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Sovereign credit rating downgrades and Growth-at-Risk

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A B S T R A C T

This paper examines whether sovereign credit rating changes are linked to increased future macroeconomic downside risks based on the Growth-at-Risk framework by Adrian et al. (2019). Our findings reveal that downgrades significantly increase tail risk by lowering the 5th percentile of four-quarters ahead GDP growth by 2.95 percentage points, whereas upgrades yield a smaller and inconsistent effect of 0.45 percentage points. Standard panel OLS results show a reduced impact of 1.11 percentage points on GDP growth following a downgrade, underscoring the importance of examining effects beyond the mean. Further analysis reveals an asymmetrical impact across quantiles and time horizons, with speculative-grade countries particularly vulnerable to downgrades. Downgrades from all major agencies affect tail risk, with Fitch having the largest negative impact, while only Moody's upgrades have a significant effect. Moreover, our empirical evidence suggests that the effect of credit rating downgrades is, at least partially mitigated, by the adoption of post-GFC regulatory reforms, aligning with these policies' aim to reduce reliance on CRAs and enhance financial stability. Lastly, our analysis identifies investment and sovereign bond spreads as key channels through which downgrades affect macroeconomic outcomes, however, only the latter is significantly associated with downside risks to GDP growth. Robustness tests that include endogeneity checks, additional controls, alternative CRA data and quantile regression methodology, confirm our findings.

1. Introduction

Credit rating agencies (CRAs) play a crucial role in the financial markets by assessing the creditworthiness of governments, corporations, and financial instruments. Despite the fact that CRAs originally started as information intermediaries, they have been integrated into the regulatory framework providing information and certification services.[1] Policymakers have widely argued that CRAs have contributed to the escalation of the Great Financial Crisis (GFC) that was exacerbated by a combination of faulty rating methodologies and overreliance on rating agencies (Sy, 2009; Deb et al., 2011). More specifically, CRAs were heavily criticised for their poor timeliness, conflicts of interest, opaque rating methodologies and limited accountability. In response to that, the Dodd-Frank Act was introduced in the USA in 2010, which imposed stricter oversight and accountability measures for CRAs, including reducing conflicts of interest and increasing transparency in rating methodologies. Similarly, the European Union (EU) introduced several regulatory measures after the 2008 financial crisis to enhance market confidence and investor protection. The regulation, established

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[1] Financial institutions such as banks and pension funds are obliged to consider credit ratings when making investment decisions and only invest in securities that meet minimum credit rating criteria to comply with regulatory guidelines.

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in 2009 and amended in 2011 and 2013, aims to reduce overreliance on CRAs, improve rating transparency, and mitigate conflicts of interest.[2]

However, CRAs might still face incentive conflicts in the upward phase of the business cycle which leads to inflated ratings and risk mispricing (Dilly and Mählmann, 2016). As a result, their rating quality exhibits countercyclical behaviour. The positive bias in the upward phase of the business cycle remains strong despite any reputational concerns (Bar-Isaac and Shapiro, 2013) and greater competition (Bolton et al., 2012). When we enter the downward phase of the business cycle, this "*boom bias*" is usually followed by credit rating corrections and sizeable downgrades. During that time, negative rating changes can be perceived as indicators of upcoming financial distress, they signal a reassessment of credit risk and can trigger an immediate response from market participants.

In this paper, we present novel insights into the impact of sovereign credit rating changes on the macroeconomy. We propose a general and parsimonious approach to explore the impact of CRAs not on economic growth alone, but also on its tail risk dynamics. We build on the *Growth-at-risk* framework that links economic growth and macro-financial conditions as introduced by Adrian et al. (2019). This methodology allows us to examine the impact of CRAs' decisions not only on the conditional mean, but also on the tail of the conditional distribution. Our analysis yields five critical findings that deepen our understanding of how sovereign credit rating changes influence macroeconomic risks. First, our results suggest that a credit rating downgrade is associated with a decline (increase) of 2.95 percentage points in the left tail of GDP growth distribution (tail risk), whereas upgrades have a weaker, but statistically significant positive effect. Second, the impact varies across quantiles and estimation horizons. The impact of a sovereign credit rating downgrade weakens at higher percentiles, which highlights the importance of studying the tail risk of the GDP growth distribution. In terms of the duration of the impact, it presents its peak six quarters after the credit rating change and gradually diminishes and dissipates four quarters afterwards. Third, we conduct a sub-sample analysis, revealing that the effect is more pronounced in developed countries, but also in those that CRAs classify their government bonds as speculative (non-investment) grade. Fourth, we examine the role of CRA regulation implemented in the post-GFC period, which aimed to enhance transparency, strengthen oversight, and reduce reliance on CRAs. Our findings indicate that these reforms partially mitigate the adverse effects of downgrades, reducing market overreactions and aligning with regulatory objectives to enhance financial stability. Finally, we explore the channels through which sovereign rating downgrades affect macroeconomic outcomes. Drawing on prior literature, we focus on two potential mechanisms: sovereign bond spreads and investment activity. We first show that downgrades increase borrowing costs and reduce investment. In a second step, we examine how each channel relates to the distribution of future GDP growth. Our analysis shows that increases in sovereign bond spreads are significantly associated with downside risks to GDP growth, whereas the impact of investment changes is weaker and concentrated around the mean of the distribution.

Our empirical findings hold up to a series of robustness tests, such as alternative quantile regression methodology, the use of multiple CRAs' ratings and additional control variables. In addition to account for periods of increased uncertainty that could affect credit rating quality (Attig et al., 2021), we show that our results hold even when we exclude crisis periods, such as the GFC and the COVID-19 pandemic. The focus of this paper is on credit rating changes, however CRAs issue outlook announcements that reflect the most current information and offer a consistent signal of credit quality. Hence, for robustness purposes, we also extend our analysis to include outlook changes. Our findings suggest that changes to a negative outlook are adversely associated with the lower quantiles of future GDP growth distribution, but the effect is not as sizeable as that of the rating changes. Finally, we focus on the EU sub-sample which provides a good case study for further analysis. To validate our findings, we use an alternative measure of financial stress as a control variable, i.e. the Composite Indicator of Systemic Stress (CISS) from the ECB, which is available for 16 European countries, and the results continue to hold.

Our paper bridges two strands of literature: the emerging body of work on Growth-at-Risk and macroeconomic tail risks (Adrian et al., 2019; Aikman et al., 2019; Galán, 2024; Franta and Gambacorta, 2020; Suarez, 2022) and the established literature on sovereign credit rating changes (Alsakka and Ap Gwilym, 2010; Afonso et al., 2012; Baum et al., 2016; Klusak et al., 2019). We contribute to both by moving beyond average effects and focusing instead on how credit rating downgrades shape downside risks to growth. Our empirical findings show that sovereign downgrades are not only statistically significant but also economically meaningful. This has important implications for policymakers and central banks, as it underscores the systemic role of CRAs in amplifying macro-financial vulnerabilities (Bolton et al., 2012; Sahibzada et al., 2022; Kladakis and Skouralis, 2024). By applying and extending the Growth-at-Risk framework to sovereign ratings, we connect sovereign credit risk with broader macro-financial fragility and shed light on the channels through which rating actions affect economic outcomes.

Finally, to address potential endogeneity concerns in the relationship between sovereign credit ratings and GDP growth and explore the robustness of our results, we develop a novel instrumental variable strategy. More specifically, we construct an instrument based on the textual content of annual reports from a sample of large systemically important banks in countries that experienced at least one sovereign credit rating downgrade. We create a country-level variable capturing the frequency of references to "sovereign credit rating (s)" in these reports. Since these reports are published with a lag and largely reflect prior-year expectations and also enter the model with a lag, the instrument is exogenous to future GDP growth while remaining strongly correlated with subsequent sovereign credit rating actions. This approach introduces a novel use of bank disclosures to capture market expectations and provides a forward-looking and conceptually sound instrument that helps address concerns of reverse causality between credit ratings and economic performance.

The remainder of the paper is structured as follows. Section 2 discusses the paper's contribution to the literature and develops the main hypotheses we aim to test. Section 3 describes the data and the empirical methodology. Section 4 presents the empirical results,

[2] Other countries, including Japan, Canada, and Australia, have similarly strengthened their regulatory frameworks for CRAs, focusing on mitigating overreliance and improving market stability.

including the main findings, robustness tests, sub-sample analyses, the impact of regulatory changes, transmission channels, and endogeneity tests. Finally, Section 5 concludes.

2. Literature review and hypotheses development

This paper contributes to the strand of the literature that examines the effects of credit rating announcements. Previous studies highlight the important role that CRAs play with regards to macroeconomic stability. Rating announcements can form market expectations and they are associated with greater stock and bond market volatility (Afonso et al., 2012; Brooks et al., 2015), increased pressure on the banking system (Alsakka and Ap Gwilym, 2013) and changes in banks' liquidity and capital structure (Drago and Gallo, 2017; Wojewodzki et al.,2020). More recently, Sahibzada et al. (2022) find that sovereign rating downgrades are associated with greater systemic risk[3] and therefore they could pose a threat to a country's macro-financial stability. In a study related to ours, Chen et al. (2016) find that countries' economic growth varies significantly following sovereign rating changes and they identify two main transmission channels, namely, interest rates and capital flows. With regard to the first channel, a downgrade can directly impact the creditworthiness of the borrower country and thus result in significant increases in their bond spreads (Gande and Parsley, 2005) and CDS spread (Afonso et al., 2012) and consequently in their total debt portfolio. With regards to the second channel, a country downgrade increases sovereign credit risk and exchange rate volatility and therefore results in reallocation of funds among global portfolios and flows of capital across countries (Baum et al., 2016).

Although previous studies have examined the effects of sovereign credit ratings on GDP, both directly and indirectly, to the best of our knowledge, this is the first paper to move beyond average effects and explicitly investigate downside risk. The strand of the literature on macroeconomic dynamics was initiated with Cecchetti and Li (2008) who use quantile regressions and vector autoregression modelling to quantify the impact of equity and property booms on the extreme tails of output distribution. This approach was further developed and promoted by the influential paper published by Adrian et al. (2019),[4] which shows that the lower quantiles of the distribution of the US GDP growth rate fluctuate more and are more influenced by financial conditions than the upper quantiles, thus supporting the focus of macroprudential surveillance and policies on the lower quantiles. This *Growth-at-risk* framework is now built on central banks' early warning system, and it constitutes a useful tool for enhancing risk assessment and policy scenarios.

Building on the *Growth-at-Risk* framework, other *at-risk* models have been developed. More specifically, Deghi et al. (2020) extend the model to capture tail risks in the housing market and Kennedy et al. (2021) and Deghi et al. (2021) apply the *at-risk* framework to measure downside risk in the commercial property capital values. In addition, Gelos et al. (2022) employ the *at-risk* framework to predict the future capital flows distribution based on a set of variables that capture global financial conditions, domestic structural characteristics, and policy changes. Finally, the recent inflationary pressures in the post-pandemic period also turn the focus on inflation risks. Banerjee et al. (2024) and Lopez-Salido and Loria (2024) use a global panel of countries and measure the (upper) tail inflation risk via the *inflation-at-risk* framework. In addition, a growing body of the literature on this empirical framework is focusing on the role of policy changes on *Growth-at-Risk*. More specifically, a strand of literature examines the role of macroprudential policies (Franta and Gambacorta, 2020; Galán, 2024; Suarez, 2022) in mitigating downside risks. More recently, Furceri et al. (2025) evaluate how macro-financial and political variables affect the predicted future government debt distribution.

This paper contributes to the growing *at-risk* literature by extending the framework to analyse the impact of sovereign credit rating changes on GDP tail risks, a dimension that, to the best of our knowledge, has not been explored. We control for financial conditions and treat the rating changes as an additional factor that can result in an increase in macroeconomic tail risk. Overreliance on CRAs has posed risks in the past, and the framework allows us to focus on tail risk, providing a deeper understanding of the systemic risks posed by CRAs, which are often overlooked by the linear models commonly used in the literature (Chen et al., 2016).

Adrian et al. (2019) emphasize the importance of examining beyond the mean, suggesting that financial conditions provide strong predictive insights for the lower quantiles of future GDP growth, while their effect on the upper quantiles is weak and often statistically insignificant. The heterogeneous impact is not only across quantiles, but also in terms of the forecast horizon. Credit and property price booms pose sizeable downside macroeconomic risks in the medium-term (Aikman et al., 2019) and their impact varies over time (Hasler et al., 2023), whereas financial stress indices are consistently associated with future economic tail risks and their impact is more immediate (Adrian et al., 2019). Based on the above, we expect the effect of credit rating changes to be greater on the left tail of GDP growth distribution compared to the mean (as captured by the standard OLS model). Moreover, we anticipate a greater effect on the short-term rather than the medium-longer term, in line with the financial conditions/stress variables.

H.1.a. ***Sovereign credit rating changes have a stronger negative effect on the lower quantiles of future GDP growth.***

H.1.b. ***The effect of sovereign credit rating changes is more pronounced over shorter forecast horizons.***

Turning to the information content of rating events, the literature suggests that downgrades are more informative than upgrades. This holds for both sovereign (Gande and Parsley, 2005; Brooks et al., 2015; Sahibzada et al., 2022) and firm-level credit ratings (Afik and Zabolotnyuk, 2023; Kladakis and Skouralis, 2024). In other words, upgrades and downgrades are symmetric on the sign, but asymmetric on the extent of their consequences (Afonso et al., 2012). That can be partially explained due to the fact that markets

[3] Kladakis and Skouralis (2024) find that bank credit rating downgrades are also associated with increased bank-level systemic risk.

[4] The methodology was first introduced in the 2017 IMF Global Financial Stability Report (GFSR). Prasad et al. (2019) present a comprehensive analysis of the methodology and guidance for policymakers on how to implement it in their country's setting.

appear to react more to negative news that tend to have a greater impact on individuals' attitudes than positive news do. In other words, market participants value more the probability of upcoming losses than they do about the chance of expected gains of equal magnitudes. Another explanation behind this asymmetric effect is given by Gande and Parsley (2005) who suggest that CRAs are less keen to downgrade a country considering the political pressures by the affected government and the possibility of being denied access to vital information in the future. In addition, financial markets tend to be more responsive to credit rating changes in the period after the GFC, whereas the effect of upgrades is significantly weaker (Huang and Shen, 2015). Alsakka and Ap Gwilym (2013) study how the exchange markets react to sovereign credit news before and after GFC and they find that negative news from all three major CRAs has an impact, whereas only Moody's positive news produces a reaction. Given the above, it is evident that the impact of sovereign credit rating changes is not uniform and is influenced by market expectations, political pressures, and the inherent bias towards negative news. Therefore, examining the differential impact of downgrades versus upgrades on GDP growth distribution is crucial for understanding the broader economic implications of credit rating changes. This leads to Hypothesis 2 that sovereign credit rating downgrades have a stronger effect across the GDP growth distribution than upgrades.

H.2. ***Sovereign credit rating downgrades have a stronger negative impact on the lower quantiles of GDP growth than upgrades.***

In addition, we expect the effect of a credit rating change to vary depending on the affected economy. Firstly, we examine whether developed or developing countries are more exposed to CRAs' announcements. Developing countries rely heavily on external financing to fund their development projects and maintain economic stability, which makes their financial system particularly vulnerable to sovereign distress (Dell'Ariccia et al., 2018; Feyen and Zuccardi Huertas, 2019; Deghi et al., 2022). A downgrade can make it more expensive for governments and corporations to borrow internationally, exacerbating existing fiscal pressures. Therefore, it may trigger investor panic and increased market volatility (Bales and Malikane, 2020), leading to currency depreciation and reduced foreign investment. On the other hand, developed countries typically have stronger economies and more stable financial systems. As a result, downgrades in these nations often point to serious economic issues or fiscal mismanagement, which significantly diverge from market expectations. This divergence intensifies market reactions, leading to more substantial macroeconomic repercussions. In addition, almost half of the countries in our sample are European economies that were heavily impacted by the sovereign debt crisis (Afonso et al., 2012; Alsakka et al., 2014; Baum et al., 2016), and therefore we expect that they can affect our results.

Furthermore, we expect the effect of credit changes to depend on the initial rating grade category of the affected economy. In other words, we expect that a downgrade within the speculative grade rating range would have a more adverse impact compared to a downgrade within the investment grade range.[5] This hypothesis is consistent with Jung et al. (2024) who find that the effect of credit rating affirmations is more pronounced for firms with non-investment grade rating. Specifically, they find that stock prices of those firms react considerably to CRAs, whereas the effect is insignificant for investment-grade firms.

H.3.a. ***Sovereign credit rating downgrades have a stronger negative effect on GDP growth in developing than in developed countries.***

H.3.b. ***Sovereign credit rating downgrades have a stronger negative effect in speculative-grade countries than in investment-grade countries.***

Finally, we focus our analysis on the impact of the regulatory framework introduced shortly after the GFC. These reforms, implemented across the world, aimed to address market participants' overreliance on ratings and to mitigate the influence of CRAs on financial stability, as well as to reduce the element of shock from sudden ratings changes. In Europe, a series of measures was adopted to strengthen the regulatory and supervisory framework for CRAs. These included the introduction of the EU CRA Regulation in December 2009 and its subsequent amendments (CRA II in 2011 and CRA III in 2013). These reforms aimed to restore market confidence, enhance investor protection, and reduce overreliance on credit ratings by mandating increased transparency, stricter oversight, and the independence of rating methodologies. Similarly, in the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 introduced a comprehensive framework to enhance the accountability and reliability of CRAs. Furthermore, it mandated greater transparency in rating methodologies and established the Office of Credit Ratings under the Securities and Exchange Commission (SEC) to oversee and enforce compliance.

Other countries also introduced CRA-specific regulations tailored to their financial markets, emphasizing local accountability and improved practices. In Australia, CRA regulation was introduced in 2010, imposing licensing requirements and mandating measures to manage conflicts of interest, improving the reliability of credit ratings in the Australian financial system. In Japan, amendments to the Financial Instruments and Exchange Act in 2010 introduced stricter oversight of CRAs, requiring their registration and imposing obligations to ensure transparency and the disclosure of rating methodologies and potential conflicts of interest. Moreover, in the same year, India strengthened its CRA regulation to enhance transparency and manage conflicts of interest, and South Korea brought CRAs under formal supervision with the implementation of the Financial Investment Services and Capital Markets Act in 2009, introducing mandatory licensing and oversight. In Canada, the Canadian Securities Administrators (CSA) introduced National Instrument 25–101 in 2012, requiring CRAs to register and comply with the International Organization of Securities Commissions (IOSCO) Code of Conduct, thereby aligning Canada's regulatory framework with global best practices. Brazil also introduced a new regulatory framework in the same year, requiring CRAs to register and comply with stricter operational standards. More recently, in 2013, a new regulatory framework was introduced in Mexico, which was recognized as equivalent to the EU CRA Regulation in 2014. Israel also

[5] It is worth noting that not only developing countries but also developed countries, such as Greece and Portugal, were classified as speculative.

introduced a comprehensive CRA regulatory framework in 2015, under the Credit Rating Agencies Law, which introduced detailed disclosure and governance requirements, aligning its practices with international standards. Finally, Indonesia and Turkey implemented significant reforms later, in 2015 and 2016, respectively, enhancing CRA independence and disclosure practices.

The impact of the CRA-related regulations has been previously researched in terms of their effectiveness in reducing market volatility following CRA announcements and improving rating quality. Alsakka et al. (2015) examine the effect of the 2011 EU regulations on stock returns and volatility from 2008 to 2013, finding no conclusive evidence regarding improvements in rating quality or market stability. Klusak et al. (2019) investigate the effect of the 2012 European reforms on credit rating quality, uncovering a mixed outcome: while downgrade quality improved, upgrade quality appears to have diminished. Similar findings are presented by Dimitrov et al. (2015), who find that the Dodd-Frank in the USA is not associated with more accurate or informative credit ratings. More recently, Sahibzada et al. (2022) find that regulatory reforms have partially reduced market reliance on CRAs, measured through systemic risk. Specifically, the reforms did not effectively mitigate the impact of negative announcements by CRAs, but did reduce the impact of positive announcements from Moody's and Fitch. Drawing on this literature, we hypothesize that the CRA regulatory framework has likely reduced the systemic importance of CRAs. However, whether this effect is symmetric between downgrades and upgrades, or of significant magnitude, requires further exploration.

H.4. ***CRA regulation reduces the negative impact of sovereign credit rating downgrades on GDP growth.***

3. Methodology and data

The *Growth-at-Risk* empirical literature finds that the left tail of the economic growth distribution is less stable and its volatility can be captured by the changes in financial markets (Adrian et al., 2019). In other words, macro-financial vulnerabilities can provide significant signals with regard to the evolving risks in economic activity (Prasad et al., 2019) and tightening financial conditions are expected to pose significant macroeconomic risks. For the purposes of our analysis, the selection of these financial control variables is closely following the literature on *Growth-at-Risk* modelling (Galán, 2024; O'Brien and Wosser, 2021). More specifically, we include four control variables. Firstly, one of the main drivers of future growth is current levels of growth and therefore including current real GDP growth could capture persistence in economic cycles. Lagged GDP growth enhances the robustness and predictive power of the forecasting exercise by capturing important temporal dynamics and relationships within the data. In other words, an increase in current growth rates should result in a higher forecast growth rate, especially in the short term.

Secondly, to quantify changes in the financial markets we use the quarterly volatility of each country's stock market index. The use of an appropriate indicator of financial conditions is crucial since the framework is based on financial variables' high degree of informativeness regarding future macroeconomic developments. Figueres and Jarociński (2020) study alternative financial conditions indicators to identify which one is better capturing future GDP growth distribution. They find that CISS performs best in an out-of-sample predictive density evaluation, followed by the 30-day implied volatility of the EURO STOXX 50 (VSTOXX) and the TED spread. The main disadvantage of CISS is its limited number of countries that it covers. Similarly, other measures of financial conditions, such as IMF's Financial Conditions Indicator (FCI) is available for a larger sample of countries but only up until 2016Q3. Therefore, we employ the stock market volatility index, which is available for all countries and captures the level of uncertainty in the market and episodes of financial distress. For robustness purposes, we also present the results with both FCI and CISS and our initial findings remain robust to the change of the financial condition variable.

Thirdly, we include the credit-to-GDP ratio to account for periods of excessive credit that have been associated with bubbles in asset markets (Goodhart and Hofmann, 2008; Pavlidis et al., 2016). Credit and our fourth control variable, house price growth, are mid-term early warning indicators of cyclical macro-financial risks (Galán, 2024) and therefore play an important role in GDP growth forecasting. According to the findings by Aikman et al. (2019), credit and property price booms could pose significant downside risks to growth in the medium term, which can be partially reduced by a well-capitalized banking sector.

Our analysis is based on a global dataset of thirty-three countries[6] over the period 1990Q1-2023Q4. For each country, we collect data on real GDP growth and house price growth provided by the OECD database. Moreover, we employ data on stock market indices from Compustat, while data on the credit-to-GDP ratio is provided by the BIS. Table 1 displays the summary statistics. The country selection is determined solely by data availability. The BIS dataset covers 44 economies, with credit rating and stock market data available for 41 of these, excluding those with very limited stock market activity. Among these 41 countries, the OECD provides GDP data for 35 and house price data for 33, forming our final sample.

Finally, we include data on sovereign credit ratings as provided by Moody's Analytics and Bloomberg. Fig. 1 displays the number of sovereign credit rating changes that occurred in the examined period for thirty-three countries and across the three main CRAs. In total and across all CRAs, we examine the case of 264 upgrades and 357 downgrades. The three main CRAs present similar patterns across countries. The country with the most downgrades is Greece, followed by Turkey, Italy and Russia. On the other hand, developing countries experienced more upgrades than downgrades during the sample period. For instance, Brazil had at least 8 upgrades, for all three agencies, during the examined period. The number of downgrades is similar across the three agencies with 33 % of the total downgrades announced by Moody's, 36 % by S&P and 31 % by Fitch. On the contrary, Moody's is more conservative in its upgrades

[6] The countries included in our analysis are the following: Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czechia, Germany, Denmark, Finland, France, Greece, Hungary, Indonesia, Israel, India, Italy, Japan, South Korea, Mexico, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, Turkey, UK, and the US.

Table 1
Summary statistics

	Mean	Median	25th quantile	75th quantile	Min	Max	Source
GDP growth	2.629	2.598	1.000	4.374	−21.944	25.732	OECD Database
VIX	1.458	1.103	0.803	1.571	0.000	136.656	Compustat
Credit-to-GDP	1.328	1.330	0.796	1.736	0.149	3.965	BIS Data Portal
HP growth	1.991	1.875	−2.073	5.871	−22.314	76.495	OECD Database
DOWNGRADE	0.021	0	0	0	0	1	Moody's Analytics
UPGRADE	0.026	0	0	0	0	1	Moody's Analytics

Note: The Table displays the summary statistics of the explanatory variables used in the benchmark model specification. The statistics are based on a panel of 33 countries and of the period 1990Q1-2023Q4. The total number of observations is 3,188.

with 28 % of the total upgrades, with the remaining 38 % by Fitch and 34 % by S&P.

The CRAs' rating changes enter the model as dummy variables together with the four aforementioned control variables.[7] Our analysis is based on a panel quantile regression model specification that allows us to study the dynamics between sovereign credit ratings and GDP growth. Koenker and Bassett (1978) proposed quantile regressions as a useful tool for uncovering the heterogeneity in the distribution of a variable of interest rather than concentrating solely on the conditional mean. We employ a panel quantile regression model with country (denoted by i) and time fixed effects to avoid estimation bias. We follow Canay (2011) and Aikman et al. (2019) and assume that country fixed effects represent shifts in the entire distribution, with these fixed effects remaining consistent across various percentiles. The dependent variable, $Y_{i,t,t+h}$, is the average real year-on-year ($t-4, t$) GDP growth of country i over the specified horizon (h) as depicted in Equation (1):

$$Y_{i,t,t+h} = \frac{\sum_{n=1}^{h} GDPgrowth_{i,t+n-4,t+n}}{h} \tag{1}$$

In the benchmark model, we follow the literature and use $h = 4$ as the forecast horizon. The estimation is based on a two-step procedure. Firstly, we estimate a pooled linear panel regression model with OLS. The matrix of explanatory variables ($X_{i,t}$) includes current GDP growth, credit-to-GDP ratio, stock market volatility, real house prices growth and the sovereign credit rating dummies. More specifically, we use two credit rating change variables, namely DOWNGRADE and UPGRADE, which take the value one if there is a negative or positive change in Moody's sovereign credit ratings, respectively. The model includes country, year and quarter fixed effects.

The mathematical representation of the model is the following:

$$Y_{i,t,t+h} = a_{i,h} + X'_{i,t}\beta_h + \varepsilon_{i,t} \tag{2}$$

In the second step, we define a new dependent variable:

$$Y^*_{i,t,t+h} = Y_{i,t,t+h} - \widehat{a_{i,h}} \tag{3}$$

$Y^*_{i,t,t+h}$ is the dependent variable in Equation (2) after subtracting the country fixed effects. To obtain the quantile regression estimated coefficients, we then proceed by using a standard quantile regression model and by minimizing the following function:

$$\widehat{\beta}_{h,q} = \text{argmin} \sum_{t=1}^{T-h} \rho_q \left(Y^*_{i,t,t+h} - X'_{i,t}\beta_{h,q} \right) \tag{4}$$

where q is the examined quantile and ρ_q is the standard asymmetric absolute loss function. For inference, we use bootstrapping with 500 replications to estimate the standard errors. More specifically, our approach involves resampling the data with replacement to create multiple bootstrap samples, each of the same size as the original dataset. For each bootstrap sample, we repeat the two-step process of the Canay (2011) method for 500 iterations and we generate a distribution of the estimated quantile regression coefficients for each explanatory variable. This iterative resampling framework not only enhances the reliability of the estimated coefficients but also allows us to evaluate the consistency of our results across different quantiles of the GDP growth distribution. Moreover, it enables the estimation of robust standard errors and the construction of confidence intervals without relying on parametric assumptions about the underlying data distribution.[8]

[7] In the Appendix, Table A1 presents the correlation matrix of all independent variables used in our analysis. Tables A2 and A3 display the summary statistics of the GDP growth per country and per year.

[8] For robustness purposes, we use the Moving Block Bootstrap (MBB) to preserve the time-series structure, but its block-wise resampling retained the high correlation between GDP growth at (t+1:t+h) and t, causing multicollinearity and rank-deficient matrices. The standard bootstrap avoids this by resampling independently, disrupting such correlations. To address this, we tested MBB without GDP growth as an explanatory variable, and the results for DOWNGRADE and UPGRADE remained similar and consistent with our benchmark model.

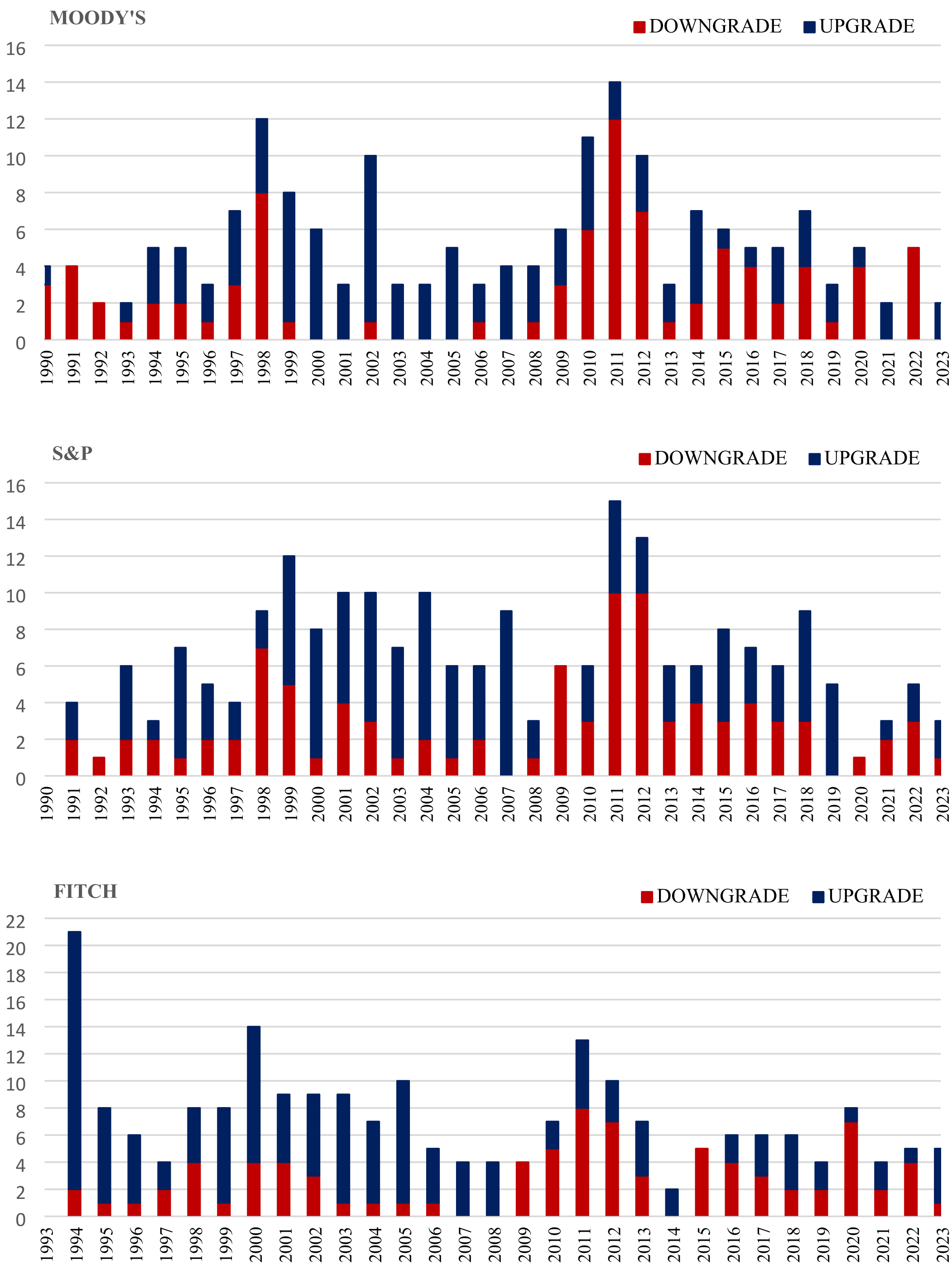

Fig. 1. Number of sovereign credit rating changes per year. Note: The Figure displays the number of upgrades and downgrades in CRAs' sovereign credit ratings over the period spanning from 1990Q1 to 2023Q4. Our sample includes data from 33 developing and developed countries, namely Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czechia, Germany, Denmark, Finland, France, Greece, Hungary, Indonesia, Israel, India, Italy, Japan, South Korea, Mexico, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, Turkey, UK and the US.

4. Empirical results

This section presents the main findings of the empirical analysis. Section 4.1 outlines the results from the benchmark model specification. Section 4.2 examines the impact of incorporating credit rating outlook announcements into the analysis. Section 4.3 details the robustness tests, including the addition of control variables, alternative definitions of credit rating changes, the use of data from other CRAs, and an alternative quantile regression methodology. Section 4.4 investigates the role of CRA regulations in shaping the relationship between credit rating changes and macroeconomic tail risk. Section 4.5 analyses the transmission channels of credit rating changes through borrowing costs and investments. Finally, Section 4.6 addresses potential endogeneity concerns.

4.1. Main findings

Fig. 2 displays the estimated quantile regression coefficients with 90 % confidence bands. The focus of this paper is on the impact of sovereign credit ratings, which are presented in Fig. 2.E and 2.F. Comprehensive results are provided in Table 2, where the first column (Model 1) presents outcomes from a panel fixed effect linear regression model, and the subsequent columns (Models 2–6) present outcomes from panel quantile regression models. As depicted in both Fig. 2.E and Table 2, quantile regression slopes significantly diverge from those of a simple linear regression model, underscoring the importance of employing techniques capable of capturing effects across the distribution tails. More specifically, the findings indicate that sovereign credit rating downgrades are associated with a further decline in the lower quantiles of the conditional future GDP growth distribution, but there is a clear heterogeneity across quantiles. The lower tail of the conditional distribution is more sensitive to a downgrade than the median and the upper quantiles. In the case of the latter, the impact is gradually declining and becoming statistically insignificant after the median quantiles. On the other hand, upgrades have a stronger effect on the upper quantiles, but overall and, in line with our expectations, their effect is not as significant as that of downgrades.

The marginal effects of other independent variables also demonstrate variability across quantiles. Our analysis reveals that deteriorating financial conditions, characterized by heightened stock market stress, correspond to a decrease in the tail of future GDP growth distribution, whereas the effect diminishes on the median and upper quantiles. On the other hand, both current GDP growth and house price growth are positively associated with future GDP growth. We find that the impact of contemporaneous GDP growth is consistent across all quantiles of the estimated growth distribution, whereas house prices exhibit a stronger relationship with the lower tail of the future GDP growth distribution. Our findings are in line with the asymmetries previously presented in past literature (Adrian et al., 2019; Galán, 2024).

In addition, we explore another dimension of the heterogeneous effect of sovereign credit rating downgrades on the conditional distribution of GDP growth by looking at the impact across various horizons. This exercise is important since early-warning financial variables are more effective in forecasting GDP growth in longer horizons, whereas lagged GDP growth performs better in shorter horizons. Fig. 3 plots the estimated quantile regression coefficients with 90 % confidence bands. Our findings suggest that the impact of a sovereign credit rating downgrade is significant one year after the shock, peaks at 6 quarters, and gradually weakens and becomes insignificant eight quarters after the change. In addition, the effect of current GDP growth is stronger in the short term and dissipates over time. Finally, we find that the effect of cyclical risk and financial conditions on *Growth-at-risk* is consistently negative. Stock market volatility has a more immediate effect, while cyclical risk becomes more pertinent over the medium-term.[9]

4.2. Incorporate credit rating outlook announcements

Our empirical findings thus far are based solely on changes in credit ratings. However, CRAs also issue outlook announcements that reflect current information and provide valuable insights into analysts' perspectives on future macroeconomic conditions. These outlooks could significantly impact a country's sovereign risk. Therefore, we extend our analysis to include outlook changes and examine whether these have predictive power regarding macroeconomic tail risk. We construct three dummy variables, each set to one when Moody's changes its outlook to negative, stable, or positive, respectively. These variables replace the DOWNGRADE and UPGRADE variables used in the benchmark model specification. Results from both the linear (OLS) and quantile regression models are presented in Table 3. Models (4) and (2) report the quantile regression estimates with and without the inclusion of periods with concurrent rating changes, respectively.

Our findings indicate a negative and statistically significant relationship between negative outlook announcements and macroeconomic tail risk, whereas changes to stable or positive outlooks show insignificant effects. As expected, the results are more robust in Models (3) and (4), which include changes in both the outlook and credit rating. Credit rating outlook announcements often precede rating changes, providing market participants with lead time to adjust their positions and expectations. As a result, the impact of outlook announcements may be partially reflected in market prices before any subsequent rating change occurs. In Models (5) and (6), we present a split-sample analysis that isolates sovereign credit rating downgrades that follow a negative outlook in the current or previous quarter, compared to downgrades occurring without such prior signalling. In both cases, the estimated coefficient is negative and statistically significant, however, the effect is stronger for downgrades following a negative outlook change. Overall our results suggest that although markets may begin to price in negative expectations upon receiving a negative outlook, actual downgrades continue to have a distinct and economically meaningful impact on downside growth risks. In other words, both outlooks and downgrades appear to convey valuable and complementary information, rather than being redundant signals.

In Models (7)-(10), we examine the impact of the CRAs' outlook (rather than changes in outlook) on future GDP growth. Consistent with our previous findings, we observe that periods of negative outlooks are associated with increased macroeconomic tail risk, whereas a positive outlook influences only the average (as captured by the OLS model), and not the lower quantiles of the future GDP

[9] In the Appendix, Table A4 presents the estimated coefficients and their corresponding robust standard errors for alternative horizons from two to twelve quarters ahead.

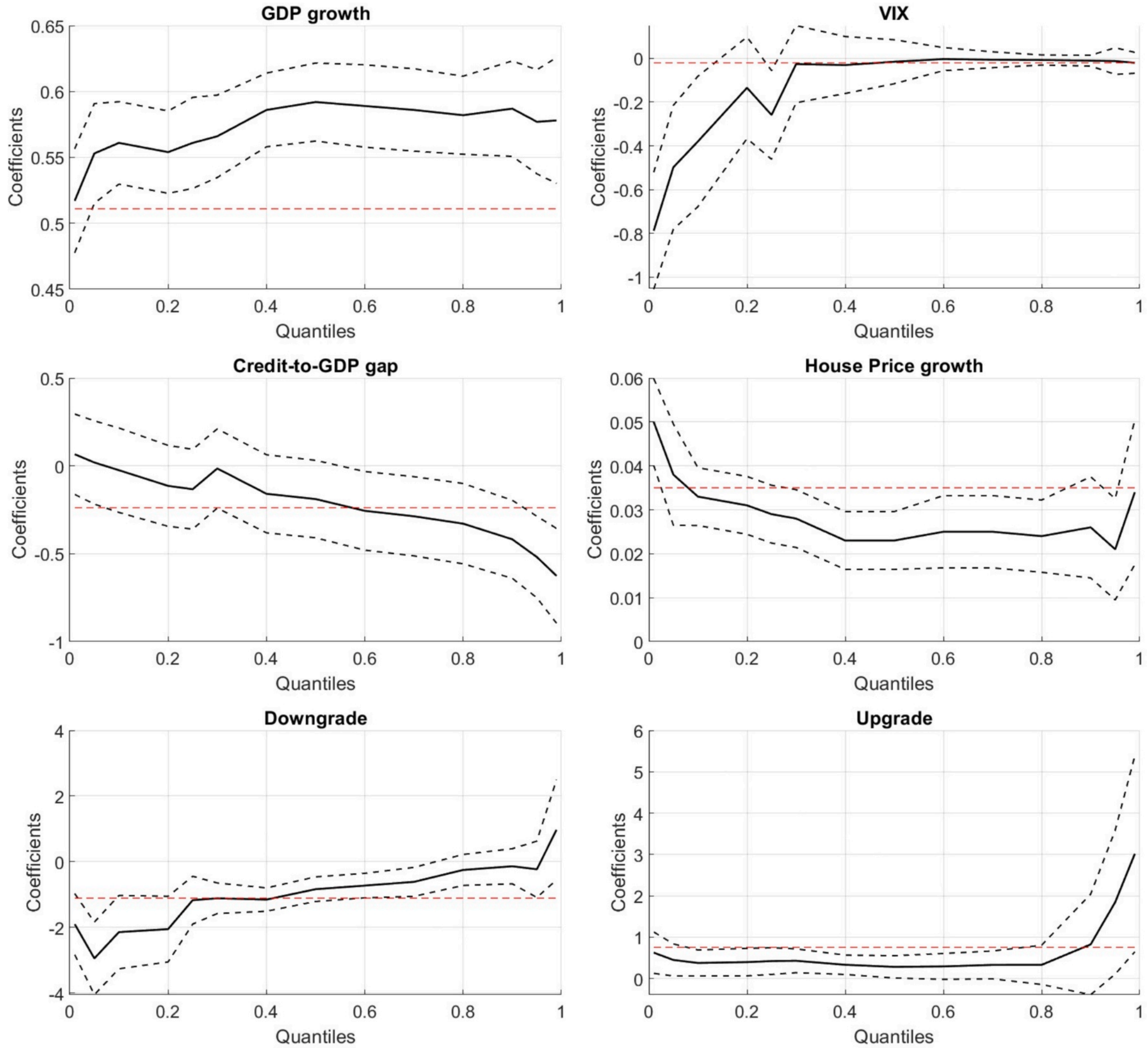

Fig. 2. Quantile regression coefficients per quantile. Note: The Figure displays the estimated quantile regression coefficients employing the two-step estimation method by Canay (2011) for different quantiles. Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable is the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. The straight red dotted line represents the OLS-estimated coefficient. The black dotted lines represent the 90 % confidence interval, calculated using bootstrapped standard errors with 500 replications.

growth distribution. In addition, we split the sample to assess the impact of credit rating downgrades occurring during periods of negative versus stable/positive outlooks. Our results, shown in Models (9) and (10), suggest that the effect of a downgrade is stronger when the outlook in the current or prior period is negative.

4.3. Robustness analysis

4.3.1. Additional controls and alternative financial conditions indicators

Our first robustness test includes additional macroeconomic controls that could explain the tail dynamics of the GDP growth distribution. In Table 4, Models (2) and (4), we include the debt-to-GDP ratio, government deficit, inflation, and economic uncertainty. By incorporating these additional controls, we aim to account for the economic conditions that precede and potentially predict sovereign credit rating downgrades, therefore ensuring that our estimated coefficients more accurately reflect the direct effect of a sovereign downgrade on future GDP growth. The inclusion of these variables reduces our sample size, so for comparison purposes, Models (1) and (3) present the results for the same sample but without the additional controls. This selection of variables is based on data limitations and previous empirical studies (Afonso et al., 2011; Reusens and Croux, 2017; Attig et al., 2021). The results remain robust, reinforcing the validity of our findings. Moreover, we present results using short-term interest rates and macroprudential policy

Table 2
Quantile Regression Results

Models:	(1)	(2)	(3)	(4)	(5)	(6)
Quantiles:	OLS	5 %	25 %	50 %	75 %	95 %
DOWNGRADE	**−1.111****	**−2.948*****	**−1.173*****	**−0.838*****	−0.350	−0.232
	(0.413)	(0.672)	(0.443)	(0.228)	(0.291)	(0.522)
UPGRADE	**0.755*****	**0.449***	**0.422****	**0.282***	**0.423***	**1.846***
	(0.231)	(0.236)	(0.196)	(0.163)	(0.246)	(1.057)
Current GDP growth	0.511***	0.553***	0.561***	0.592***	0.580***	0.577***
	(0.028)	(0.024)	(0.021)	(0.027)	(0.019)	(0.024)
VIX	−0.021	−0.498***	−0.026	−0.016	−0.007	−0.013
	(0.017)	(0.172)	(0.123)	(0.061)	(0.018)	(0.038)
Credit-to-GDP	−0.238	0.019	−0.133	−0.189	−0.293**	−0.519***
	(0.134)	(0.144)	(0.004)	(0.138)	(0.139)	(0.141)
HP growth	0.035**	0.038***	0.029***	0.023***	0.024***	0.021***
	(0.413)	(0.005)	(0.443)	(0.004)	(0.005)	(0.007)
Constant	0.794	−0.953*	−0.413	0.660	1.306	4.741***
	(0.477)	(0.506)	(0.422)	(0.590)	(0.977)	(1.099)
Country FE	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,188	3,188	3,188	3,188
R^2 / Pseudo – R^2	0.681	0.662	0.557	0.529	0.538	0.588

Note: The Table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

dummies as controls. Short-term interest rates are included to control for changes in monetary policy, and the findings remain unchanged. The estimated coefficient for monetary policy is negative, suggesting that expansionary policies shift the GDP growth distribution to the right, thereby reducing macroeconomic tail risk, at least in the short term. To capture the role of macroprudential policies, we include two dummy variables derived from the data by Alam et al. (2019). This dataset provides a comprehensive collection of macroprudential policy indicators across countries and over time, identifying the introduction and tightening/loosening of specific policy instruments such as loan-to-value (LTV) caps, countercyclical capital buffers, and reserve requirements. The two variables, MPP TIGHTENING and MPP EXPANSION, take the value 1 if contractionary or expansionary macroprudential policies, respectively, were introduced in the given country and quarter, and 0 otherwise. By incorporating these dummies, we account for policy interventions aimed at stabilizing financial systems and mitigating systemic risks. The results, presented in Models (5) and (6), align with our earlier findings.

With regard to the selection of a financial stress index, in our baseline analysis, we use the quarterly volatility of each examined country's stock market index. Our choice is based on the high data availability among all countries and time periods and on the fact that the volatility index is not directly related to the changes in credit ratings. For robustness purposes, in Models (7) and (8), we include two alternative indicators. First, the Financial Conditions Index (FCI) by IMF, which is available for a large number of developed and developing countries (28), but only up until 2016Q3. Second, the Composite Indicator of Sovereign Stress (CISS) by ECB. Figueres and Jarociński (2020) study which measures of financial conditions are more informative in the context of the *Growth-at-risk* framework. Its main disadvantage is that it is only available for 16 countries. CISS is provided at daily and monthly frequency and we use the average value per quarter. The empirical results as presented in Table 4, confirm our initial findings. The impact of credit rating downgrades is negative and statistically significant across both models. In line with our baseline findings, upgrades have a weaker or statistically insignificant effect. Finally, we investigate whether the impact of credit rating changes is driven by recession periods such as the 2008 financial crisis or the COVID-19 pandemic. In Models (9) and (10), we exclude the GFC period (2008–2010) and the COVID-19 period (2020–2022) and the results hold.

4.3.2. Controlling for the size of credit rating changes

In our benchmark model specification, we use binary variables for upgrades and downgrades motivated by the literature on the impact of credit ratings (Afonso et al., 2012; Alsakka and Ap Gwilym, 2013; Kladakis and Skouralis, 2024). This approach allows us to decompose the heterogeneous impact of distinct negative and positive economic signals, but it does not capture the magnitude of rating changes. Firstly, to ensure that our results are not driven by persistent differences in sovereign credit quality, we include a fixed effect for the lagged rating group (investment vs. speculative) as a robustness test. The results presented in Models (1) and (2) remain virtually unchanged, suggesting that the estimated effect of downgrades is not mechanically driven by a country's prior rating status.

Secondly, to address the aforementioned limitation, we follow Chen et al. (2016), who employ two distinct variables, which capture the magnitude of rating upgrades and downgrades while being set to zero otherwise. Their findings indicate that a one-notch upgrade or downgrade leads to an average change in five-year annual growth rates of approximately + 0.6 % and −0.3 %, respectively. In Table 5, Models (3)-(8), we replicate and extend this framework by incorporating both linear and quantile regression models. The

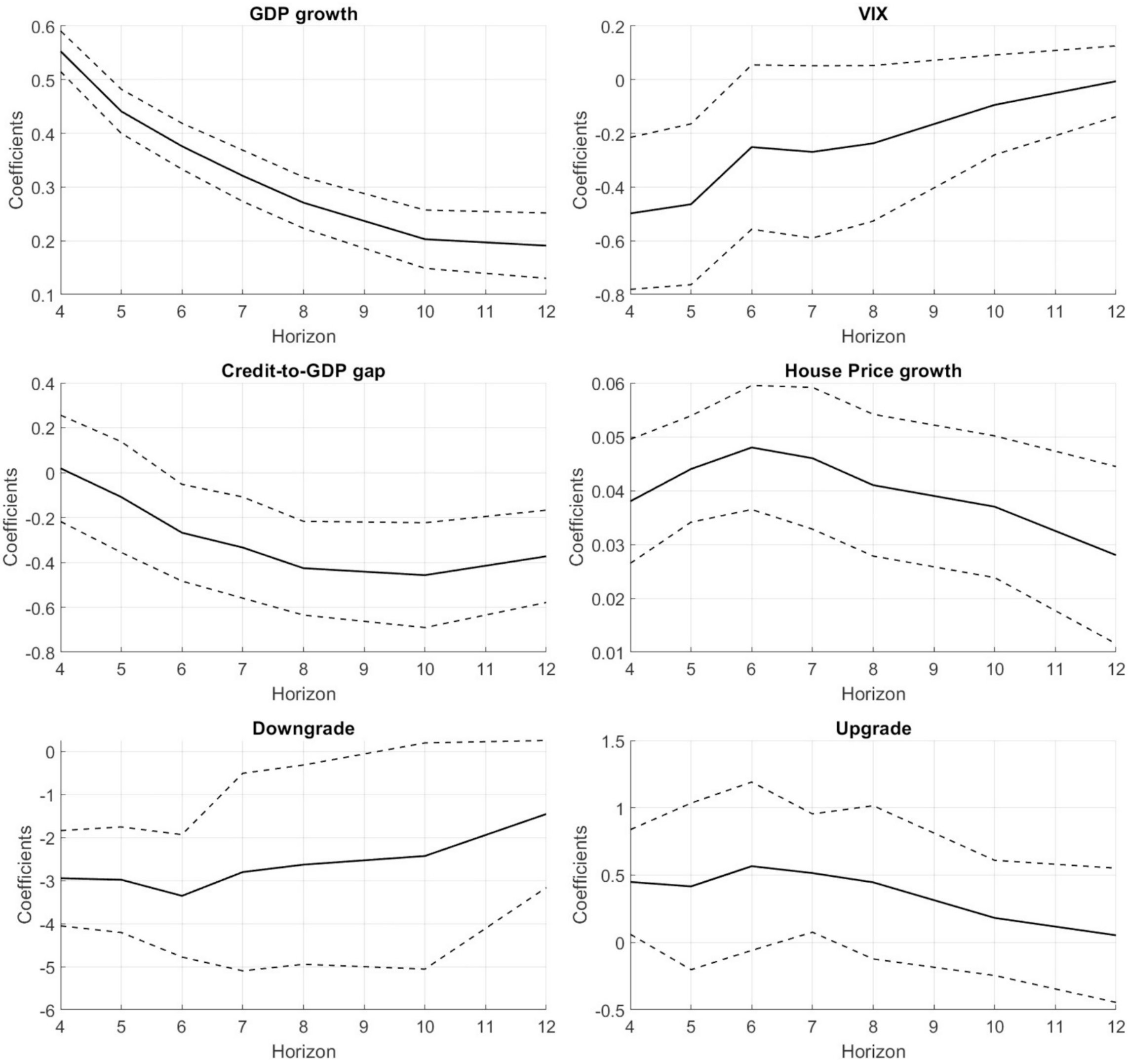

Fig. 3. Quantile regression coefficients per alternative horizons. Note: The Figure displays the estimated quantile regression coefficients (q = 0.05) employing the two-step estimation method by Canay (2011) for different estimation horizons. Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable is the average GDP growth between one and h periods ahead (t + 1, t + h), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. The black dotted lines represent the 90 % confidence interval, calculated using bootstrapped standard errors with 500 replications.

dependent variable is defined as the one- and three-year average GDP growth rate, while upgrades and downgrades follow the Chen et al. (2016) specification. Our OLS estimates for upgrades range from 0.54 % (three-year ahead) to 0.6 % (one-year ahead), aligning closely with the results of Chen et al. (2016). For downgrades, the OLS coefficients are notably larger, at −1% (one-year ahead) and −0.68 % (three-year ahead). The quantile regression estimates suggest a more pronounced negative effect, with coefficients ranging from −1.9 % (one-year ahead) to −0.8 % (three-year ahead). To further validate our approach, Models (7)-(8) use a five-year average GDP growth rate, consistent with Chen et al. (2016). The OLS results yield coefficients of −0.26 % for downgrades and 0.54 % for upgrades, closely matching their estimates of −0.3 % and 0.6 %. However, our study primarily focuses on the tail behaviour of the growth distribution. Consistent with our expectations, the quantile regression results for five-year ahead growth are statistically insignificant, supporting previous findings that the tail effects of credit rating changes dissipate within two years.

In addition, in Table 5 Models (9) and (10), we adopt Alsakka et al. (2014)'s methodological approach and we define two dummy variables for UPGRADE and DOWNGRADE both equal to zero if there is no change, but the first is equal to one if the bank rating changes by one notch and the second set of dummy variables is equal to one if the change is of 2 or more notches. Our analysis indicates that the magnitude of the downgrade indeed matters. More specifically, the impact of a two-level downgrade is more than twice as large (−4.76) as that of a single-level downgrade (−1.93). This finding aligns with our expectations that more severe downgrades signal greater financial distress. However, the majority of downgrades in our sample are of one notch, and therefore we did not include

Table 3
Credit rating outlook announcements

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantiles:	OLS	5 %	OLS	5 %	OLS	5 %	OLS	5 %	OLS	5 %
	No rating change		Including rating change							
Change to NEGATIVE OUTLOOK	−0.376	**−1.830****	**−0.864****	**−2.598*****						
	(0.406)	(0.880)	(0.361)	(0.779)						
Change to STABLE OUTLOOK	−0.107	0.233	−0.089	−0.357						
	(0.274)	(0.297)	(0.228)	(0.776)						
Change to POSITIVE OUTLOOK	−0.061	−0.321	0.384	−0.247						
	(0.189)	(0.672)	(0.228)	(0.593)						
DOWNGRADE					**−1.866*****	**−3.773*****				
(if change OUTLOOK $<$ 0)					(0.560)	(0.771)				
DOWNGRADE					−0.326	**−1.570*****				
(if change OUTLOOK $\geq$ 0)					(0.362)	(0.571)				
NEGATIVE OUTLOOK							**−0.459*****	**−1.343*****		
							(0.166)	(0.459)		
POSITIVE OUTLOOK							**0.391****	0.251		
							(0.183)	(0.223)		
UPGRADE					0.748***	0.466***			**0.753*****	**0.452***
					(0.228)	(0.232)			(0.230)	(0.239)
DOWNGRADE									**−1.240*****	**−3.077*****
(NEG. OUTLOOK)									(0.456)	(0.694)
DOWNGRADE									−0.349	−1.590
(STA or POS. OUTLOOK)									(0.514)	(1.402)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,188	3,188	3,188	3,188	3,188	3,188	3,188	3,188
R^2 / Pseudo – R^2	0.711	0.649	0.712	0.654	0.714	0.664	0.712	0.559	0.713	0.662

Note: The Table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead ($t + 1$, $t + 4$), with the independent variables referring to the quarter t. Models (1) and (2) captures their impact during quarters without rating adjustments, whereas Models (3) and (4) incorporates periods when rating changes occur. Models (5) and (6) present the results of the linear and quantile regression models, respectively, for *DOWNGRADE* when there is a negative change in the outlook ($OUTLOOK < 0$) and when there is no prior signalling ($OUTLOOK \geq 0$). Finally, Models (7)–(10) report the effects of CRAs' outlook (rather than changes in outlook) on future GDP growth. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table 4
Robustness

	Additional controls				Incl. Monetary and Macroprudential policies		FCI	CISS	Excl. GFC	Excl. COVID
Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DOWNGRADE	**−2.765*****	**−2.399*****	**−3.214*****	**−3.098*****	**−3.028*****	**−2.837*****	**−5.547****	**−2.884****	**−2.869*****	**−2.950*****
	(0.574)	(0.486)	(1.076)	(1.087)	(1.087)	(1.096)	(1.640)	(1.016)	(0.722)	(0.783)
UPGRADE	**0.513*****	**0.594*****	0.326	0.244	0.175	0.184	0.551	**0.553****	**0.611*****	0.553
	(0.195)	(0.203)	(0.420)	(0.363)	(0.395)	(0.399)	(1.178)	(0.246)	(0.182)	(0.485)
DEBT (% GDP)		−0.028		−0.316	−0.309	−0.329				
		(0.305)		(0.375)	(0.386)	(0.471)				
GOV. DEFICIT		0.049***		0.012	0.031	0.021				
		(0.016)		(0.035)	(0.039)	(0.039)				
UNCERTAINTY				−0.644	−0.637	−0.534				
				(0.412)	(0.402)	(0.390)				
INFLATION				−0.249***	−0.120*	−0.142**				
				(0.041)	(0.069)	(0.066)				
STINT					−0.183***	−0.190***				
					(0.070)	(0.071)				
MPP TIGHTENING						0.230*				
						(0.125)				
MPP EXPANSION						0.121				
						(0.200)				
FCI							−0.124*			
							(0.072)			
CISS								−0.018***		
								(0.006)		
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,608	2,608	1,318	1,318	1,318	1,318	2,148	1,133	2,180	2,180
No of countries	28	28	14	14	14	12	28	16	33	33
Pseudo – R^2	0.684	0.691	0.715	0.731	0.732	0.733	0.499	0.712	0.701	0.701

Note: The Table presents estimated coefficients from panel fixed-effects quantile regressions, using the two-step estimation method outlined by Canay (2011). The analysis covers the period from 1990Q1 to 2023Q4. The dependent variable across all models is the average GDP growth between one and four periods ahead (t + 1 to t + 4), while the independent variables correspond to quarter t. All models include control variables: GDP growth, stock market volatility, credit-to-GDP gap, and house price growth. Additionally, debt and deficit (as percentages of GDP), inflation rate, and the Business Uncertainty Index are included as controls. In Models (5) and (6), STINT (short-term interest rate) and a macroprudential policy dummy, based on data from Alam et al. (2019), are also included. The Financial Conditions Index (FCI) in Model (7) is sourced from the IMF Database up to 2016Q3, while the Composite Indicator of Systemic Stress (CISS) in Model (8) is provided by the ECB for European countries. Models (9) and (10) exclude the Global Financial Crisis (GFC) period (2008–2010) and the COVID-19 period (2020–2022), respectively. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, based on 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table 5
Analysis of the magnitude of credit rating change

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantiles:	OLS	$q = 5\%$	OLS	$q = 5\%$	OLS	$q = 5\%$	OLS	$q = 5\%$	$q = 5\%$	$q = 5\%$
Horizon:	$h = 4$	$h = 4$	$h = 4$	$h = 4$	$h = 12$	$h = 12$	$h = 20$	$h = 20$	$h = 4$	$h = 12$
DOWNGRADE	**−1.105****	**−2.684*****							**−1.928****	−1.002
	(0.408)	(0.680)							(0.794)	(2.059)
UPGRADE	**0.726*****	0.404							**0.798*****	0.197
	(0.233)	(0.269)							(0.195)	(0.486)
DOWNGRADE × CRC			**−1.040*****	**−1.886*****	**−0.680*****	**−0.834*****	**−0.262*****	−0.364		
			(0.216)	(0.554)	(0.228)	(0.321)	(0.075)	(0.516)		
UPGRADE × CRC			**0.597*****	**0.544****	**0.541*****	0.566	**0.541*****	0.239		
			(0.205)	(0.221)	(0.131)	(0.398)	(0.138)	(0.197)		
DOWNGRADES (2 or more)									**−4.796*****	**−4.068*****
									(1.185)	(1.377)
UPGRADES (2 or more)									0.181	**1.111***
									(0.632)	(0.664)
Lagged Rating FE	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,187	3,187	3,188	3,188	2,934	2,934	2,747	2,747	3,188	2,934
R^2 / Pseudo – R^2	0.714	0.662	0.714	0.662	0.533	0.379	0.533	0.391	0.664	0.377

Note: The table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effects quantile regressions, employing the two-step estimation method outlined by Canay (2011). DOWNGRADE and UPGRADE are dummy variables that take the value of one if there is a respective change. CRC represents the absolute change in credit ratings. The analysis is based on a global sample of 33 countries spanning the period from 1990Q1 to 2023Q4. The dependent variable across all models is the average GDP growth between one and four periods ahead ($t + 1$ to $t + 4$), while the independent variables correspond to quarter t. All models include control variables: GDP growth, stock market volatility, credit-to-GDP gap, and house price growth and incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, based on 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

this analysis as a benchmark model. With respect to the upgrades, only the one notch change provides significant results in the baseline four-quarters ahead GDP growth. This could be attributed to the limited number of larger upward changes in the ratings.

4.3.3. Alternative CRAs' data

In this section, we provide further empirical evidence to support our findings by using data from alternative CRAs. Although the three major CRAs (Moody's, S&P, and Fitch) exhibit considerable co-movements on the rating decisions, the literature finds that the importance of rating agencies' announcements varies significantly. These three agencies account for the majority of the market with Moody's and S&P together covering 80 % and Fitch 15 % (Alsakka and ap Gwilym, 2010) of the market. However, the three agents present differences. S&P and Fitch are more active than Moody's which appears to be more cautious (Alsakka et al., 2014; Afonso et al., 2012). This cautious approach may increase Moody's credibility, as markets interpret infrequent actions as well-considered and thus more impactful. The latter could potentially explain the literature that suggests that Moody's announcements produce the greatest impact on financial markets. For instance, Baum et al. (2016) and Williams et al. (2015) argue that rating announcements by Moody's tend to have the most persistent effect on government bonds and bank stock prices compared to those of the other two CRAs. Additionally, this persistence could stem from Moody's methodology, which is perceived as more conservative and rigorous by market participants. Finally, Sahibzada et al. (2022) find that Moody's actions have a stronger impact on systemic risk, followed by S&P and Fitch.

To provide a robustness test for our initial findings in Table 6, we present results from our benchmark model using the S&P and Fitch rating changes and announcements instead of those issued by Moody's. We find that the estimated quantile regression coefficients for rating downgrades and upgrades show similar patterns across all three agencies, with Fitch exhibiting the greatest impact. Notably, the effect of downgrades diminishes across all models for the upper quantiles, aligning with our initial findings (Table 2), and the estimated OLS coefficient is smaller than the coefficient for the lower quantile (5 %). For credit rating upgrades, the Moody's benchmark model shows a statistically significant positive relationship, with a stronger effect in the upper quantiles. S&P upgrades are statistically significant only in the upper quantiles, while Fitch upgrades display no substantial effect on the future GDP growth distribution.

Our findings align closely with those of Alsakka and ap Gwilym (2013), who found that positive news from Moody's alone impacted the exchange rate market, while negative news from all three CRAs produced adverse responses, with Fitch having the greatest negative effect. These differences in market responses among the CRAs may be attributed to the frequency of rating changes. Although each agency contributes similarly to the total number of downgrades in our sample period, Fitch accounts for 38 % of the upgrades, followed by S&P, and Moody's. Our results suggest an inverse relationship between the frequency of rating changes and their impact on macroeconomic stability. In other words, we observe a trade-off: while Fitch is more active, the market seems to react more strongly to Moody's actions, likely due to perceived reliability. Finally, we present results for combined CRA actions, where the dummy variables ALL DOWNGRADE and ALL UPGRADE are set to one if at least one CRA changes the rating of the examined country. In this case, the results further support our findings, as the coefficients for both downgrades and upgrades are statistically significant and

Table 6
Empirical results from alternative CRAs

Quantiles:	OLS	5 %	25 %	50 %	75 %	95 %
S&P Credit rating changes						
DOWNGRADE	**−1.182*****	**−3.132*****	**−0.943***	**−0.597*****	**−0.492*****	−0.001
	(0.422)	(0.598)	(0.498)	(0.164)	(0.191)	(0.558)
UPGRADE	0.230	0.276	0.096	0.109	0.678***	0.772*
	(0.155)	(0.210)	(0.117)	(0.117)	(0.145)	(0.443)
FITCH Credit rating changes						
DOWNGRADE	**−1.303*****	**−3.338*****	**−1.090***	**−0.734****	**−0.496****	−0.119
	(0.456)	(0.767)	(0.607)	(0.314)	(0.236)	(0.497)
UPGRADE	0.171	0.321	0.137	0.075	0.132	0.010
	(0.170)	(0.476)	(0.109)	(0.118)	(0.173)	(0.476)
All CRAs: Credit rating changes						
ALL DOWNGRADE	**−0.775*****	**−2.766*****	**−0.837*****	**−0.444*****	−0.213	0.276
	(0.260)	(0.649)	(0.206)	(0.142)	(0.135)	(0.275)
ALL UPGRADE	0.325***	0.369**	0.194**	0.158*	0.125	0.533*
	(0.115)	(0.171)	(0.093)	(0.093)	(0.106)	(0.322)
Country controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,188	3,188	3,188	3,188

Note: The Table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. The credit rating changes refer to Moody's, S&P and Fitch data. In the ALL CRAs model specification, the dummy variables ALL DOWNGRADE and ALL UPGRADE are equal to one if at least one of the three CRAs change its rating and zero otherwise. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

show the expected signs.

4.3.4. Alternative QR methodology

For robustness purposes, we use an alternative approach to capture individual fixed effects in a quantile-regression panel format: the Method of Moments-Quantile Regression (MM-QR) proposed by Machado and Santos Silva (2019). The methodology extends quantile regression to panel data with unobserved heterogeneity. This estimator allows for consistent estimation of quantile-specific slope coefficients while controlling for country fixed effects. Unlike traditional fixed-effects quantile methods (e.g., Canay, 2011), the MM-QR estimator allows for fixed effects that vary across quantiles through a location-scale structure. Specifically, fixed effects enter the model as $a_i + \delta_i q(\tau)$, where $q(\tau)$ is the τ-th quantile of the standard normal distribution. These fixed effects are accounted for through a two-step transformation. In the first step, a location model is estimated to isolate fixed effects. In the second step, quantile-specific slope coefficients are estimated using moment conditions derived from the check function. This ensures valid inference and consistency even in high-dimensional panels and addresses the incidental parameters problem common in nonlinear fixed-effects models. The MM-QR framework models the conditional quantile as:

$$\widehat{Q}_{Y_{i,t+h}|X_{i,t}}(\tau|X_{i,t}) = a_i + \delta_i q(\tau) + X'_{i,t}\beta + X'_{i,t}\gamma q(\tau) \tag{5}$$

where τ denotes the examined quantile and t stands for time. The MM-QR methodology is used in the at-risk framework literature by Banerjee et al. (2024), Lopez-Salido and Loria (2024) and Furceri et al. (2025). The method is particularly well-suited for this context as it permits the distributional effects of these variables to vary across the conditional GDP growth distribution while accounting for unobserved country heterogeneity. Our specification includes current GDP growth, stock market volatility, the credit-to-GDP gap, real house price growth, and sovereign rating upgrades and downgrades. The model also includes year and quarter fixed effects.

The empirical findings are presented in Tables 7 and 8. We present the findings for the 5th, 25th, 50th (median), 75th and 95th quantiles and for five alternative estimation horizons ($h = 2,3,4,5,6$). The results confirm our initial findings: a sovereign credit rating downgrade has a significant impact on the lower quantiles of the future GDP growth distribution, with the effect weakening in the right tail of the conditional distribution. In contrast, upgrades show a weak positive effect at the 25th percentile, but they do not impact either the upper or lower tails (95 % and 5 %, respectively). Regarding the time variation of the impact, the results from the MM-QR model are similar but indicate that the effect is more short-lived. Specifically, we observe that the effect peaks four quarters after the credit rating change and becomes insignificant two quarters later, whereas in our benchmark model, the impact remained statistically significant up to seven quarters ahead.

4.3.5. Sub-sample analysis

We then examine which countries drive our results. Table 9 presents the sub-sample and group-specific results. First, we divide our sample into developed and developing countries. We find that the coefficients for sovereign credit rating downgrades are statistically significant only for developed economies, while the relationship is negative but insignificant for developing countries. In both groups, the coefficients of upgrades are statistically insignificant. These findings can be partially attributed to two factors. First, downgrades in developed countries often signal extreme economic conditions or fiscal mismanagement, representing a considerable deviation from market expectations. Consequently, these downgrades trigger amplified market reactions and macroeconomic consequences. By

Table 7
MM-QR Results

Models:	(1)	(2)	(3)	(4)	(5)
Quantiles:	5 %	25 %	50 %	75 %	95 %
DOWNGRADE	**−2.506****	**−1.641*****	**−1.149****	−0.567	0.423
	(1.048)	(0.522)	(0.583)	(0.555)	(1.166)
UPGRADE	0.587	**0.691***	0.228	0.202	0.158
	(0.742)	(0.370)	(0.310)	(0.295)	(0.621)
Current GDP growth	0.517***	0.514***	0.517***	0.512***	0.502***
	(0.068)	(0.034)	(0.038)	(0.036)	(0.076)
VIX	−0.059	−0.035	−0.020	−0.008	0.014
	(0.090)	(0.045)	(0.050)	(0.048)	(0.099)
Credit-to-GDP	0.004	−0.146	−0.265	−0.322	−0.420
	(0.477)	(0.238)	(0.269)	(0.256)	(0.539)
HP growth	0.044***	0.038***	0.036***	0.032***	0.026
	(0.016)	(0.008)	(0.010)	(0.009)	(0.018)
Country FE	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,188	3,188	3,188

Note: The Table presents estimated coefficients derived from a panel fixed-effect quantile regressions, following Machado and Santos Silva (2019). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table 8
MM-QR Results | Alternative Horizons

Models:	(1)	(2)	(3)	(4)	(5)
Horizon:	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
DOWNGRADE	0.195	**−3.376*****	**−2.506****	**−2.822***	−2.752
	(0.503)	(1.372)	(1.048)	(1.562)	(2.392)
UPGRADE	0.232	0.767	0.587	0.806	0.806
	(0.573)	(0.973)	(0.742)	(1.536)	(1.536)
Control variables	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,188	3,188	3,188

Note: The Table presents estimated coefficients derived from a panel fixed-effect quantile regressions (q = 0.05), following Machado and Santos Silva (2019). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and h periods ahead (t + 1, t + h), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table 9
Sub-sample analysis

Models:	(1)	(2)	(3)	(4)	(5)	(6)
	Developed countries	Developing countries	Developed and Developing countries	Investment grade	Speculative grade	Investment and Speculative grade
DOWNGRADE	**−3.244****	**−0.341**		**−1.637**	**−1.496****	
	(0.720)	(1.114)		(1.147)	(0.745)	
UPGRADE	0.364	0.411		0.376	−0.075	
	(0.259)	(0.746)		(0.457)	(0.418)	
DEVELOPED*DOWN			**−3.234*****			
			(0.790)			
DEVELOPED*UP			**0.410***			
			(0.247)			
DEVELOPING*DOWN			**−2.497*****			
			(0.807)			
DEVELOPING*UP			−1.061			
			(1.084)			
DEVELOPED			**0.584*****			
			(0.204)			
SPEC*DOWN						**−3.154*****
						(0.836)
SPEC*UP						**1.187*****
						(0.443)
INV*DOWN						−1.591
						(1.136)
INV*UP						0.451
						(0.347)
SPEC_GRADE						−0.086
						(0.290)
Control variables	YES	YES	YES	YES	YES	YES
Country, Year & Quarter FE	YES	YES	YES	YES	YES	YES
Observations	2,660	528	3,188	2,962	226	3,188
Pseudo – R^2	0.686	0.661	0.667	0.656	0.769	0.662

Note: The Table presents estimated coefficients derived from a panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. Countries with a Moody's rating of Ba1 or below are considered "Speculative" while those rated above Ba1 are classified as "Investment" grade. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

contrast, developing countries tend to have lower ratings and higher inherent risk already priced in, which may dampen the additional impact of a downgrade. Second, fewer downgrades occur in developing countries within our sample, resulting in a smaller number of observations. Additionally, only 16.6 % of our observations correspond to developing countries, reflecting the dataset's imbalance due to constraints in BIS and stock market data availability. This limited representation likely affects the statistical power of our analysis and contributes to the weaker observed effects in developing countries. Third, most developed countries in our sample are Euro Area members, many of which were impacted by the Sovereign Debt Crisis. In Model (3), we introduce interaction terms by incorporating dummy variables for developed and developing countries. Our findings reveal that downgrades are statistically significant for both groups, with a stronger effect in developed economies. Upgrades exhibit a statistically significant positive effect only in developed countries.

Additionally, we investigate whether the initial rating category affects the impact of potential rating changes. We divide our sample into investment-grade and speculative-grade ratings based on Moody's classification.[10] The results, presented in Models (4) to (6), show that despite the smaller sample size (226 quarterly observations from countries with speculative-grade ratings), the coefficient for downgrades is negative and statistically significant, and the model's goodness-of-fit is considerably high. Interestingly, speculative-grade ratings are not exclusive to developing countries. Developed economies, such as Greece, Portugal, and, for shorter periods, Ireland and South Korea have also been classified as speculative-grade for extended periods.[11] In these cases, downgrades attract heightened market scrutiny due to elevated credit risk and sensitivity to macroeconomic and market conditions. In contrast, the estimates for investment-grade economies are not statistically significant, suggesting they are less vulnerable to rating changes. This aligns with the notion that downgrades within speculative-grade territories often signal larger deviations from expectations, prompting stronger investor reactions. One possible explanation is that speculative-grade developed countries are subject to higher investor scrutiny due to elevated credit risk and greater sensitivity to market sentiment. When these countries experience a downgrade, it can prompt a stronger reaction from investors, especially in Euro Area economies. This contrasts with developing countries, where investors may already account for a higher inherent risk and economic volatility, making the impact of downgrades less pronounced.

4.4. The role of CRA regulation

Following the 2008 financial crisis, significant regulatory reforms were introduced globally to address deficiencies in the functioning of CRAs that were highlighted during the crisis. These reforms aimed to enhance transparency, reduce overreliance on ratings, and improve oversight of CRAs. This regulatory evolution provides a natural experiment to evaluate how regulatory interventions can shield economies from the adverse impacts of credit rating downgrades and upgrades. In this section, we empirically test whether the adoption of these frameworks mitigates the effects of credit rating changes. The results are presented in Table 10 and include all countries in our sample, alongside a CRA regulation dummy variable (REGULATION), which for the majority of countries captures reforms introduced in the period following the GFC. The variable REGULATION takes the value one in periods after the adoption of CRA regulatory reforms and zero otherwise. We focus specifically on regulatory changes introduced after the GFC that are aligned with the EU regulatory framework and/or the International Organization of Securities Commissions (IOSCO) Code of Conduct. In addition to the European countries and the US, our analysis also accounts for reforms adopted in Australia (2010), Japan (2010), India (2010), South Korea (2009), Canada (2012), Brazil (2012), Switzerland (2012), Mexico (2013), Israel (2015), Indonesia (2015), and Turkey (2016).

The findings in Models (1) and (2) highlight that downgrades have a statistically significant negative effect on GDP growth across both pre- and post-regulation periods. Notably, the adverse effect is stronger in the period before the adoption of these regulatory reforms. To further investigate this issue, we employ interaction terms to explicitly test the statistical significance of differences between the two periods. The results are presented in Models (3) and (4) for European countries alone and the extended sample of thirty countries, respectively. In both models, we exclude year fixed effects to prevent them from absorbing the variation of interest.[12] The coefficient for DOWNGRADE remains negative and statistically significant as expected, with the coefficient of the interaction term REGULATION $\times$ DOWNGRADE being positive. This suggests that the adverse effects of sovereign credit rating downgrades on GDP growth were more pronounced before the implementation of regulatory frameworks. In the post-2009 period, the results indicate that the negative impact of downgrades weakens significantly, consistent with the hypothesis that regulation dampens market over-reaction and over-reliance on ratings. For robustness, we also present the results with year and quarter fixed effects in Model (5), confirming that the mitigating effect of regulation persists, although its magnitude appears slightly reduced.

We further extend the analysis in Models (6)–(9) by incorporating credit rating changes from all CRAs, as detailed in Table 6. The findings remain consistent, showing that the adoption of regulation mitigates the economic consequences of rating downgrades across a broader spectrum of cases. This evidence aligns with prior literature suggesting that CRA regulation primarily aims to reduce market over-reaction (Alsakka et al., 2015) and over-reliance on credit ratings (Sahibzada et al., 2022). Overall, our findings reinforce the argument that regulatory reforms succeeded in moderating the amplification of adverse economic effects associated with credit rating downgrades, thereby enhancing the stability of financial markets.

[10] Countries with a Moody's rating of Ba1 or below are considered "Speculative" while those rated above Ba1 are classified as "Investment" grade.

[11] When we re-estimate the model excluding developed countries during periods in which they fell into the speculative-grade range (based on Moody's ratings), the results are no longer statistically significant. This suggests that these countries are key drivers of the heterogeneous effects observed between developed and developing economies.

[12] Klusak et al. (2019), who study the impact of ESMA regulatory identifiers on the quality of ratings also did not include time fixed effects in their model. A similar approach was adopted by Brunnermeier et al. (2020), who study the impact of asset bubbles on systemic risk. They argue that if two countries exhibit a bubble simultaneously, then banks will experience the same increase in systemic risk and in this case, their bubble dummy variable that captures the change in systemic risk relative to the average of the two countries, will be statistically insignificant.

Table 10
The role of CRA regulation

Models:	Moody's					All CRAs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pre-REG	Post-REG	Full period Europe only	Full period All countries	Full period All countries (with time FE)	Pre-REG	Post-REG	Full period Europe only	Full period All countries
DOWNGRADE	**−5.016*****	**−2.008****	**−2.243***	**−2.323*****	**−4.399*****	**−3.777*****	**−1.970*****	**−2.237****	**−2.038****
	(1.397)	(0.678)	(1.164)	(0.737)	(1.257)	(1.507)	(0.602)	(0.999)	(0.829)
UPGRADE	**0.554****	**0.922****	**1.514*****	−0.648	0.658**	0.294	**0.433***	**0.865*****	0.598
	(0.250)	(0.440)	(0.387)	(0.894)	(0.320)	(0.210)	(0.242)	(0.270)	(0.411)
REGULATION			−1.344***	−1.497***	−0.466*			−1.353**	−1.461***
			(0.520)	(0.355)	(0.277)			(0.572)	(0.320)
REGULATION × DOWNGRADE			**3.070*****	**2.575*****	**2.469***			**3.050****	**2.064***
			(1.188)	(0.840)	(1.408)			(1.253)	(1.084)
REGULATION × UPGRADE			−4.942	2.356	0.078			−4.301	−2.123
			(3.015)	(2.746)	(0.411)			(2.870)	(2.560)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	NO	NO	YES	YES	YES	NO	NO
Observations	1,569	1,456	1,816	3,025	3,025	1,588	1,456	1,835	3,207
No of countries	30	30	17	30	30	30	30	17	30
Pseudo – R^2	0.720	0.640	0.463	0.448	0.667	0.715	0.645	0.469	0.625

Note: The Table presents estimated coefficients derived from a panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 30 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. REGULATION is a dummy variable that equals one if the country has adopted a CRA regulation and zero otherwise. Models (1)–(5) are based on credit rating changes by Moody's, while Models (6)–(9) also incorporate changes by S&P and Fitch. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

4.5. Transmission channels

As we discussed beforehand, sovereign credit ratings have a significant impact on GDP growth through two primary channels: borrowing costs (bond spreads) and investments/capital flows. A downgrade in a country's creditworthiness signals heightened risk to investors, leading to an increase in bond spreads as investors demand higher compensation for the elevated uncertainty. This rise in borrowing costs not only impacts sovereign debt financing but also translates into higher costs for corporate borrowing. Simultaneously, downgrades erode business confidence, resulting in significant declines in both domestic and foreign investments. This dynamic, often referred to as the "*flight to quality*" channel (Caballero and Krishnamurthy, 2008), combined with elevated borrowing costs (Cantor and Packer, 1996), hinders both governmental and corporate investment initiatives, ultimately reducing economic activity.

In this section, we extend the *Growth-at-Risk* (GaR) framework to examine the transmission channels through which credit rating changes affect macroeconomic outcomes. More specifically, we follow Fernández-Gallardo Romero and Lloyd (2023), who explore the transmission channels of macroprudential policy in the *at-risk* framework. They focus on the role of credit, which they use as the dependent variable in their quantile regression model to estimate *credit-at-risk*. Their findings suggest that tightening macroprudential policy pushes down the upper tail of future credit distribution, and therefore appears to be effective in mitigating excessive credit growth. In a two-step procedure, they incorporate *Credit-at-risk* in the *Growth-at-risk* model by using a variable for periods of excessive credit (credit boom). Their results suggest that there is a strong negative relationship between the 90th percentile of credit growth and the lower tail of the GDP growth distribution.

Building on their methodology, we analyse the tail impact of credit rating changes on the future distribution of bond spreads and investments. For bond spreads, we use the spread between the examined country's 10-year government bond and the US 10-year bond as a benchmark. For investments, we employ Gross Fixed Capital Formation (year-on-year growth), provided by the OECD database, as a consistent measure across countries. The results, presented in Table 11, reveal that credit rating downgrades significantly influence the right tail of the bond spread distribution, consistent with the notion that downgrades increase borrowing costs. Conversely, upgrades show no statistically significant effect. For investments, downgrades exhibit a stronger effect on the left tail of the investment distribution, confirming that negative credit events reduce investment activity. Importantly, in both cases, the effects observed at the 95th percentile for bond spreads and the 5th percentile for investments are statistically distinct from the coefficients estimated using OLS, underscoring the value of employing quantile regression to capture these dynamics.

We then incorporate both investments and bond spreads into the *Growth-at-Risk* model as predictors, alongside other macroeconomic factors. The results, summarized in Table 12, suggest that the impact of these variables on GDP growth is not homogeneous across the distribution. Investments are positively associated with future GDP growth, but their influence is largely confined to the median of the distribution. This implies that changes in investment levels primarily affect central economic tendencies and can be adequately captured using linear models. In contrast, bond spreads show a strong negative relationship with the lower quantiles of the GDP growth distribution, indicating that increases in borrowing costs significantly heighten macroeconomic downside risk. The results highlight that bond spreads, rather than investments, are the primary driver of tail risks for GDP growth. Additionally, the results remain robust to the inclusion of control variables such as debt levels, government deficit, inflation, and uncertainty as shown in Models (3) and (4) of Table 12.

Overall, our findings suggest that bond spreads play a pivotal role in driving downside risks, as evidenced by their significant impact on the lower quantiles of the GDP growth distribution. Conversely, the investment channel is present, but its impact is more pronounced on the central tendency of GDP growth and does not contribute significantly to macroeconomic tail risk.[13]

4.6. Endogeneity test

Although the Growth-at-Risk (GaR) framework is inherently a forecasting model and not necessarily a tool for causal inference, concerns around reverse causality between credit rating downgrades and future GDP growth may still arise. Past economic conditions may influence CRAs' decisions, which could in turn bias the estimated impact of ratings on macroeconomic outcomes. To address these endogeneity concerns, we implement a two-stage least squares (2SLS) approach using a novel instrument based on textual analysis. More specifically, we develop BANK_SOVRAT, a variable capturing the frequency of the term *"sovereign credit rating(s)"* (and close variants)[14] in the narrative sections of annual reports published by systemically important banks[15] in countries that experienced at

[13] The findings are consistent across countries. In Appendix Table A5, we present the results for both developing and developed countries, and a similar pattern is observed across the two groups. Alternative categorizations, such as high-debt and low-debt countries, also yield comparable results. Furthermore, the findings remain robust when addressing potential endogeneity concerns by analysing investments and bond spreads in separate regressions.

[14] Alternative terms were tested, however, including words such as "downgrade" and "upgrade" introduced noise and weakened the instrument's predictive power.

[15] Systemically important banks are selected based on designations of the European Banking Authority (EBA) for European countries and equivalent national sources for non-European countries and data availability. Our sample includes 42 large banking institutions across fifteen countries: Austria, Belgium, Brazil, Chile, Spain, Finland, France, Greece, Hungary, Italy, Japan, Mexico, Portugal, Turkey, and the UK and the period 2006–2023. We deliberately exclude smaller financial institutions, which are more likely to exhibit idiosyncratic risk profiles, and whose disclosures are typically less representative of broader financial sector expectations.

Table 11
Transmission channels: Stage 1

Quantiles:	OLS	5 %	25 %	50 %	75 %	95 %
Bond Spread ($t+1$, $t+4$)						
DOWNGRADE	**1.049***	**−0.068**	**0.175**	**0.446*****	**0.770***	**5.564*****
	(0.560)	(0.124)	(0.148)	(0.161)	(0.437)	(1.539)
UPGRADE	0.096	0.053	0.038	−0.038	−0.044	0.513
	(0.066)	(0.134)	(0.071)	(0.069)	(0.100)	(0.898)
Investments ($t+1$, $t+4$)						
DOWNGRADE	**−4.286*****	**−12.744*****	**−6.416*****	**−2.852*****	**−2.333*****	**−2.532*****
	(1.241)	(2.400)	(1.701)	(1.147)	(0.834)	(3.945)
UPGRADE	2.747***	3.395***	1.727***	1.615***	1.567*	9.317***
	(0.631)	(1.515)	(0.718)	(0.547)	(0.884)	(3.945)
Country controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES

Note: The Table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable is the average Bond Spread and Investments, respectively, between one and four periods ahead (t + 1, t + 4), with the independent variables referring to the quarter t. All models incorporate country controls and country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table 12
Transmission channels: Stage 2

Models:	(1)	(2)	(3)	(4)
	OLS	5 %	OLS	5 %
INVESTMENTS (t)	**0.025*****	0.008	**0.032*****	0.018
	(0.008)	(0.008)	(0.101)	(0.012)
BOND SPREAD (t)	**−0.176*****	**−0.204****	**−0.111****	**−0.143***
	(0.036)	(0.040)	(0.041)	(0.074)
Country controls	YES	YES	YES	YES
Additional country controls	NO	NO	YES	YES
Country FE	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES
Observations	2,980	2,980	1,319	1,319

Note: The Table presents estimated coefficients derived from a linear panel (OLS) model and panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). The dependent variable is the four-quarters ahead average GDP growth and Investments and Bond Spreads are among the explanatory variables. All models incorporate the benchmark model's country controls and country, year, and quarter fixed effects. Models (3)-(4) include additional country controls, such as debt and deficit (as percentages of GDP), inflation rate and business uncertainty. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses.***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

least one downgrade during the sample period. Aggregated at the country-year level, this text-based measure reflects the forward-looking attention that large financial institutions devote to sovereign rating risks. Importantly, while these private institutions' annual reports may reflect expectations of future changes in sovereign credit ratings, they do not have any direct effect on the macroeconomy. To further mitigate simultaneity bias, we lag the instrument: when the dependent variable is GDP growth in year T or T+1, we use the annual report published in year T–1, which generally refers to financial and economic conditions in year T–2 (and sometimes up until T–1 Q1). This ensures that the content precedes both the rating change and subsequent macroeconomic outcomes.

The results are presented in Table 13, and they confirm the instrument's relevance. BANK_SOVRAT is a strong and statistically significant predictor of subsequent sovereign rating downgrades across specifications with and without control variables, and for both the European subsample and the full country sample.[16] The second-stage results provide robust evidence of a negative causal effect of sovereign credit rating downgrades on future GDP growth. In our specification we use ΔMoody's as the endogenous variable, which is defined as the quarter-on-quarter change in the country's Moody's sovereign credit rating. The IV estimate is negative and statistically significant, which suggests that sovereign rating downgrades lead to a substantial decline in future GDP growth. Overall, these results strengthen the argument that sovereign credit rating downgrades exert a direct and economically meaningful impact on future economic activity and underscore the importance of sovereign credit risk as a driver of macroeconomic outcomes.

[16] The reported Kleibergen-Paap F-statistics are well above the conventional threshold of 10, alleviating concerns about weak instruments.

Table 13
Endogeneity test

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All countries	All countries	Europe	Europe	All countries	All countries	Europe	Europe
Dependent variable:	First stage ΔMOODY'S	Second stage GDP (t + 1, t + 4)	First stage ΔMOODY'S	Second stage GDP (t + 1, t + 4)	First stage ΔMOODY'S	Second stage GDP (t + 1, t + 4)	First stage ΔMOODY'S	Second stage GDP (t + 1, t + 4)
L4.BANK_SOVRAT	**0.107***** (0.026)		**0.108***** (0.029)		**0.089***** (0.026)		0.097*** (0.030)	
ΔMOODY'S_predicted		**3.661**** (1.575)		**−4.523***** (1.671)		**2.332*** (1.410)		**2.701*** (1.384)
Current GDP growth					0.021*** (0.008)	0.413*** (0.049)	0.021** (0.011)	0.347*** (0.054)
VIX					−0.069** (0.027)	−0.649 (0.455)	−0.024 (0.050)	−1.225 (0.219)
Credit-to-GDP					−0.284*** (0.099)	0.224 (0.667)	−0.159 (0.102)	1.256* (0.676)
HP growth					0.003 (0.003)	0.053*** (0.018)	0.003 (0.005)	0.092*** (0.022)
Constant	0.053 (0.059)	3.438*** (0.339)	0.028 (0.050)	3.642*** (0.376)	0.390** (0.157)	2.149* (1.160)	0.165 (0.161)	1.363 (0.967)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,020	1,020	680	680	980	980	672	672
Kleibergen-Paap Wald rk F statistic		17.22		13.84		11.90		10.59

Note: This table presents the results of an endogeneity test using a two-stage least squares (2SLS) model to evaluate the effect of changes in sovereign credit ratings (ΔMOODY'S) on the lower tail of the future GDP growth distribution. The analysis is based on a sample of 15 countries, including a subsample of 10 European countries, covering the period from 2006Q1 to 2023Q4. The instrument (L4.BANK_SOVRAT) is constructed from a textual analysis of annual reports of each country's systemically important banks, capturing the number of references to the term "sovereign credit rating(s)". The instrument enters the model with a one-year (four quarters) lag (L4). The dependent variable is the average GDP growth between one and four quarters ahead (t + 1 to t + 4), while the independent variables refer to quarter t. All models include country, year, and quarter fixed effects, and robust standard errors. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

5. Conclusions

CRAs play a critical role in financial markets by providing assessments of sovereign and corporate creditworthiness, which in turn influence investor behaviour, borrowing costs, and economic policy. Using the *Growth-at-Risk* approach introduced by Adrian et al. (2019), we explore the impact of sovereign credit rating changes on the future GDP growth distribution, focusing not only on the mean, but also on the tail risks of GDP growth. Our findings reveal that sovereign downgrades increase macroeconomic tail risk, with the strongest effects observed in the lower quantiles of the GDP growth distribution, while the impact diminishes in the upper quantiles. This asymmetric effect emphasises the importance of analysing the entire distribution of GDP growth, as downgrades disproportionately affect downside risks rather than the average economic outcome. Additionally, we observe that the effect of downgrades is transitory, peaking approximately six quarters after the rating change and dissipating within two years, suggesting that market reactions to downgrades are significant but not enduring.

Our results hold under several robustness tests, including alternative quantile regression methodologies, ratings by all three major CRAs, other indicators of financial stress, additional control variables, and endogeneity tests. Our empirical analysis offers additional insights. More specifically, the effect of rating changes varies across countries and creditworthiness categories. Developed countries and those classified as speculative (non-investment grade) experience a stronger impact from downgrades, likely due to greater market sensitivity to creditworthiness signals. In addition, we examine the role of global CRA regulatory frameworks introduced after the GFC. These reforms aimed to reduce overreliance on CRAs, improve transparency, and strengthen accountability. Our findings suggest that the adverse effects of downgrades have weakened post-regulation, aligning with the objective of enhancing market stability by reducing overreliance on CRAs. Finally, we focus on two main channels through which credit rating changes affect the macroeconomy: increased borrowing costs and reduced investment. Our results indicate that the interest rate channel is significantly associated with downside risks to GDP growth, whereas the investment channel primarily influences the central tendency (median) of GDP growth rather than the tail risks. In summary, our empirical results underscore the importance of incorporating sovereign credit ratings into comprehensive risk assessment frameworks like *Growth-at-Risk* to enable policymakers to monitor systemic risks more effectively.

CRediT author contribution statement

George Kladakis: Methodology, Formal analysis, Investigation, Resources, Writing – Original Draft, Writing – Review & Editing.
Alexandros Skouralis: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing –

Original Draft, Writing – Review & Editing.

CRediT authorship contribution statement

George Kladakis: Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Data curation. **Alexandros Skouralis:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Data Statement

The article makes use of existing (secondary) data which are cited at the references. Some of the data is confidential for business purposes and some from paid subscriptions to financial databases.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Correlation Table

	GDP growth	VIX	Credit-to-GDP	HP growth	Moody's DOWN	Moody's UP
GDP growth	1.000					
VIX	−0.030	1.000				
Credit-to-GDP	−0.196	−0.024	1.000			
HP growth	0.270	−0.043	0.048	1.000		
Moody's DOWN	−0.165	0.060	−0.004	−0.107	1.000	
Moody's UP	0.056	0.011	−0.085	0.005	−0.020	1.000

Note: The Table presents the correlation between the benchmark model's independent variables. The statistics refer to our benchmark sample that includes data from 33 countries and the period 1990Q1-2023Q4.

Table A2
GDP growth summary statistics

Country	Observations	Mean	Std. Dev.	Min	Max
Australia	91	2.792	1.258	−2.126	6.013
Austria	88	1.433	2.454	−7.182	8.073
Belgium	128	1.815	1.860	−5.307	8.338
Brazil	56	1.532	3.040	−4.823	7.592
Canada	129	2.249	2.006	−5.029	6.378
Chile	80	3.516	3.514	−7.082	12.985
China	48	6.528	2.063	1.700	9.650
Colombia	61	4.039	2.493	−2.540	12.829
Czechia	56	1.622	2.724	−5.626	5.604
Germany	118	1.320	1.928	−5.628	4.957
Denmark	129	1.813	2.006	−5.131	7.831
Finland	129	1.667	3.094	−8.067	7.062
France	129	1.556	2.049	−7.573	7.921
Greece	81	−0.207	5.117	−11.309	10.877
Hungary	60	1.916	3.471	−6.610	9.768
Indonesia	80	4.972	1.664	−2.926	6.451

(*continued on next page*)

Table A2 (*continued*)

Country	Observations	Mean	Std. Dev.	Min	Max
Israel	108	3.978	2.405	−2.029	11.601
India	52	6.192	3.625	−5.823	11.222
Italy	76	0.305	3.163	−9.044	9.856
Japan	129	0.836	1.824	−6.167	4.105
South Korea	129	4.734	3.109	−5.112	12.876
Mexico	68	1.551	3.317	−8.536	8.086
Netherlands	129	2.080	2.077	−3.992	8.094
Norway	118	2.183	1.714	−2.279	5.610
Poland	68	3.856	2.344	−2.934	9.804
Portugal	120	1.514	2.917	−8.842	10.395
Russia	35	4.477	4.380	−7.011	9.686
Spain	129	1.936	3.098	−11.166	9.586
Sweden	129	2.098	2.318	−5.353	6.551
Switzerland	129	1.659	1.655	−2.610	6.574
Turkey	48	5.543	3.179	−1.191	12.146
UK	129	1.921	2.951	−11.594	14.090
USA	129	2.484	1.662	−3.222	6.418

Note: The Table presents the summary statistics of GDP growth (t + 1, t + 4) by country. The statistics refer to our benchmark sample that includes data for the period 1990Q1-2023Q4.

Table A3
GDP growth per year

Country	Mean	Std. Dev.	Min	Max
1990	1.146	3.878	−5.015	10.381
1991	1.083	3.226	−5.887	10.795
1992	0.681	2.181	−3.281	6.237
1993	1.937	2.293	−2.084	8.772
1994	3.711	1.953	0.706	10.187
1995	2.928	1.892	0.383	9.629
1996	3.347	1.661	0.452	7.896
1997	3.634	1.775	−3.114	7.062
1998	2.902	2.015	−5.112	7.109
1999	4.434	2.274	−0.245	12.876
2000	3.703	1.616	1.565	9.141
2001	1.613	1.552	−2.029	7.170
2002	1.602	1.668	−1.414	7.741
2003	2.503	1.588	−0.925	5.983
2004	3.216	1.627	0.226	7.111
2005	3.324	1.526	0.722	7.785
2006	3.992	1.703	1.288	8.497
2007	3.417	2.127	−0.122	9.686
2008	−0.945	2.878	−7.058	6.021
2009	−0.401	3.274	−8.067	7.495
2010	3.136	3.347	−11.309	11.222
2011	2.277	3.424	−10.141	11.014
2012	1.321	2.934	−7.169	7.875
2013	2.322	2.272	−2.500	8.689
2014	2.533	1.910	−2.224	7.412
2015	2.411	2.198	−4.823	8.826
2016	2.628	1.853	−3.453	8.992
2017	3.206	1.666	1.055	7.917
2018	2.511	1.677	−1.191	7.126
2019	−0.378	3.107	−8.498	6.000
2020	−0.495	4.974	−11.594	11.246
2021	6.303	2.688	1.134	14.090
2022	2.710	1.872	−0.775	7.418

Note: The Table presents the summary statistics of GDP growth (t + 1, t + 4) per year. The statistics refer to our benchmark sample that includes data for the period 1990Q1-2023Q4.

Table A4
Quantile Regression Results | Alternative Horizons

Models:	(1)	(2)	(3)	(4)	(5)	(6)

(*continued on next page*)

Table A4 (*continued*)

Models:	(1)	(2)	(3)	(4)	(5)	(6)
Horizon:	$h = 2$	$h = 4$	$h = 6$	$h = 8$	$h = 10$	$h = 12$
DOWNGRADE	**−0.096**	**−2.948*****	**−3.356*****	**−2.632***	**−2.431**	**−1.458**
	(0.610)	(0.672)	(0.864)	(1.406)	(1.600)	(1.038)
UPGRADE	0.101	**0.449***	0.566	0.446	0.182	0.053
	(0.153)	(0.236)	(0.380)	(0.346)	(0.260)	(0.303)
Control variables	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES	YES	YES
Observations	3,188	3,188	3,124	3,060	2,977	2,934
Pseudo – R^2	0.381	0.662	0.563	0.460	0.420	0.374

Note: The Table presents estimated coefficients derived from a panel fixed-effect quantile regressions (q = 0.05), employing the two-step estimation method outlined by Canay (2011). Our analysis is based on a global sample that includes 33 countries over the period spanning from 1990Q1 to 2023Q4. The dependent variable across all models represents the average GDP growth between one and h periods ahead (t + 1, t + h), with the independent variables referring to the quarter t. All models incorporate country, year, and quarter fixed effects. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses. ***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Table A5
Transmission channels: Group analysis

Group:	Developed	Developing	Developed	Developing
INVESTMENTS (t)	0.005	0.006	0.021***	−0.002
	(0.007)	(0.013)	(0.041)	(0.027)
BOND SPREAD (t)	**−0.154*****	**−0.183*****	**−0.426****	−0.262
	(0.033)	(0.060)	(0.196)	(0.274)
Country controls	YES	YES	YES	YES
Additional country controls	NO	NO	YES	YES
Country FE	YES	YES	YES	YES
Year & Quarter FE	YES	YES	YES	YES
Observations	2,633	1,213	347	125
Number of countries	24	6	12	2

Note: The Table presents estimated coefficients derived from panel fixed-effect quantile regressions, employing the two-step estimation method outlined by Canay (2011). The dependent variable is the four-quarters ahead average GDP growth and Investments and Bond Spreads are among the explanatory variables. All models incorporate the benchmark model's country controls and country, year, and quarter fixed effects. The last two columns also include additional country controls, such as debt and deficit (as percentages of GDP), inflation rate and business uncertainty index. Bootstrapped standard errors, derived from 500 replications, are reported in parentheses.***, **, and * indicate significance levels at 1 %, 5 %, and 10 %, respectively.

Data availability

The authors do not have permission to share data.

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