of tail behavior in the conditional distribution. These metrics offer a different perspective by quantifying the potential extremity of growth outcomes directly from the conditional distribution.

In Figure 7, panels A and B show that both downside and upside entropies for one-quarter and one-year periods are equally volatile. However, panels C and D reveal that the 5% expected shortfall measure is more volatile than the 95% expected longrise measure. This suggests that the predicted path of GDP growth is highly vulnerable to unexpected shocks, as indicated by the volatility in both the entropy measures and the 5% expected shortfall measure. These findings imply that while downside growth risks are critically important in the context of unexpected *CLIMATE* and economic (current GDP) shocks, the potential for upside growth risk also plays a significant role and should not be overlooked.

3.6 Out-of-sample versus in-sample

In this part of the analysis, we compare the out-of-sample predictions with the in-sample predicted conditional distributions for two forecasting horizons: one quarter and one year. The in-sample estimations, covering a period from 2008Q1 to 2016Q4, are used to generate the predicted distribution for 2017:Q1. This process is then iterated by expanding the sample quarter by quarter until the end of the data set, resulting in approximately a six-year time series of out-of-sample density forecasts for each horizon.

Figure 8 provides insights into these comparisons. Panels A and B show the selected quantiles and downside entropy computed using both the full sample (in-sample) and out-of-sample predictions. The results indicate that the out-of-sample predictions closely match the in-sample predictions for most of the time, with the notable exception of the COVID-19 period (2020:Q1-2022:Q1). In addition, the predictions for the one-year ahead horizon are more consistent between in-sample and out-of-sample estimates.

Panels C and D further illustrate that, aside from the COVID-19 period, the stability of the out-of-sample estimates suggests that the downside vulnerability in GDP growth can be

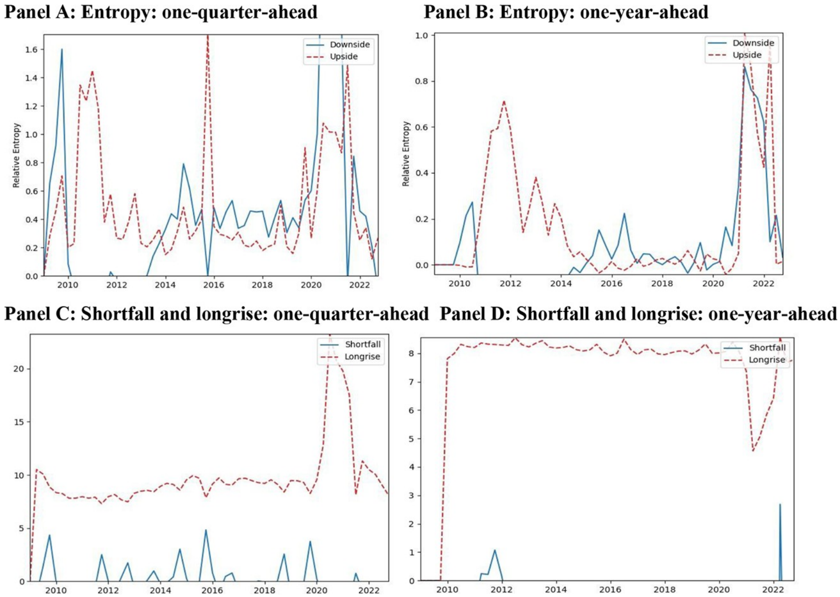

Figure 7. Growth entropy and expected shortfall

Note(s): This figure shows the time series evolution of relative downside and upside entropy and the 5% expected shortfall and longrise

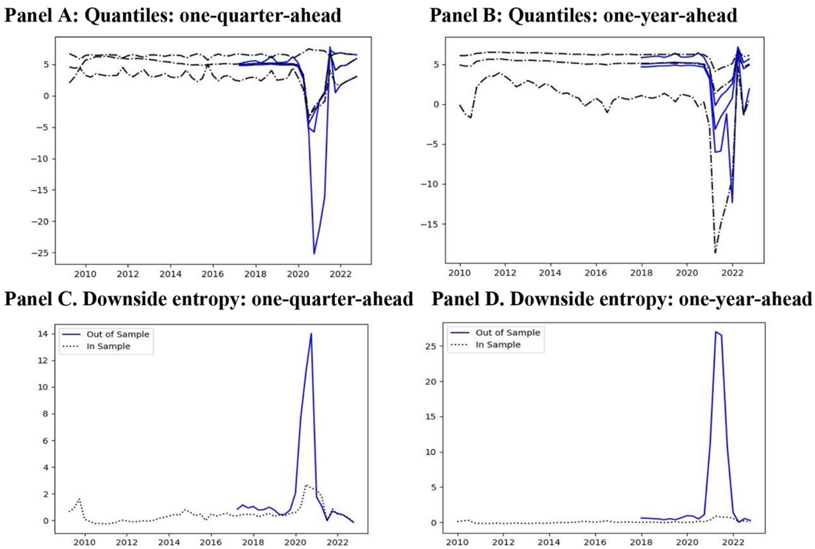

Figure 8. Out-of-sample predictions

Note(s): This figure compares out-of-sample and in-sample predictive densities of future GDP growth for the 5th, 50th and 95th quantiles (Panels A and B). The downside entropy for the future real GDP are provided in panels C and D effectively detected using the *CLIMATE* variable. This finding underscores the importance of incorporating climate data into predictive models, particularly for identifying periods of increased economic risk.

3.7 An explanation of the results

Our key finding is that climate change matters most to lower tail risks and this effect is statistically significant and positive. We argue that when the economy is not doing well (lower tail) and it is battered by climate change, the resulting fiscal stimulus aimed at recovery from climate change ends up stimulating economic growth. In this section, we test this claim by regressing real GDP growth on fiscal expenditure on climate change related disasters, which is estimated to be around 5% of the total fiscal expenditure. The quantile regression results are plotted in Figure 9 below. We see that at the lower tails the effect of fiscal stimulus is 2–3 times more than those observed at higher tails. The lower quantile slope coefficients are statistically different from zero with a minimum *t*-statistic of 2.44. However, at quantile 0.8 and 0.9, the slope coefficients are statistically insignificant at the 5% level with a *t*-statistic in the range of 1.19–1.81. The key implication from this analysis is that the main channel of the climate change-economic growth positive relation is fiscal expenditure on climate change related disasters.

4. Concluding remarks

There is a vast body of literature on the relationship between climate change and economic growth, with many studies predominantly showing a negative effect of climate change on economic growth. However, this relationship requires a deeper understanding, both economically and statistically. Specifically, the nexus between economic growth and climate change is conditional on two key factors: (a) whether the analysis focuses on short-run versus long-run effects, and (b) the state of the economy – whether it is in an expansionary phase or underperforming.

When considering the state of the economy, it is crucial to test the hypothesis not just at the mean level but across various quantiles. Quantile analysis is particularly relevant because it exposes tail risks; lower quantiles capture the state of the economy when it is underperforming, while upper quantiles reflect periods of strong economic performance. The

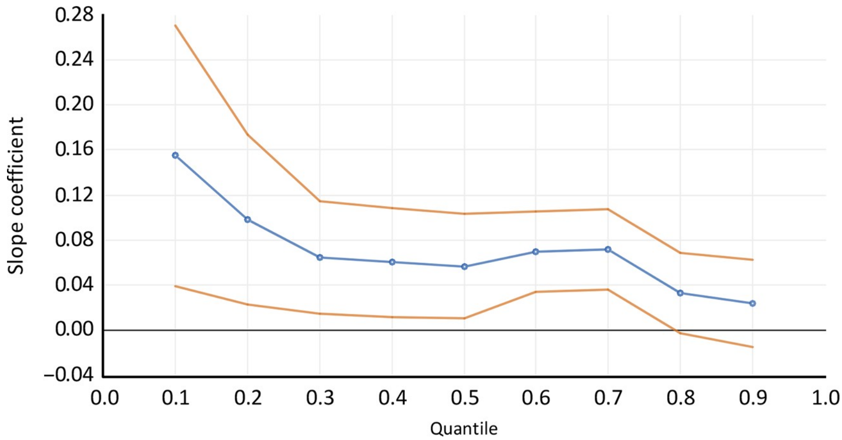

Figure 9. Fiscal expenditure on climate change and economic growth effects

impact of climate change on economic growth can differ depending on these conditions, especially because climate-induced fiscal response, such as stimulus measures, may have varying effects depending on whether the economy is thriving or struggling.

This paper adopts this perspective and makes its contribution by exploring how climate change affects economic growth across different economic states, emphasizing the importance of considering both short-term and long-term effects, as well as the economy's current performance level.

We set up a GaR model for the Indonesian economy, where economic growth and its future trajectories are modeled as a function of climate change. Among our key findings, we uncover evidence that climate change has the most significant impact on lower tail risks, with this effect being both statistically significant and positive. Our analysis suggests that when the economy is struggling and simultaneously impacted by climate change, the fiscal stimulus aimed at recovery not only mitigates the damage but also stimulates economic growth.

The regression models we employed demonstrate that fiscal stimulus has a pronounced effect on boosting economic growth at lower quantiles, which correspond to periods when the economy is underperforming. However, this effect diminishes at higher quantiles. This pattern indicates that the primary channel through which climate change positively influences economic growth is through fiscal expenditure directed toward recovery from climate-related disasters.

Our findings based on the GaR framework have important implications for policy formulation. The analysis indicates that employing a linear method to assess climate effects on economic growth may be inadequate. Evaluating the impact of climate change across different levels of economic development is crucial for comprehensively understanding economic resilience to climatic fluctuations during periods of both growth and contraction. It also enables rigorous assessment of macro-level climate policy effectiveness throughout these cycles. This study offers several promising directions for future research: integrating key climate change indicators, particularly those reflecting extreme weather phenomena; conducting province-level analyses that consider regional variations in temperature and precipitation; and investigating sector-specific effects of climate change.

The presence of Islamic banking in Indonesia may shape the policy implications of our findings. By emphasizing asset-based financing and risk-sharing, Islamic banks may be less exposed to speculative cycles and can contribute to greater financial resilience during climate-related shocks. In a dual-banking system, climate-induced fiscal stimulus may therefore be transmitted through a more stable credit channel, particularly when growth is weak. These insights extend beyond Indonesia, suggesting that in Muslim-majority and dual-banking economies, integrating climate-responsive fiscal policy with Islamic finance instruments – such as sukuk and profit-and-loss sharing – can enhance macroeconomic resilience to climate risks.

Notes

[1.] Also see, https://climateknowledgeportal.worldbank.org/climate-change-overview

[2.] Sourced from https://dicf.unepgrid.ch/indonesia/climate-change

[3.] Also see, https://climateknowledgeportal.worldbank.org/sites/default/files/2021-05/15504-Indonesia%20Country%20Profile-WEB_0.pdf

[4.] Also see, https://climateknowledgeportal.worldbank.org/sites/default/files/2021-05/15504-Indonesia%20Country%20Profile-WEB_0.pdf

[5.] The left tail is associated with low level of GDP, and *vice versa*. This means that a left-skewed distribution is associated with recessions (or downside risks) while during expansions (upside risks), the conditional distribution is closer to being symmetric.

[6.] We summarise the intuitive explanation as in Adrian *et al*. (2019). For the actual formulars refer to Adrian *et al*. (2019).

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Appendix

Table A1. Data description

Time series	Source
Output data	
Historical data GDP	Bank Indonesia
Climate change data	
Temperature	Climate engine
Rainfall	Climate engine
Floods (all forms)	National agency for disaster countermeasure (BNPB)

Corresponding author
Paresh Kumar Narayan can be contacted at: paresh.narayan2014@gmail.com