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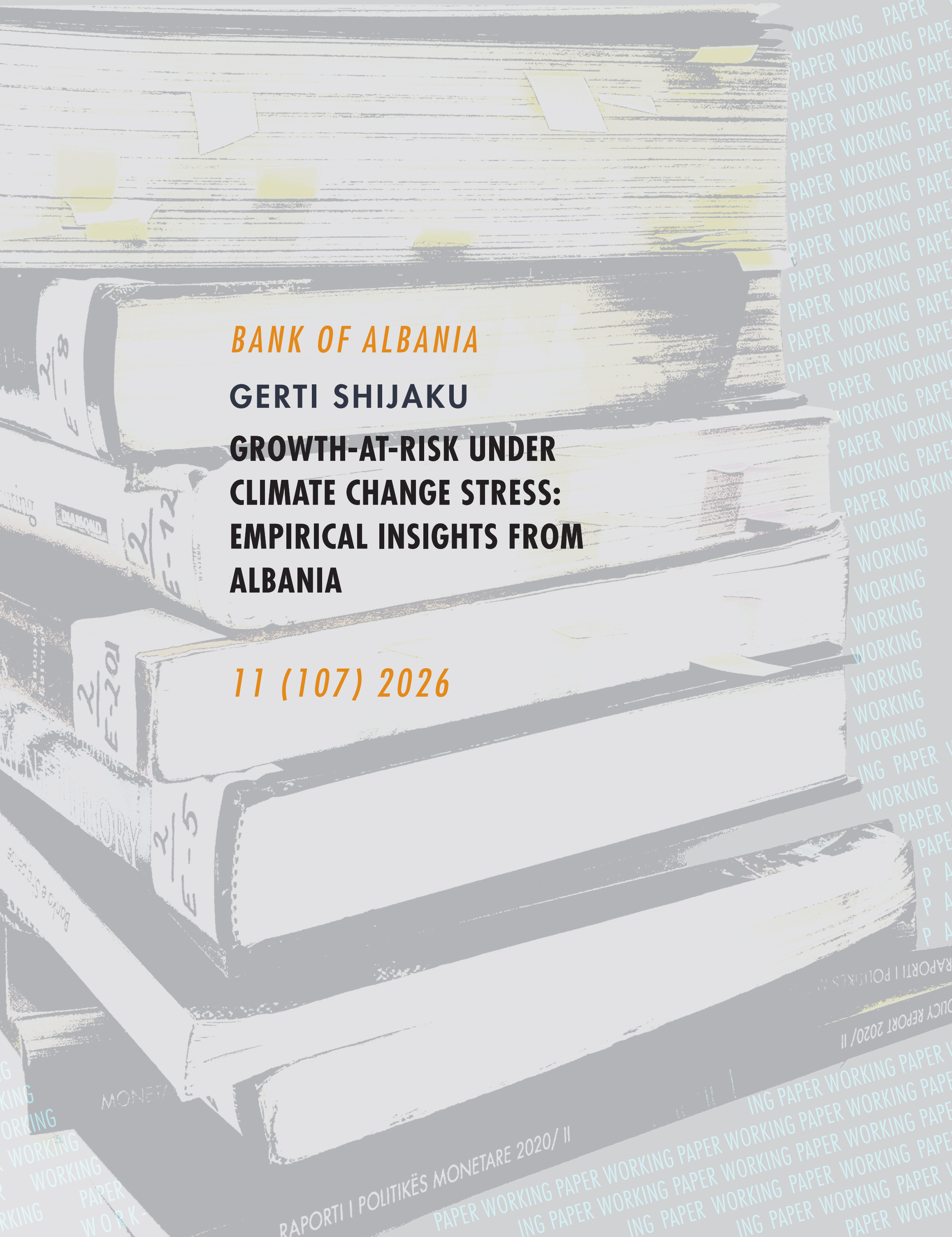

*BANK OF ALBANIA*

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# GROWTH-AT-RISK UNDER CLIMATE CHANGE STRESS: EMPIRICAL INSIGHTS FROM ALBANIA

*11 (107) 2026*

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# ABSTRACT

*Climate change presents profound risks not only for the environment but also for economic stability. These risks are intricately linked to growth outcomes, and understanding their impact requires a forward-looking analytical framework. This paper applies the Growth-at-Risk (GaR) approach, using Albanian macro-financial and climate-related data alongside quantile regression, to assess how climate vulnerabilities influence the likelihood and severity of future episodes of weak or negative economic growth. The results show that climate stress significantly amplifies downside tail risks to GDP, with non-linear effects across the growth distribution, most pronounced in low-growth scenarios. Physical risks have a stronger impact on adverse outcomes than transitional risks, although their influence diminishes at higher quantiles, where transitional risks gain relevance. These findings highlight the critical role of climate risk mitigation in preserving economic stability and reducing vulnerability to future growth shocks.*

*Keywords: Growth-at-Risk (GaR), climate change risk, financial stability, quantile regression, tail risk, macro-financial vulnerability, Albania.*

*JEL Codes: E17, E44, O13, Q54.*

**Disclaimer**: *The views expressed herein are of the author and do not necessarily represent the views of the Bank of Albania. The author is grateful to his colleagues in the Research Department, particularly Altin Tanku, Director of the Research Department, for their valuable comments and suggestions on earlier drafts of this paper.*

# 1. INTRODUCTION

Economic growth remains a foundational pillar of social progress, driving advancements in living standards, employment, and economic opportunity. However, climate-related risks are increasingly recognized as systemic threats to macro-financial stability, with the potential to disrupt productivity, investment flows, and financial markets (NGFS, 2022). The transition to a low-carbon economy, while essential, introduces financial risks that are systemic in nature, affecting asset portfolios, institutional viability, and market dynamics (Battiston et al., 2017). Once viewed primarily through an environmental lens, climate change is now understood to pose multifaceted macroeconomic risks through two principal channels: physical and transition risks (Agarwala et al., 2021). Physical risks—including rising global temperatures, extreme weather events, and sea-level rise—can severely damage infrastructure, reduce agricultural yields, impair labour productivity, and destabilize supply chains, particularly in climate-sensitive regions. These disruptions amplify short-term economic volatility and erode long-term output potential. Transition risks, often associated with decarbonization efforts, encompass regulatory shifts, technological innovation, and capital reallocation. While such changes may incur short-term economic costs, they also present critical opportunities for fostering long-term resilience, driving innovation, and promoting both environmental sustainability and economic stability.

From a theoretical standpoint, much of the existing literature continues to emphasize long-term growth trajectories, offering limited guidance on recession dynamics and the identification of macro-financial vulnerabilities—particularly regarding the limitations of standard models in capturing GDP exposure to "tail risks", understood as a degeneration of the unconditional relative to conditional distribution (Plagborg-Møller et al., 2020; Ivanova et al., 2021). O'Brien and Wosser (2021) argue that a fundamental component of risk analysis and policy design lies in understanding the directional path and magnitude of potential growth under downside scenarios, especially those involving the gradual accumulation of vulnerabilities and external market stress. Consequently, macroprudential policy must extend beyond crisis prevention to include the estimation of downside 'tail risks'—those associated with endogenous macro-financial imbalances and exogenous shocks—prompting scholars to incorporate these risks more systematically into forecasting frameworks. Notably, Adrian et al. (2019a) introduced the Growth-at-Risk (GaR) approach, a forward-looking tool for assessing the probability of adverse growth outcomes, particularly those located in the lower tail of the GDP distribution, conditional on prevailing macro-financial conditions. By emphasizing downside vulnerabilities rather than average projections, GaR offers a more nuanced understanding of economic fragility under climate stress. Complementing this framework, Quantile Regression (QR) enables the estimation of conditional quantiles, capturing non-linear relationships and distributional asymmetries that traditional mean-based models often overlook (Adrian et al., 2019b; O'Brien & Wosser, 2021). Inspired by Value-at-Risk (VaR) methodologies, the integration of climate variables into GaR models has gained traction among central banks and international financial institutions, particularly following the IMF's Global Financial Stability Report (2017). The combined use of GaR and QR provides several analytical advantages: it accommodates crisis episodes, links macro-financial conditions to growth probabilities, and facilitates the integration of climate-related risks (Prasad et al., 2019; Iseringhausen, 2021). Unlike central-scenario projections, GaR delivers a full distributional view, enabling risk-sensitive policy choices. It also identifies key growth drivers across quantiles and forecasting horizons and supports the continuous monitoring of systemic vulnerabilities. Crucially, this framework provides a robust mechanism for quantifying the macroeconomic implications of climate change, thereby expanding the macroprudential policy toolkit and informing climate-sensitive economic strategies.

This paper applies these methodologies to assess the impact of climate change risks on the distribution of GDP growth in Albania, guided by two core motivations. First, as illustrated in Figure 1 in the Appendix, stylized facts from Albania's quarterly growth data (2004 Q1–2023 Q1) reveals a left-skewed distribution and frequent tail events. Approximately 13% of annual growth rates fall below the 10th percentile and 28% fall below the 2nd percentile, indicating heightened vulnerability to adverse shocks. Second, climate change—driven by unsustainable production and consumption patterns—poses escalating risks to economic stability, as both physical and transition risks affect productivity, infrastructure, and sectoral performance. Despite growing interest in this area, empirical evidence on the macroeconomic implications of climate risks remains limited. Drawing on the long-run risk literature (Bansal et al., 2016; Pindyck, 2012), this study incorporates a synthetic climate risk index constructed via the Entropy Weight method (Shijaku, 2022), capturing acute, chronic, adaptation, exposure, and mitigation dimensions. The index reflects both observable and latent climate vulnerabilities. Using Quantile Regression, the paper estimates the conditional distribution of GDP growth and evaluates how climate risk dynamics influence median and lower-tail outcomes. This approach allows for non-linear and quantile-specific effects and highlights the differential roles of individual climate risk components. The findings contribute to the macroprudential policy literature by offering a framework for monitoring and mitigating downside growth risks in climate-vulnerable economies.

This paper makes four key contributions. First, it introduces a novel synthetic climate change risk indicator, constructed using the Entropy Weight method, enhancing real-time monitoring and cross-country comparability. Unlike existing indices, this data-driven metric captures both quantitative and qualitative dimensions of climate risk, enabling timely supervision and informed policy decisions. Second, the indicator integrates acute, chronic, and transition risks—specifically adaptation, exposure, and mitigation dimensions—thereby addressing gaps in conventional measurement approaches and supporting a more comprehensive understanding of sustainable development. Third, the study fills a notable empirical gap in the Growth-at-Risk (GaR) literature by examining both the predictive and causal effects of climate risks on GDP growth, with a focus on an emerging small open economy, Albania. It highlights the endogenous, nonlinear, and distribution-sensitive nature of climate dynamics, and the heterogeneity across physical and transition risk channels. Fourth, the paper contributes to the macro-prudential policy discourse by demonstrating how climate risks condition the entire distribution of GDP growth, thereby offering a framework for risk-sensitive forecasting and preventive policy design. These insights are particularly relevant for central banks and institutions seeking to integrate climate risks into economic surveillance and resilience strategies.

The empirical findings confirm that Albania has experienced adverse growth episodes consistent with the Growth-at-Risk (GaR) framework, marked by elevated probabilities of severe downturns. Climate change risks exert a significant and quantile-dependent influence on GDP growth, with non-linear effects most pronounced in the lower tail of the distribution—reflecting heightened vulnerability during periods of weak economic conditions. Physical risks, such as extreme weather events, have a stronger impact on lower quantiles, while transition risks gain relevance in the upper tail, indicating differentiated effects across the growth distribution. Additional macro-financial factors—such as consumer sentiment, real estate dynamics, and interest rate burdens—contribute to downside risks, while bank prudential behaviour plays a limited role. These results suggest that climate-related vulnerabilities primarily operate through broader macroeconomic channels. Overall, the findings underscore the need to integrate climate risk assessments into Albania's macro-financial surveillance and policy frameworks to strengthen resilience and support targeted, adaptive policy responses.

The paper is structured as follows. Section 2 provides a concise review of the relevant literature. Section 3 outlines the theoretical framework, details the empirical methodology, and describes the data sources and variable construction. Section 4 reports the estimation results. Finally, Section 5 concludes with a summary of key insights and their policy implications.

# 2. LITERATURE REVIEW

Traditional neoclassical growth models, such as Solow-Swan (1956) and Cass-Koopmans (1965), historically treated environmental degradation and climate change as exogenous externalities, largely disconnected from the internal mechanics of economic growth. These foundational frameworks emphasize technological progress and capital accumulation as the primary drivers of long-run output, thereby underestimating the role of environmental feedback effects and systemic vulnerabilities.

In contrast, Integrated Assessment Models (IAMs) — notably Nordhaus's DICE model (1991) — and more recent endogenous growth frameworks have begun to use ad hoc or highly stylized function, linking temperature rise or extreme climate events to GDP loss, marking a conceptual shift toward embedding environmental risks within macroeconomic modelling. These functions often lack strong empirical grounding and may underestimate nonlinear thresholds or tipping points.

However, a growing body of empirical evidence underscores the complex and bidirectional relationship between climate dynamics and economic performance, reinforcing the case for integrating climate risks into growth models. Contemporary approaches — including panel regressions, structural vector autoregressions (SVAR), and machine learning techniques—now increasingly treat climate variables not as peripheral shocks but as endogenous forces that both influence and respond to macroeconomic trajectories. For instance, Dell et al. (2008, 2012, 2014) and Acevedo et al. (2020) document that rising temperatures significantly depress growth in low-income countries, while Burke et al. (2015) quantify long-run output penalties associated with climate volatility. Bansal et al. (2016) link climate risk to asset devaluation and long-run growth fragility. Nath et al. (2023) suggest that global growth remains interconnected, with temperature shocks reducing output in warmer regions while modestly boosting it in colder ones. Casey et al. (2023) find that temperature anomalies affect income levels more than growth rates, whereas Burke and Tanutama (2019) report persistent output losses following climate shocks. More recently, Gupta et al. (2024) develop a dynamic model in which temperature anomalies — driven by emissions — emerge as endogenous outcomes of economic activity. Their findings underscore that climate change is not merely a passive shock to the economy, but a recursive force that both shapes and is shaped by macroeconomic trajectories. This evolving climate-growth literature remains emergent, structured around two dominant methodological strands: the enumerative approach, which employs Computable General Equilibrium (CGE) models to estimate sectoral losses, and the dynamic econometric approach, which leverages econometric techniques to capture adaptation effects over time. While CGE models offer tractability, they often neglect price dynamics and sectoral interdependencies (Tol, 2022). Conversely, dynamic models provide richer insights into behavioural responses but rely heavily on spatial substitution and cross-sectional data, which may limit their generalizability (Akram, 2012).

Despite notable progress, conventional models continue to struggle with quantifying tail risks and recession dynamics (Plagborg-Møller et al., 2020). Recognizing the nonlinear nature of macro-financial conditions (Burke et al., 2015), recent research increasingly adopts non-parametric techniques to trace the full predictive distribution of GDP and identify systemic vulnerabilities (O'Brien & Wosser, 2021). Since the IMF's Global Financial Stability Report (2017), the tail-at-risk framework has gained prominence in macro-financial surveillance, reflecting growing awareness of the limitations of mean-based forecasting in capturing rare, high-impact events. These approaches enable the identification of heterogeneous climate effects across countries, sectors, and time horizons, revealing how environmental stressors—such as temperature volatility, precipitation anomalies, biodiversity loss, and carbon emissions—affect productivity, labour supply, capital accumulation, and long-run growth potential. To address climate-related risks, Bansal and Yaron's (2004) recursive utility framework inform on the development of models that account for climate-induced disasters, emphasizing the role of long-run risks and investor sensitivity to persistent shocks. Building on this foundation, Bansal et al. (2016) demonstrate that breaches of temperature thresholds significantly depress asset valuations and exacerbate macroeconomic fragility, underscoring the systemic nature of climate tail risks.

More recently, Byrne and Vitenu-Sackey (2024) apply a factor stochastic volatility model to more than a century of panel data across 30 countries, finding that global climate risk shocks exert a disproportionately negative impact on macroeconomic activity, particularly in emerging economies. Extending this line of inquiry, and building on the pioneering work of Adrian et al. (2019), recent studies have integrated Quantile Regression (QR) into the Growth-at-Risk (GaR) framework to better reflect the asymmetric and state-dependent nature of climate-economic interactions. Contributions by Kiley (2024), Ferrara et al. (2021), and Prasad et al. (2019) show that QR-based GaR models effectively capture nonlinearities and tail risks in both GDP and climate dynamics, offering a more distribution-sensitive lens for macro-financial surveillance under rising climate uncertainty. Some other climate-specific extensions further refine this methodology. Bansal et al. (2016) introduce a temperature-augmented long-run risks model, showing that breaches of climate thresholds depress asset valuations and intensify macroeconomic fragility. Similarly, Suarez (2021) develops Climate-at-Risk and Carbon Price-at-Risk metrics to trace the transmission of climate shocks through financial markets and growth trajectories. These innovations provide policymakers with forward-looking tools to assess systemic vulnerabilities and design macro-prudential strategies that enhance resilience in the face of climate-induced disruptions.

This literature increasingly differentiates between physical risks—stemming from acute climate events such as floods, droughts, and heatwaves, which disproportionately affect the lower tail of the growth distribution (Busetti et al., 2020)—and transition risks—arising from policy shifts, technological change, and structural adjustments toward de-carbonization, which tend to manifest in upper quantiles during expansionary phases (Di Febo, 2025). These asymmetric effects underscore the importance of distribution-sensitive modelling approaches. As Battiston et al. (2017) argue, both risk types pose systemic threats to financial stability, reinforcing the need for forward-looking macro-financial frameworks that can capture the full spectrum of climate-related vulnerabilities—particularly those concentrated in the tails of the growth distribution.

Despite notable progress, important limitations persist in the climate-macro-financial literature. First, data gaps concerning extreme events constrain tail-risk precision, particularly in vulnerable regions. Moreover, the reliance on narrow proxies like temperature and precipitation  overlooks broader climate dynamics such as greenhouse gas emissions, sea-level rise, and event frequency (Mitra et al., 2025). While these variables offer consistency and accessibility, they tend to oversimplify the complex transmission mechanisms through which climate change affects macroeconomic outcomes. Establishing robust empirical linkages remains particularly challenging due to latent effects and indirect pathways (Akram, 2012). Furthermore, conventional indicators frequently overlook transition risksarising from policy shifts, technological disruption, and the economic costs of adaptation and mitigation (EIB, 2021). Second, adaptation remains difficult to quantify and is frequently treated as a residual rather than an endogenous component of economic modelling, which underscores the need to rethink growth theory by embedding environmental dynamics at its core (Dietz & Stern, 2015). Third, GaR's short-term focus limits its ability to capture deep uncertainty associated with long-term climate tipping points thatunfold nonlinearly over decades (Wunderling et al., 2024), whereas climate-sensitive models (Bansal et al., 2016; Suarez, 2021) provide forward-looking approaches better suited to assessing resilience under prolonged climate disruption. Finally, while climate-sensitive tail risks remain weakly integrated into Integrated Assessment Models (IAMs), limiting comparability and policy relevance, Drenkovska and Volčjak (2022) propose composite indicators to capture both physical and transition risks, reinforcing the analytical value of QR-based GaR models for assessing multidimensional vulnerabilities. Expanding on this perspective, Phiri (2025) calls for interdisciplinary frameworks that holistically align environmental, economic, and social objectives, emphasizing the need to move beyond siloed approaches in climate risk analysis.

To address these gaps, this study proposes three contributions: (i) generating new country-level GaR estimates that account for climate-specific vulnerabilities; (ii) applying subnational Quantile Regression to capture localized tail risks and adaptation heterogeneity; and (iii) integrate macro-financial data into the GaR framework to better reflect market-based assessments of climate risk exposure. Together, these innovations aim to enhance the empirical grounding and policy utility of climate-informed macro-financial surveillance. As Coelho and Restoy (2023) emphasize, the evolving nature of climate-related financial risks demands a rethinking of macroprudential policy design—one that relies on multidimensional metrics and forward-looking surveillance tools capable of capturing systemic exposures across both physical and transition risk dimensions.

# 3. METHODOLOGY AND DATA

## 3.1. A theoretical model of coupling the economic growth and climate change risk

In the context of globalization and technological advancement, climate change and environmental degradation—driven by unsustainable production and consumption patterns—are increasingly shaping macroeconomic policymaking. A growing body of research emphasizes that these risks pose not only ecological threats but also significant challenges to economic growth and financial stability (Economides et al., 2018). As Akram (2012) observes, contemporary macroeconomic theory supports an integrated analysis of growth, business cycles, and policy, often through stylized models that incorporate climate-related dynamics[1].

At the core of this analytical framework lies the Real Business Cycle (RBC) model, in which a representative household maximizes intertemporal utility:

$$E_t \sum_{t=0}^{\gamma} \beta^t U(Y_t) \tag{1}$$

Where, $Y$ denotes output at time $t$; $\beta \epsilon (0,1)$ represents the discount factor reflecting time preferences; and $U(\cdot)$ denotes a concave utility function. Under environmental constraints and subject to budget and resource limitations, the utility function is extended to include a new factor $D_t$, representing climate-related damages:

$$E_t \sum_{t=0}^{\gamma} \beta^t U(Y_t, D_t) \tag{2}$$

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[1] *Among others, see also Nordhaus (2014), Golosov et al. (2014), and the subsequent extension by Hassler et al. (2016).*

The production function is extended to incorporate environmental stock and flow variables, such as biodiversity and emissions, thereby capturing the dual impact of physical and transition risks on economic output. This modification reflects the growing need to embed climate-related dynamics within macroeconomic modelling. Formally, the augmented production function can be expressed as follows:

$$Y_t + K_{t+1} + L_{t+1} \approx \alpha K_t + (1 - \alpha)L_t + f(K_{0,t}, L_{0,t}, F_{0,t}\, D_{0,t}) \qquad (3)$$

Or, in a more compact form:

$$Y_{t+1} \approx A_t K_t^{\alpha} L_t^{1-\alpha} + e^{\beta_i(D_t, F_t)} \qquad (4)$$

Here, $A_t$ denotes total factor productivity (TPF); $K_t$ and $L_t$ represent capital and labour inputs, respectively[2]; $a$ and $(1-a)$ are the corresponding output elasticities; $D_t$ is a stock variable (e.g., clean air or biodiversity) that captures accumulated climate-related damages; and $F_t$ is a flow variable (e.g., fuel emissions)[3] reflecting ongoing environmental pressures. The parameter $\beta$ captures the sensitivity of output to environmental degradation and climate-related damages.

Technological progress, denoted by $e$ , is driven by advancements in infrastructure, education, health, and innovation, which collectively enhance the efficiency of input utilization. Assuming a steady-state growth rate $g_t$, the evolution of productivity is given by:

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[2] *For simplicity among several authors— including Economides et al., (2018) —labour supply is assumed to be inelastic and fixed at unity. Consequently, the consumer-producer derives utility solely from private consumption, a specification that Hassler and Krusell (2018) declare to be inconsistent with longer-run data.*

[3] *Golosov et al. (2014) refer to the negative externalities arising from such activities as "damages," which are embedded into the production function.*

$$\frac{\Delta A_t}{A_t} \approx g_t + \beta d_t \tag{5}$$

Assuming an exponential form for productivity, $A_t \approx A_0 e^{z_t}$, the log-linear transformation yields:

$$log\ (A_t) \approx log\ (A_0) + z_t \tag{6}$$

Here, $z_t$[4] represents cyclical deviations from the long-run productivity trend. Following Tol (2022), this framework allows for the derivation of output growth rates that explicitly account for climate-related shocks and their influence on economic performance is expressed as:

$$g_t \approx g_0 + \alpha K_t + (1 - \alpha) L_t - (1 + D_t) \tag{7}$$

This formulation implies that climate damages reduce growth by a factor of $1/(1+D_t)$, with effects becoming more pronounced as damages accumulate over time. As Golosov et al. (2014) and Hassler et al. (2016) argue, environmental variables such as emissions and biodiversity affect both utility and output, underscoring the importance of integrating climate considerations into long-term macroeconomic modelling.

This dynamic mechanism is particularly salient in the context of physical climate risks—including heatwaves, droughts, and floods—which can disrupt supply chains, reduce agricultural yields, and depress productivity (Ripple et al., 2022; Frame et al., 2020). These risks tend to materialize rapidly and exert immediate negative effects. By contrast, transition risks—arising from climate mitigation

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[4] *Regarding the cyclical structure, as Economides et al., (2018) explain, it follows a stochastic process of order AR(1), expressed as* $z_t = \rho z_{t-1} + \varepsilon_t$, *with* $\varepsilon_t$ *following i.i.d process with normal distribution* $E_t\, \varepsilon_t = 0$ *and constant variance* $\sigma_t^2$. *In this setup, the stochastic productivity constitutes the sole source of uncertainty in the economy and serves as the driving force of the RBC methodology.*

and adaptation policies—unfold more gradually. While they may increase short-term production costs due to regulatory compliance or investment in cleaner technologies, they can enhance long-term efficiency, solvency, and disposable income. Consequently, the net effect of climate risks on economic growth is context-dependent: physical risks often suppress short-term output, whereas well-managed transition risks may foster long-term resilience and sustainability.

## 3.2. Empirical Strategy: Growth-at-Risk and climate change risks through Quantile Regression

Building on the theoretical model outlined in Equation (7), this section presents the empirical strategy used to assess how climate change risks influence the distribution of GDP growth in Albania. Following the methodology of Drenkovska and Volčjak (2022), the analysis adopts a backward-looking approach to estimate the full conditional distribution of economic growth in response to macro-financial and climate-related vulnerabilities. The baseline specification is defined as follows:

$$g_t = \beta_0 + \sum_{i \epsilon I} \beta_i X_{i,t-h} + \varepsilon_t \tag{8}$$

where $g_t$ denotes GDP growth at time $t$; $\beta_0$ is the intercept; $\beta_1$ captures the marginal contribution of explanatory variable ; $X_{i,t-h}$ represents a set of lagged macro-financial and climate-related indicators, including the Economic Sentiment Indicator (ESI), House Price Index (HPI), T-bill rate, loan-to-GDP ratio, fiscal policy stance (FP), Bank Prudential Indicator (BPI), and the Climate Change Risk Index (CCRI); and $\varepsilon_t$ denotes the error term.

Traditional linear regression estimates the conditional mean of the dependent variable, offering limited insight into distributional asymmetries — particularly in the tails, where macro-financial and climate shocks exert disproportionate effects. To address this limitation, the study applies the Growth-at-Risk (GaR) framework alongside Quantile Regression (QR), following O'Brien and Wosser (2021).

Inspired by the Value-at-Risk (VaR) concept in finance, GaR focuses on the probability that GDP growth falls below lower quantiles (e.g., 5th or 10th percentile), thereby emphasizing downside risks ( Adrian et al.,2019a; Prasad et al., 2019). QR, introduced by Koenker and Bassett (1978), complements the GaR framework by estimating conditional quantiles rather than the means[5], enabling the analysis of tail risks and heterogeneous effects across the growth distribution (Suarez, 2021).

Under the combined QR and GaR approach, Equation (8) is reformulated as follows:

$$g_t^q = \beta_0^q + \beta_1^q X_{1,t-1} + \beta_2^q X_{2,t-1} + \cdots + \beta_i^q X_{i,t-h} + \varepsilon_t^q \qquad (9)$$

Or, in a more compact form:

$$g_t^q(q|X_{i,t-h}) = \beta_0^q + \sum_{i\epsilon I} \beta_i^q \, X_{i,t-h} + \varepsilon_t^q \qquad (10)$$

where, $g_t^q(q|X_{i,t-h}) = \beta_0^q$ denotes the conditional quantile function of the dependent variable $g_t^q$ (e.g., GDP growth) at quantile level

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[5] *In economics, this approach has been used to analyse income inequality, labour market outcomes, and poverty rates. In finance, it has been employed to examine asset pricing models, risk management, and portfolio optimization. In healthcare, it has been utilized to study the impact of predictors on different quantiles of health outcomes, allowing for a more nuanced analysis of healthcare disparities. In environmental studies, it has been applied to investigate the relationship between pollution levels and health outcomes, considering the differential effects across different parts of the distribution.*

$q$, given the covariates $X_{i,t-h}$; Here, $\beta_0^q$ is the quantile-specific intercept term, and $\beta_i^q$ is a vector of quantile-dependent slope coefficients capturing the marginal effect on how each predictor (variable) $i$ affects the outcome at different points in the distribution, or quantile $q$; The term $\varepsilon_t^q$ represents the quantile-specific error. The analysis considers quantiles $q \in \{0.1, 0.2, \ldots, 0.9\}$ [6], allowing the model to estimate how the predictors influence different points of the GDP growth distribution, particularly in the tails, thereby capturing asymmetric and nonlinear effects critical for macro-financial and climate risk analysis. Within this framework, Growth-at-Risk (GaR) is defined as the threshold below which GDP growth falls with probability $q$, conditional on the information set $\varphi_t$:

$$\left(Probability(g_t^q \leq GAR_{i,t}(q|\varphi_t)\right) \leq q \tag{11}$$

where, $GAR_{i,t}\,(q \,|\, \varphi_t)$ denotes Growth-at-Risk for country $i$ at time $t$, conditional on the information set $\varphi_t$ available at time $t\text{-}h$. QR estimates this relationship by solving the following optimization problem[7]:

$$\hat{\beta}_q = \underset{b}{\operatorname{argmin}} \sum_{t=1}^{T-h} \rho_q\left(g_{t-h} - X'_{t-h} b\right) \tag{12}$$

$$\rho_q(u) = u\left(q - 1_{\{u<0\}}\right) \tag{13}$$

where, $\hat{\beta}_q$ is the estimated coefficient vector for the $q$-$th$ quantile, and $\rho_q(u)$ denotes the check function that asymmetrically weights residuals. Once the optimization problem is solved, the conditional quantile of GDP growth $(g_t^q)$ is given by $X'_{t-h}\hat{\beta}_q$.

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[6] *The confidence intervals, following Drenkovska and Volcjak (2022), are reported at a 10% level using heteroskedasticity-robust standard errors for quantile regression, as proposed byKoenker (2005).*

[7] *See, among others, Drenkovska & Volcjak (2022),and Chicana & Nivin (2022).*

The combined use of GaR and QR offers two key advantages. First, GaR accommodates crisis episodes and links macro-financial and climate conditions to the full growth distribution, enabling policymakers to assess risks beyond central projections and identify key drivers across quantiles and horizons (Prasad et al., 2019; O'Brien and Wosser, 2021). Second, QR is less sensitive to outliers and enhances this framework by capturing distributional asymmetries, tail behaviour, and robustness to outliers and non-normality (Suarez, 2021). Together, GaR and QR provide a rigorous and flexible empirical framework for analysing how climate change risks and macro-financial conditions shape the distribution of economic growth—particularly in the context of downside vulnerabilities. This approach supports risk-sensitive policy design and strengthens macroprudential surveillance in climate-vulnerable economies such as Albania.

## 3.3. Data description

This study utilizes quarterly data spanning from 2004 Q1 to 2023 Q1, comprising 77 observations. The dependent variable is the real GDP growth rate, annualized using a four-quarter moving average to reflect Albania's economic performance. The set of explanatory variables, detailed in Table 1 (Appendix), are grouped into three categories:

The first includes macroeconomic indicators: the Economic Sentiment Indicator (ESI), the 12-month T-bill rate (adjusted for inflation), the House Price Index (HPI), bank lending to the economy (Loan-to-GDP), and the fiscal policy stance (FP), measured as the ratio of total public debt—both domestic and foreign—to GDP. ESI and HPI are survey-based indicators. ESI aggregates five sectoral confidence indices (industry, services, consumer, construction, and retail trade) using seasonally adjusted balance scores ranging from –100 to +100[8]. HPI is derived from semi-annual surveys of 230

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[8] *For further information, see Kristo (2010).*

real estate agencies, capturing both qualitative and quantitative assessments of market conditions[9]. For consistency, HPI data are interpolated to quarterly frequency using a mean-based approach, while pre-2013 values are extended using historical growth rates derived from earlier methodologies. Loan-to-GDP reflects total bank lending as a share of GDP, while the real T-bill rate is calculated by subtracting annual CPI inflation from the nominal rate. FP captures the fiscal stance through the public debt-to-GDP ratio, encompassing both domestic and foreign components. The second category of explanatory variables captures bank-specific conditions through the Bank Prudential Behaviour Index (BPI)[10], a composite measure of banking sector soundness constructed using the Entropy Method. BPI reflects the prudence of individual banks based on balance sheet dynamics and is aggregated using market share weights. Higher BPI values indicate increased prudential behaviour across the banking system. The third category comprises the Climate and Environmental Risk (CCR) Index. As presented in Table 4 (Appendix), CCR is a synthetic indicator derived from 51 annual climate and environmental variables, grouped into five risk categories . These include acute and chronic risks, which represent physical climate threats; adaptation capacity, reflecting resilience to those threats; and exposure and mitigation, which capture transition risks linked to the shift toward a low-carbon economy. Together, these dimensions provide a comprehensive view of a system's vulnerability and readiness, enabling more informed decision-making in climate policy, financial planning, and sustainability assessments. Following Khalid et al. (2020), CCR is constructed using the Entropy Method, involving standardization, entropy scoring, utility weighting, and aggregation into a normalized index ranging from 0 to 1, where lower values indicate better climate risk performance[11]. Due to its annual frequency, CCR is converted to quarterly data using the

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[9] *For more details, see Bank of Albania (2020).*

[10] *The indicator was previously employed by Shijaku (2019). However, in that paper, the estimation technique included a Principal Component Analysis (PCA) approach.*

[11] *This approach is used to calculate the weight or the value dispersion in decision-making of each indicator in a composite indicators system, based on the idea of the entropy from basic information theory for the dataset. For more details see Erkhembaatar and Bataa (2020); and Zhu et al., (2020)].*

Chow-Lin interpolation method. All variables undergo a three-step transformation to ensure consistency and comparability: (1) normalization to zero mean and unit variance[12]; (2) rescaling to a [0, 1] range to prevent high-variance variables from dominating the analysis[13]; and (3) indexing to a 2010 base year (set to 100), followed by log transformation to stabilize variance and enhance interpretability (Kutner et al., 2005).

Data sources include quarterly GDP growth from the Albanian Institute of Statistics (INSTAT); BPI and CCR, constructed by the author following Shijaku (2019, 2022); fiscal policy data from the Albanian Ministry of Finance and Economy; and macro-financial indicators (ESI, T-bill, HPI, Loan-to-GDP) from the Bank of Albania. Climate-related data are sourced from international institutions, such as the IMF and the World Bank.

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[12] *The formula used in this case is* $Z_t = \frac{(X_t - \bar{X}_t)}{\delta}$*, where* $X$ *is the actual data from the BLS;* $\bar{X}$ *is the mean and* $\delta$ *is the standard deviation over the selected sample.*

[13] *The formula is given as* $Z_t' = \left(\frac{1}{(1 + exp(-Z_t))}\right)$.

# *4. EMPIRICAL ANALYSIS OF THE MAIN ESTIMATED RESULTS*

This section presents the main findings derived from the Growth-at-Risk (GaR)framework using a linear Quantile Regression (QR) approach. The analysis focuses on the relationship between climate-related variables and GDP growth across the conditional distribution, which as Galvao (2009) highlights offers robust inference across conditional quantiles and captures heterogeneity in economic dynamics. The analysis follows a three-step approach. First, the stationarity of the model variables is assessed using Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. As shown in Appendix Figure 3, apart from BPI and HPI, most variables exhibit non-stationarity at conventional significance levels, with mixed outcomes depending on the inclusion of trend or constant terms. For this reason, to avoid spurious regression, all non-stationary series were different to achieve stationarity (I(0)), while the QR estimation was conducted in levels. Second, based on Equation (10), the core results are summarized in Appendix Figure 4. The figure plots the estimated $\beta$ coefficients and their 95% confidence intervals across nine quantiles of GDP growth (from the 10th to the 90th percentile), using quarterly data from 2004 Q1 to 2022 Q4. Each coefficient reflects the marginal impact of a one-unit change in the explanatory variable on GDP growth, conditional on the quantile growth distribution level, while holding other variables constant.

The estimation results offer several important insights. First, results reveal that the size of beta *($\beta$)* coefficients vary across GDP growth quantiles. This finding confirms that predictor effects are not uniform, thereby validating the GaR framework's emphasis on tail risks. In some cases, coefficient signs even reverse, reflecting sensitivity to business cycle. Similar patterns are found in Ferrara et al. (2021) and Clark et al. (2024), who show that quantile-based models capture nonlinear and asymmetric relationships are essential for macro-financial forecasting. Second, the estimation results for the

Climate Change Risk Indicator (CCRI) reveal a consistently positive coefficient across all quantiles, as illustrated in Figure 4. This indicates a robust inverse relationship between climate-related risks and GDP growth: lower levels of climate risk are associated with higher economic performance, regardless of the position within the growth distribution. Similar patterns are observed in the World Bank's Global Economic Prospects (2025) report, which projects GDP losses exceeding 10% in vulnerable countries by mid-century due to climate-related damages, particularly in regions with limited adaptive capacity and high exposure to extreme weather events. Notably, the size of the estimated $\beta$ coefficients for CCRI are among the largest across all explanatory variables, underscoring the substantial macroeconomic impact of climate risk. The statistical significance of these estimates— confirmed by narrow confidence intervals and conventional p-values across quantiles— reinforces the reliability of the findings. These results highlight the critical importance of integrating climate risk considerations into economic planning and policy frameworks, as addressing such risks is essential for sustaining long-term growth and resilience. Importantly, the impact of climate risk is most pronounced in the lower tail of the GDP growth distribution, underscoring its asymmetric nature. At the 10th percentile ($q = 0.1$), the estimated $\beta$ coefficient reaches approximately 0.895, compared to 0.637 at the median ($q = 0.5$) and 0.464 at the 90th percentile ($q = 0.9$). This gradient suggests that during periods of heightened climate stress, a one-unit increase in climate risk corresponds to a nearly 0.9 percentage point reduction in GDP growth, whereas in more stable or expansionary conditions, the effect —though still significant — is comparatively muted. These findings reinforce the relevance of tail-sensitive frameworks like Growth-at-Risk (GaR), which are better equipped to capturing the disproportionate burden that climate risk imposes on downside growth scenarios.

The analysis provides a granular view of how different types of climate-related risks—physical and transition— affect the distribution of economic growth. Physical risks, which encompass acute climate shocks like floods, hurricanes, droughts, and heatwaves, exhibit a disproportionately strong and statistically significant impact on the lower tail of the GDP growth distribution. This means that during periods of economic stress or fragility, the presence of physical climate shocks tends to exacerbate downside risks, increasing the likelihood of severe contractions in output. These effects are particularly pronounced in vulnerable economies with limited adaptive capacity or infrastructure resilience. Interestingly, the analysis finds that transition risks are more salient in the upper quantiles of the growth distribution. This suggests that during periods of strong economic performance, the economy becomes more exposed to reallocation effects and adjustment costs associated with climate policy implementation and structural transformation. These empirical findings carry significant implications for macroeconomic policy design, particularly in the context of climate-related vulnerabilities and cyclical risk management. The strong and asymmetric effects of climate change risk on GDP growth—most pronounced in the lower tail of the distribution—underscore the urgency of integrating climate-sensitive indicators into macro-prudential frameworks. Policymakers should therefore prioritize early warning systems and stress-testing tools that account for both physical and transition risks, particularly during periods of heightened climate stress.

Beyond climate-related factors, another set of results provides important insights into the role of fiscal and financial variables in shaping growth outcomes. Notably, fiscal policy burden and credit provision to the economy emerge as the second most influential factors after climate risk. The estimated beta *(β)* coefficients for fiscal burden are consistently negative across all quantiles, indicating that reducing fiscal pressure is associated with higher GDP growth. Likewise, the loan-to-GDP ratio shows a positive relationship throughout the distribution, suggesting that increased credit availability supports economic expansion. Both effects are statistically significant, reinforcing their relevance for macroeconomic performance. Crucially, the magnitude of these effects varies across the distribution. The impact of fiscal burden is strongest at the lower tail (q = 0.1), where economic vulnerability is highest, and weakest at the upper tail (q = 0.9). This implies that fiscal consolidation is particularly beneficial during periods of economic stress. Conversely, the effect of credit provision intensifies toward the upper quantiles, with the strongest impact observed at q = 0.9, suggesting that credit growth plays a more prominent role in supporting expansion during stable or high-growth periods. Overall, these findings highlight the asymmetric influence of fiscal and financial variables across the growth distribution and reinforce the need for targeted policy interventions that account for cyclical conditions and distributional dynamics. Notably, the magnitude of these effects varies across the growth distribution. The impact of fiscal burden is strongest in the lower quantiles (q = 0.1), where economic vulnerability is highest, implying that fiscal consolidation is particularly beneficial during downturns. In contrast, the effect of credit provision intensifies toward the upper quantiles (q = 0.9), indicating that credit growth plays a more prominent role in sustaining expansion during stable or high-growth periods. These findings highlight the need for cyclically sensitive policy interventions, including fiscal tightening during stress episodes and credit facilitation during recovery phases.

The remaining results suggest that other indicators such as consumer confidence, real estate dynamics, and interest rate burden show minimal and inconsistent impact within the GDP growth distribution. Bank prudential behavior appears to exert even less influence in this context. Their estimated effects are small in magnitude, statistically insignificant, and unstable across quantiles, suggesting limited utility for macro-prudential policy targeting. From a policy perspective, this differentiation is critical. It implies that effective macro-financial surveillance and risk mitigation should prioritize variables with robust and quantifiable influence on growth outcomes, particularly under adverse conditions. Climate-sensitive indicators, fiscal levers, and credit dynamics should therefore be central to early warning systems and stress-testing frameworks. Meanwhile, indicators with weak or unstable relationships to GDP growth may be better suited for sectoral monitoring or supplementary analysis rather than core macro-prudential design. These findings reinforce the value of the GaR–QR approach for informing targeted, data-driven policy interventions. By capturing distributional asymmetries and tail risks, this framework enables policymakers to anticipate vulnerabilities more precisely and allocate resources more effectively in response to evolving economic and environmental shocks.

# 5. CONCLUSIONS

In an era marked by rapid technological advancement and globalization, climate change and environmental degradation—driven by unsustainable production and consumption patterns—are fundamentally reshaping the landscape of economic policymaking. Research increasingly confirms that both the current and projected implications of these risks render the "business as usual" approach untenable. Climate change, deforestation, and pollution pose systemic threats not only to the planet but also to economic growth and stability. Rising sea levels, temperature increases, extreme weather events, and resource scarcity disrupt supply chains, elevate production costs, reduce productivity, and damage infrastructure—ultimately impeding growth if left unaddressed. The economic costs of these risks are substantial, particularly for sectors such as agriculture, energy, and infrastructure. While climate-related risks may appear detrimental to growth, transitioning to a low-carbon economy and adopting sustainable practices—such as investing in renewable energy and climate-resilient infrastructure—can mitigate these threats, foster innovation, and unlock new economic opportunities. These challenges not only hinder economic progress but also erode social cohesion and environmental sustainability. Addressing them requires a multi-dimensional policy response, including international cooperation, inclusive and progressive taxation, sustainable development strategies, climate-friendly regulations, and investment in human capital. Above all, it is imperative that policymakers recognize the urgency of these issues and take proactive, coordinated action.

To address the impact of climate change risks and vulnerabilities on the dynamics of adverse GDP growth outcomes, this paper employs the Growth-at-Risk (GaR) framework, using Albanian macro-financial data and a synthetic climate-related indicator, alongside quantile regression, and the Quantile Regression method. The contribution is threefold. First, to the best of our knowledge, this represents the first empirical application of this integrated approach in the context of a small open economy. Second, the GaR framework provides a robust tool for monitoring macro-financial risks by capturing the relationship between climate change risks, macro-financial conditions, and the full distribution of GDP growth. Its flexibility enables counterfactual scenario analysis, which is instrumental in identifying risk sources and guiding policy responses. Third, the use of Quantile Regression allows for a more granular understanding of how climate risks affect different segments of the GDP growth distribution. Unlike traditional mean-based models, this method reveals asymmetries, tail behaviour, and heterogeneity across quantiles, making it particularly valuable for analysing skewed or heavy-tailed data and mitigating the influence of outliers. Together, these tools provide a comprehensive framework for assessing and communicating the economic implications of climate-related risks.

The empirical findings confirm that Albania has experienced episodes of adverse economic performance consistent with the Growth-at-Risk (GaR) framework, where the probability of severely negative growth outcomes—"tail risk"—is elevated. The analysis further reveals that climate change risks exert a significant and quantile-dependent influence on GDP growth, particularly given Albania's structural exposure as a small open economy. The effects are non-linear and most pronounced in the lower quantiles, indicating that climate-related shocks disproportionately affect periods of economic vulnerability. This underscores the importance of analysing the full distribution of growth outcomes and highlights the strategic role of climate risk mitigation in enhancing economic resilience and reducing downside risks. The analysis further distinguishes between physical and transition risks. Physical risks, such as extreme weather events, have a stronger and statistically significant impact on the lower tail of the growth distribution, while their influence diminishes at higher quantiles. In contrast, transition risks—linked to policy and structural adjustments—become more prominent in the upper quantiles, suggesting their relevance during periods of stronger economic performance. Additionally, macro-financial variables such as consumer confidence, real estate dynamics, and interest rate burdens contribute to downside risks, whereas bank prudential behaviour appears to play a limited role. This suggests that climate-related vulnerabilities operate primarily through broader economic channels rather than direct financial sector fragility. Taken together, these results underscore the imperative of integrating climate risk assessments into the national macro-financial policy and surveillance frameworks. Doing so would enhance the capacity of policymakers to identify emerging vulnerabilities, design targeted interventions, and build resilience against future climate-induced economic disruptions.

Importantly, this study represents the first empirical application of the Growth-at-Risk (GaR) framework and synthetic climate risk indicators to Albania's economy, laying a robust foundation for future research. Several promising avenues emerge from this work. First, methodological extensions could include the application of dynamic quantile regression with panel data techniques across Western Balkan economies. This would enable the analysis of regional spillovers, cross-country heterogeneity, and shared vulnerabilities in climate-growth dynamics. Another valuable enhancement involves the disaggregation of climate risk components—distinguishing between chronic risks (e.g., gradual temperature rise) and acute shocks (e.g., floods, droughts)—to assess their differential impacts across the GDP growth distribution. Second, sectoral and structural vulnerability analysis should investigate how climate risks affect key sectors such as agriculture, tourism, and energy, and quantify their contribution to aggregate downside risks. In parallel, developing institutional resilience metrics would allow for the evaluation of national capacity to manage climate risks and mitigate macro-financial vulnerabilities. Finally, future research should extend the analysis to explore how climate-related shocks interact with long-term productivity trends, innovation capacity, and economic resilience. Additionally, examining the interplay between climate risks and macroeconomic policy instruments—particularly within the GaR framework—could yield valuable insights into their implications for financial stability and policy design.

# *LITERATURE*

*Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? Journal of Macroeconomics, 65.*

*Adrian, T., Grinberg, F., Liang, N., Malik, S., & Yu, J. (2019a). The term structure of growth-at-risk. IMF Working Paper, WP/18/180, Monetary and Capital Markets Department.*

*Adrian, T., Boyarchenko, N., & Giannone, D. (2019b). Vulnerable growth. American Economic Review, 109(4), 1263–1289.*

*Agarwala, M., Burke, M., Klusak, P., Mohaddes, K., Volz, U., & Zenghelis, D. (2021). Climate change and fiscal sustainability: Risks and opportunities. National Institute Economic Review, 258, 28–46. Cambridge University Press.*

*Akram, N. (2012). Is climate change hindering economic growth of Asian economies? Asia-Pacific Development Journal, 19(2), December 2012.*

*Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change. Nature Climate Change 7, 283-288.*

*Bank of Albania. (2020). Survey Real Estate Market Performance - Methodological Note and Questionnaire. Department of Financial Stability, Bank of Albania.*

*Bansal, R., & Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. Journal of Finance, 59(4), 1481–1509.*

*Bansal, R., Kiku, D., & Ochoa, M. (2016a). What do capital markets tell us about climate change? Meeting Papers, Vol. 542, Society for Economic Dynamics.*

*Bansal, R., Kiku, D., & Ochoa, M. (2016b). Price of long-run temperature shifts in capital markets. NBER Working Paper Series, No. 22529, August 2016.*

*Bansal, R., Ochoa, M., & Kiku, D. (2016c). Climate change and growth risks. NBER Working Paper No. 23009, December 2016.*

*Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change, 7(4), 283–288.*

*Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527(7577), 235–239.*

*Burke, M., & Tanutama, V. (2019). Climatic constraints on aggregate economic output. NBER Working Paper No. 25779, April 2019.*

*Busetti, F., Caivano, M., Delle Monache, D., & Pacella, C. (2020). The time-varying risk of Italian GDP. Bank of Italy, Temi di Discussione (Working Paper) No. 1288.*

*Byrne, J.P., & Vitenu-Sackey, P.A. (2024). The Macroeconomic Impact of Global and Country-Specific Climate Risk. Environmental and Resource Economics, 87(3), 655–682.*

*Casey, G., Fried, S., & Goode, E. (2023). Projecting the impact of rising temperatures: The role of macroeconomic dynamics. IMF Economic Review, 71, 688–718.*

*Coelho, R., & Restoy, F. (2023). Macroprudential policies for addressing climate-related financial risks: Challenges and trade-offs (FSI Briefs No. 18). Bank for International Settlements.*

*Dell, M., Jones, B. F., & Olken, B. A. (2008). Climate change and economic growth: Evidence from the last half century. NBER Working Paper No. 14132, June 2008.*

*Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66–95.*

*Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. Journal of Economic Literature, 52(3), 740–798.*

*Di Febo, E. (2025). Transition Risk in Climate Change: A Literature Review. Risks, 13(4), 66.*

*Dietz, S., & Stern, N. (2015). Endogenous Growth, Convexity of Damage and Climate Risk: How Nordhaus' Framework Supports Deep Cuts in Carbon Emissions. The Economic Journal, 125(583), 574–620.*

*Drenkovska, M., & Volcjak, R. (2022). Growth-at-risk and financial stability: Concept and application for Slovenia. Bank of Slovenia, Discussion Paper No. 5.*

*Economides, G., Papandreou, A., Sartzetakis, E., & Xepapadeas, A. (2018). The economics of climate change. Climate Change Impacts Study Committee, Bank of Greece, June 2018.*

*Erkhembaatar, N., & Bataa, O. (2020). Entropy weight method for evaluating indicators of ICT development index. International Journal of Current Advanced Research, 9(12), 23500–23504.*

*European Investment Bank (EIB). (2021). Assessing climate change risks at the country level: The EIB scoring model. Economics Working Papers 2021/03.*

*Frame, D., Rosier, S., Noy, I., Harrington, L., Carey-Smith, T., Sparrow, S., Stone, D., & Dean, S. (2020). Climate change attribution and the economic costs of extreme weather events: A study on damages from extreme rainfall and drought. Climatic Change, 162(2), 781–797.*

*Galvao, A. F. (2009). Unit root quantile autoregression testing using covariates. Journal of Econometrics, 152(2), 165–178.*

*Gondo, R. (2020). Financial vulnerability and growth at risk (GaR). Central Reserve Bank of Peru, Working Paper Series.*

*Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. Econometrica, 82(1), 41–88.*

*International Monetary Fund (IMF). (2017). Financial conditions and growth at risk. In Global Financial Stability Report: Is Growth at Risk? (Chapter 3). IMF, October 2017.*

*Iseringhausen, M. (2021). A time-varying skewness model for growth-at-risk. European Stability Mechanism, Working Paper Series No. 49.*

*Ivanova, N., Shmygel, A., & Lubchuk, I. (2021). The growth-at-risk (GaR) framework: Implication for Ukraine. IHEID Working Papers, No. 10-2021, Economics Section, The Graduate Institute of International Studies.*

*Hassler, J., Krusell, P., & Smith, A. (2016). Environmental macroeconomics. In J. Taylor & H. Uhlig (Eds.), Handbook of Macroeconomics (Vol. 2, Chapter 24, pp. 1893–2008). Elsevier.*

*Hassler, J., & Krusell, P. (2018). Environmental macroeconomics: The case of climate change. In Handbook of Environmental Economics (Vol. 4, pp. 1–12). Elsevier.*

*Hengge, M. (2019). Uncertainty as a predictor of economic activity. Economics Section, Graduate Institute of International Studies, Working Paper No. 19-2019.*

*Henseler, M., & Schumacher, I. (2019). The impact of weather on economic growth and its production factors. Climatic Change, 154(3), 417–433.*

*Kiley, M. T. (2024). Growth at risk from climate change. Economic Inquiry, 62(3), 1134–1151.*

*Khalid, A., Sharma, S., & Dubey, A. (2020). Data gap analysis, indicator selection and index development: A case for developing economies. Social Indicators Research, 148, 893–960.*

*Koenker, R., & Bassett, G. (1978). Regression quantiles. Econometrica, 46(1), 33–50.*

*Koenker, R. (2005). Quantile Regression. Cambridge University Press.*

*Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., & Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. Nature Climate Change, 11(4), 319–325.*

*Kotz, M., Levermann, A., & Wenz, L. (2022). The effect of rainfall changes on economic production. Nature, 601(7892), 223–227.*

*Kahn, M., Mohaddes, K., Ng, R., Pesaran, H., Raissi, M., & Yang, J.-C. (2019). Long-term macroeconomic effects of climate change: A cross-country analysis. IMF Working Paper No. WP/19/215, October 2019.*

*Letta, M., & Tol, R. S. J. (2018). Weather, climate and total factor productivity. Environmental and Resource Economics, 73(2), 283–305.*

*Mitra, P., Raissi, M., Versailles, B., Centorrino, S., Ivanyna, M., Kirabaeva, K., Massetti, E., Montes de Oca Leon, M., Nguyen, H., Oman, W., Rebei, N., Tagklis, F., Zhang, A. T., Ungerer, C., Uruñuela López, J., & Yu, S. (2025). Integrating climate change into macroeconomic analysis: A review of impact channels, data, models, and scenarios. IMF Working Paper No. 2025/170.*

*Nath, I., Ramey, V., & Klenow, P. (2023). How much will global warming cool global growth? Federal Reserve Bank of San Francisco.*

*Network for Greening the Financial System (NGFS). (2022). Macroeconomic and Financial Stability Implications of Climate Change. Network for Greening the Financial System Technical document.*

*Nordhaus, W. D. (1991). To slow or not to slow: The economics of the greenhouse effect. Economic Journal, 101(407), 920–937.*

*Nordhaus, W. D. (2014). Estimates of the social cost of carbon: Concepts and results from the DICE-2013R model and alternative approaches. Journal of the Association of Environmental and Resource Economists, 1(1/2), 273–312.*

*O'Brien, M., & Wosser, M. (2021). Growth at risk and financial stability. Central Bank of Ireland, Financial Stability Notes, 2021(2).*

*Pindyck, R. S. (2012). Uncertain outcomes and climate change policy. Journal of Environmental Economics and Management, 63(3), 289–303.*

*Plagborg-Møller, M., Ricco, G., Reichlin, L., & Hasenzagl, T. (2020). When is growth at risk? Brookings Papers on Economic Activity, Spring 2020.*

*Prasad, A., Elekdag, S., Jeasakul, P., Lafarguette, R., Alter, A., Xiaochen, A., & Wang, C. (2019). Growth at risk: Concept and application in IMF country surveillance. IMF Working Paper No. WP/19/36.*

*Shijaku, G. (2019). Does banks' prudential behaviour affect their solvency conditions? Forthcoming Bank of Albania Working Paper. Presented at the 12th South-Eastern European Economic Research Workshop, December 2018.*

*Shijaku, G., & Monnin, P. (2022). A synthetic metric approach to assess climate change-related risk developments in the Western Balkan countries. Forthcoming Bank of Albania Working Paper. Presented at the 16th SEE Research Workshop, Tirana, 5–6 December 2022.*

*Suárez, J. (2021). Growth-at-Risk and macroprudential policy design. European Systemic Risk Board, Occasional Paper Series No. 19, September 2021.*

*Tol, R. S. J. (2022). A meta-analysis of the total economic impact of climate change. CESifo Working Paper No. 9919.*

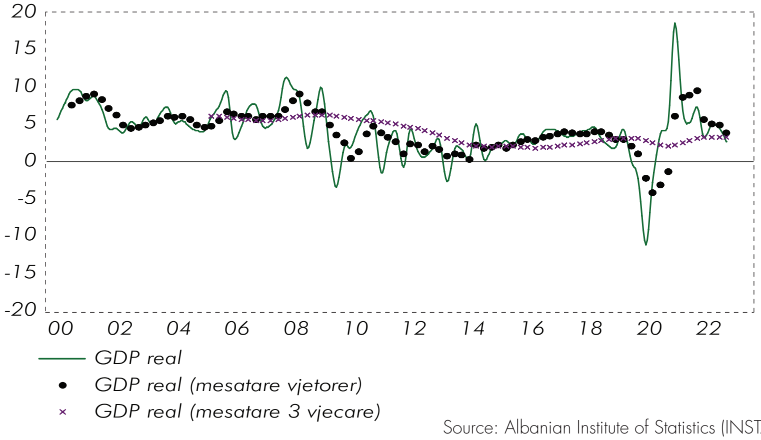
*World Bank. (2025). Global Economic Prospects, June 2025. Washington, DC: World Bank.*

*Wunderling, N., von der Heydt, A., Aksenov, Y., Barker, S., Bastiaansen, R., Brovkin, V., Brunetti, M., Couplet, V., Kleinen, T., Lear, C., Lohmann, J., Roman Cuesta, R. M., Sinet, S., Swingedouw, D., Winkelmann, R., Anand, P., Barichivich, J., Bathiany, S., Baudena, M., Bruun, J., Chiessi, C. M., Coxall, H., Docquier, D., Donges, J., Falkena, S., Klose, A. K., Obura, D., Rocha, J., Rynders, S., Steinert, N. J., & Willeit, M. (2024). Climate tipping point interactions and cascades: A review. Earth System Dynamics, 15(1), 41–74.*

*Zhu, Y., Tian, D., & Yan, F. (2020). Effectiveness of entropy weight method in decision-making. Mathematical Problems in Engineering, 2020, Article ID 3564835.*

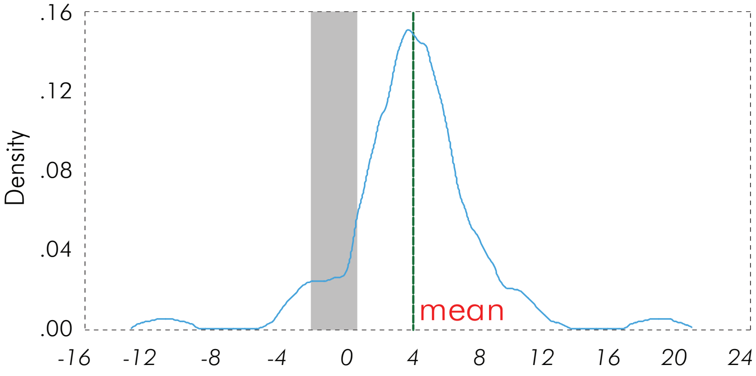
# APPENDIX

Figure 1. Real GDP growth during the period 2000 Q1 – 2023 Q1.



Source: Albanian Institute of Statistics (INSTAT).

Figure 2 Kernel Density Distribution of real GDP growth, 2004 Q1 – 2023 Q1



Source: Author's calculations.

*Table 1. Descriptive Statistics on real GDP annual growth rate.*

| | | 2004Q1-2023 Q1 | 2009Q1 - 2023Q1 |
|---|---|---|---|
| Mean | | 3.7 | 2.9 |
| Median | | 4.1 | 3.2 |
| Maximum | | 18.5 | 18.5 |
| Minimum | | -11.2 | -11.2 |
| Std. Dev. | | 3.8 | 3.8 |
| Skewness | | -0.1 | -0.05 |
| Kurtosis | | 7.7 | 9.4 |
| Jarque-Bera | | 70.2 | 98.3 |
| Probability | | 0.0 | 0.0 |
| Sum | | 288.5 | 164.4 |
| Sum Sq. Dev. | | 1078.7 | 809.5 |
| Quantile (Percentile) | 5 | -1.81 | 2.32 |
| | 10 | 0.47 | 0.15 |
| | 50 | 4.27 | 4.06 |
| | 75 | 6.05 | 5.2 |
| IQR | | 3.94 | 4.99 |
| Observations | | 77 | 57 |

*Source: Author's calculations.*

*Table 2. One way Tabulation of real GDP annual growth, 2004Q1 - 2023Q1 (77 observations.)*

| Value Count | | Non-cumulative | | Cumulative | |
|---|---|---|---|---|---|
| | | Percent | Count | Percent | |
| 1. | [-12, -10) | 1 | 1.3 | 1 | 1.3 |
| 2. | [-4, -2) | 4 | 5.19 | 5 | 6.49 |
| 3. | [-2, 0) | 3 | 3.9 | 8 | 10.39 |
| 4. | [0, 2) | 14 | 18.18 | 22 | 28.57 |
| 5. | [2, 4) | 15 | 19.48 | 37 | 48.05 |
| 6. | [4, 6) | 24 | 31.17 | 61 | 79.22 |
| 7. | [6, 8) | 10 | 12.99 | 71 | 92.21 |
| 8. | [8, 10) | 4 | 5.19 | 75 | 97.4 |
| 9. | [10, 12) | 1 | 1.3 | 76 | 98.7 |
| 10. | [18, 20) | 1 | 1.3 | 77 | 100 |
| Total | | 77 | 100 | 77 | 100 |

*Source: Author's calculations.*

*Table 3. One way Tabulation of real GDP annual growth, 2009Q1 -2023Q1 (57 observations)*

| Value Count | | Non-cumulative | | Cumulative | |
|---|---|---|---|---|---|
| | | Percent | Count | Percent | |
| 1. | [-12, -10) | 1 | 1.75 | 1 | 1.75 |
| 2. | [-4, -2) | 4 | 7.02 | 5 | 8.77 |
| 3. | [-2, 0) | 3 | 5.26 | 8 | 14.04 |
| 4. | [0, 2) | 13 | 22.81 | 21 | 36.84 |
| 5. | [2, 4) | 14 | 24.56 | 35 | 61.40 |
| 6. | [4, 6) | 15 | 26.32 | 50 | 87.72 |
| 7. | [6, 8) | 5 | 8.77 | 55 | 96.49 |
| 8. | [8, 10) | 1 | 1.75 | 56 | 98.25 |
| 9. | [18, 20) | 1 | 1.75 | 57 | 100.00 |
| Total | | 57 | 100.00 | 57 | 100.00 |

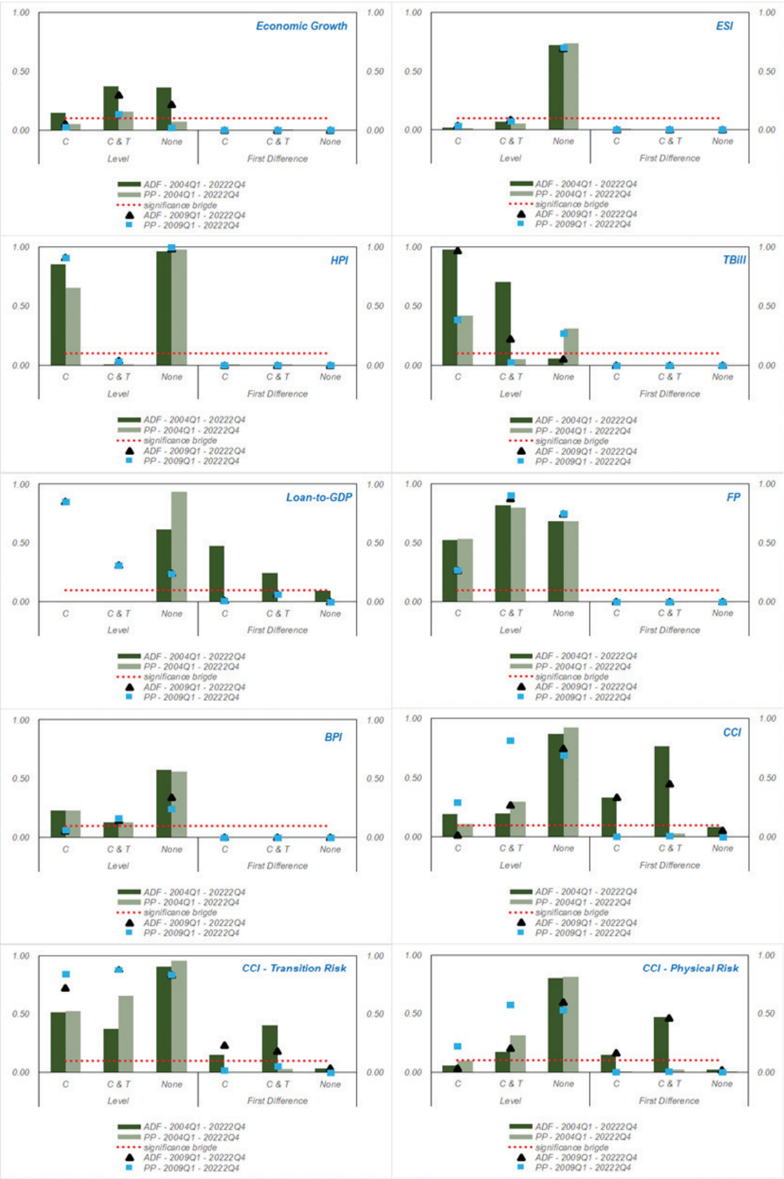
*Source: Author's calculations.*

*Table 4. Dataset of 51 indicators used to assess CCR at the country level based on the EIB (2021) scoring model.*

| Category | | Indicator | Sign |
|---|---|---|---|
| Physical Risk | Physical Risk (Acute ) | Climate-related disasters frequency, Number of Disasters: TOTAL | [-] |
| | | 5 years AV Change % of (Climate-related disasters frequency, Number of Disasters: TOTAL) | [-] |
| | | GCCR | [-] |
| | | Total Damages, Adjusted ('000 US$) | [-] |
| | | Land area where elevation is below 5 meters (% of ztotal Land Area) | [-] |
| | Physical Risk (Chronic) | Temperature changes with respect to a baseline climatology, corresponding to the period 1951-1980 | [-] |
| | | 5-year average | [-] |
| | | World Temperature changes with respect to a baseline climatology, corresponding to the period 1951-1980 / country level | [+] |
| | | 5-year average | [+] |
| | | Crop production index (2014-2016 = 100) | [+] |
| | | Livestock production index (2014-2016 = 100) | [+] |
| | | Agriculture, forestry, and fishing, value added (% of GDP) | [+] |
| | | Agriculture, forestry, and fishing, value added per worker (constant 2015 US$) | [+] |
| | | Agriculture, forestry, and fishing, value added per worker (constant 2015 US$) / World Ratio | [+] |
| | Adaption Capacity | Comparative advantage in environmental goods | [+] |
| | | Comparative advantage in low carbon technology products | [+] |
| | | Total trade in environmental goods / EMU ratio | [+] |
| | | Total trade in environmental goods as percent of GDP (mean value) | [+] |
| | | Environmental Taxes | [+] |
| | | Expenditure on environment protection | [+] |
| | | Government Effectiveness: Estimate | [+] |
| | | HDI | [+] |
| | | Tax Revenue / GDP | [+] |
| | | Total debt service (% of GNI) | [-] |
| | | Income Index | [+] |
| | | Forest Coverage Rate (in %) | [+] |
| | | Arable land (hectares per person) | [+] |
| | | Climate Altering Land Cover Index | [+] |
| Transition Risk | Exposure (revenues and costs) | PM2.5 air pollution, mean annual exposure (micrograms per cubic meter) | [-] |
| | | Total current greenhouse gas emissions (kt of CO2 equivalent) | [-] |
| | | Total greenhouse gas emissions (kt of CO2 equivalent) average 5-year change | [-] |
| | | Total GHG emissions including land-use, land-use change and forestry (Million metric tons of CO2 equivalent) | [-] |
| | | Gap of IMF estimated GHG emissions including land-use, land-use change and forestry under a Business as Usual assumption (Million metric tons of CO2 equivalent) | [+] |
| | | 5- year Average Gap of Total GHG emissions including land-use, land-use change and forestry with the IMF 2030 baseline | [+] |
| | | Fossil fuel energy consumption (% of total) | [-] |
| | | Fertilizer consumption (kilograms per hectare of arable land) | [-] |
| | | Agricultural methane emissions (thousand metric tons of CO2 equivalent) | [-] |
| | | Agricultural nitrous oxide emissions (thousand metric tons of CO2 equivalent) | [-] |
| | | Total natural resources rents | [+] |
| | Mitigation | Renewable energy consumption (% of total final energy consumption) | [+] |
| | | Renewable electricity output (% of total electricity output) | [+] |
| | | Renewable internal freshwater resources per capita (cubic meters) | [+] |
| | | Combustible renewables and waste (% of total energy) | [+] |
| | | Access to clean fuels and technologies for cooking (% of population) | [+] |
| | | Adjusted savings: natural resources depletion (% of GNI) | [-] |
| | | Adjusted savings: net forest depletion (% of GNI) | [-] |
| | | Adjusted savings: carbon dioxide damage (% of GNI) | [-] |
| | | Adjusted savings: energy depletion (% of GNI) | [-] |
| | | Adjusted savings: particulate emission damage (% of GNI) | [-] |
| | | Current Electric power consumption (kWh per capita) | [-] |
| | | 5-year Av Annual Change Electric power consumption (kWh per capita) | [-] |

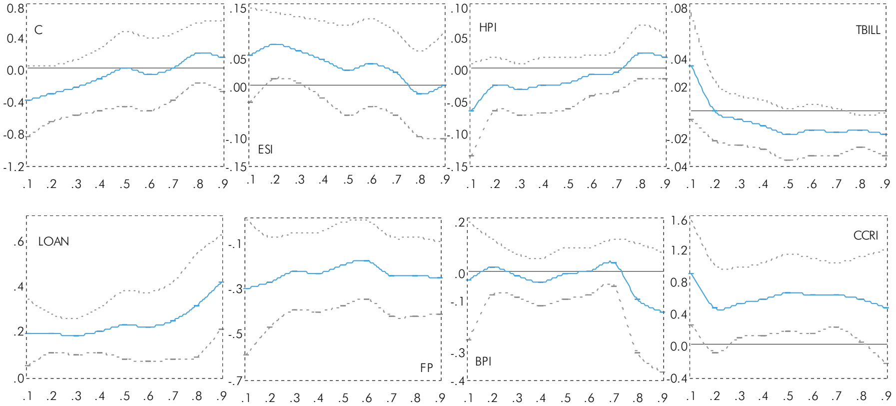
*Source: UNDP, World Bank, IMF, EM-DAT, Eurostat, National Authorities*

Figure 3 Unit Root Test Analysis



Source: Author's calculations.

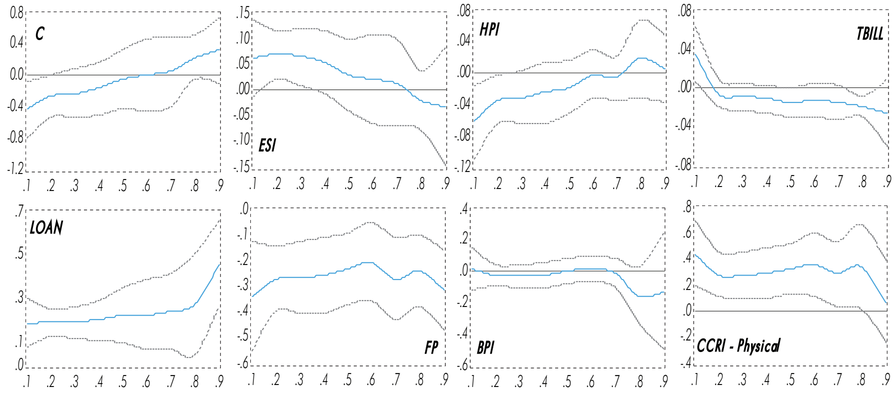
Figure 4 Empirical results of CCI on Economic Growth rate using QR approach, 2004Q1-2022Q4



Note: The light-blue horizontal line denotes the size of each beta (β) coefficient estimated through the Quantile regression at different points of the quantile distribution and represents the linkage between the explanatory variable and growth, at different points of distribution of GDP growth. The horizontal grey dash lines denote confidence intervals at 5%, estimated using heteroskedasticityrobust standard errors for Quantile regression, and when they cross the x-axis, this signals the absence of statistical significance of the predictor. The horizontal x-axis represents the quantiles of distribution, i.e. at 0.1, 0.2, 0.3, ..., 0.9. The vertical y-axis denotes the impact of each explanatory variable at different points of quantile distribution.

Source: Author's calculations.

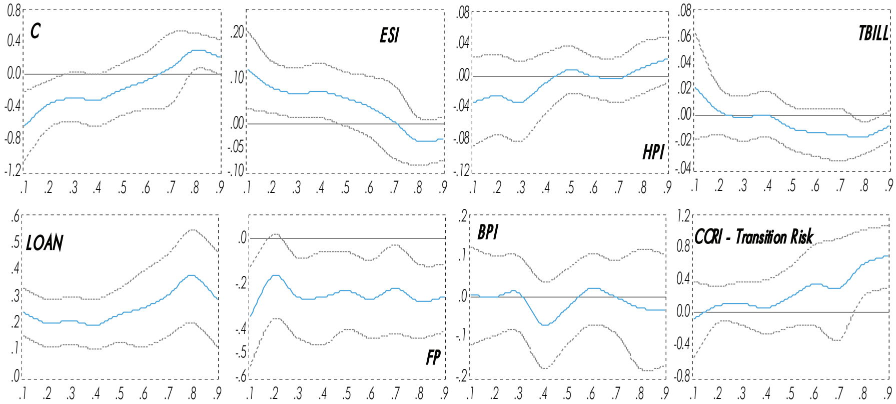
Figure 5. Empirical results of "CCRI – Physical Risks" on Economic Growth rate using QR approach, 2004Q1-2022Q4.



Note: The light blue horizontal line denotes the size of each beta (β) coefficient estimated through the Quantile regression at different points of quantile distribution and represent the linkage between the explanatory variable and growth, at different points of distribution of GDP growth. The horizontal grey dash lines denote confidence intervals at 10%, estimated using heteroskedasticity-robust standard errors for Quantile regression, and when they cross the x-axis, this signals the absence of statistical significance of the predictor. The horizontal x-axis represents the quantile of distribution, i.e. at 0.1, 0.2, 0.3, ..., 0.9. The vertical y-axis denotes the impact of each explanatory variable at different points of quantile distribution.

Source: Author's calculations.

Figure 6 Empirical results of "CCRI – Transition Risks" on Economic Growth rate using QR approach, 2004Q1-2022Q4



Note: The horizontal light blue line denotes the size of each beta (β) coefficient estimated through the Quantile regression at different points of quantile distribution and represent the linkage between the explanatory variable and growth, at different point of distribution of GDP growth. The horizontal grey dash lines denote confidence intervals at 10%, estimated using heteroskedasticity- robust standard errors for Quantile regression, and when they cross the x-axis, this signals the absence of statistical significance of the predictor. The horizontal x-axis denotes the quantile of distribution, i.e. at 0.1, 0.2, 0.3, …, 0.9. The vertical y-axis denotes the impact of each explanatory variable at different points of quantile distribution.

Source: Author's calculations.

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