On the Structural Determinants of Growth-at-Risk*

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We examine structural differences in growth vulnerabilities across countries associated with financial risk indicators. Considering trade openness, financial sector size, the public spending ratio, and government effectiveness, our findings suggest the existence of a structural gap and a risk sensitivity gap. Hence, structural country characteristics not only drive level differences in growth-at-risk (GaR) but also give rise to differences in the responsiveness of GaR to financial risks. Furthermore, we show that the impact of structural characteristics varies over the forecasting horizon. A proper understanding of structural country characteristics in the context of the GaR framework is important to facilitate the use of the concept in macroprudential policy.

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1. Introduction

The empirical growth-at-risk (GaR) concept introduced by Adrian, Boyarchenko, and Giannone (2019) suggests that deteriorating financial conditions are associated with increased downside risks to economic growth. While standard forecasts focus on the expected value of future gross domestic product (GDP) growth, the GaR approach places a particular emphasis on the probability and magnitude of potential adverse outcomes. Similar to the value-at-risk

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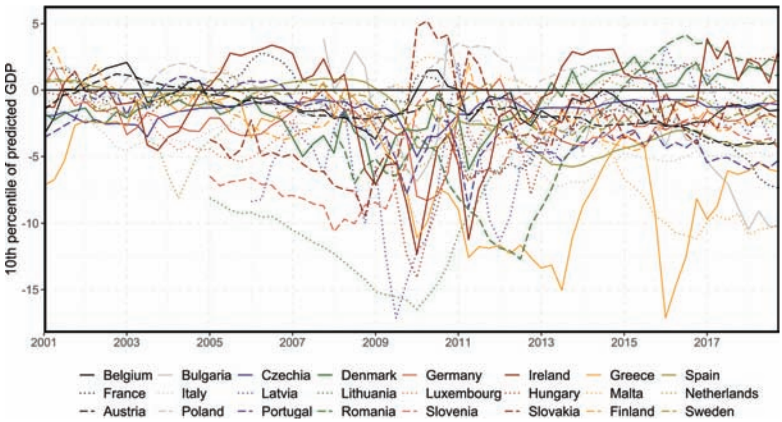
concept in finance, the GaR of an economy for a given time horizon is defined as a specific low quantile of the distribution of the projected GDP growth rate for the respective horizon (see, for instance, Suarez 2022). In this context, Adrian, Boyarchenko, and Giannone (2019) show that the left tail of the distribution of (projected) GDP growth is less stable and more affected by financial conditions than the upper quantiles of the distribution. Against this background, the GaR concept is a useful and intuitive policy tool to identify and quantify systemic risk and has therefore gained traction among policymakers in recent years.

In the last few years, the GaR concept has been extended in various directions. While financial conditions have turned out to be highly relevant for the conditional GDP growth distribution at relatively short time horizons (i.e., up to one year), risk indicators from the financial cycle literature also have been introduced into the GaR framework. In this context, recent empirical studies indicate that external imbalances, excessive credit growth, and house price booms are associated with increasing growth vulnerabilities in the medium term, typically defined as longer time horizons between six quarters and five years (Aikman et al. 2019; Arbatli-Saxegaard, Gerdrup, and Johansen 2020; Duprey and Ueberfeldt 2020). In a similar vein, characterizing the term structure of GaR, it has been highlighted that the sensitivity of downside risks to growth depends on the respective time horizon. These findings imply not only differing term structures depending on financial risk indicators but also a possible intertemporal trade-off, i.e., lower growth vulnerability at medium and long horizons may come at the cost of lower expected growth (or GaR) in the short term (Adrian et al. 2022).

By linking observed financial risk indicators as well as policy indicators to the distribution of projected growth outcomes, the GaR concept also is increasingly used as a measure of systemic risk at the individual country level (see, for instance, Adrian et al. 2019; European Systemic Risk Board (ESRB) 2019; Prasad et al. 2019). In this context, the application of the GaR concept enables policymakers to quantify the probability of adverse scenarios, thereby facilitating an appropriate and timely policy reaction. Previous studies suggest that downside risks can be mitigated to some extent by respective policy measures, e.g., by increasing the capitalization of the banking system (Aikman et al. 2019) or by applying other macroprudential or

Figure 1. Estimated 10th Percentile of Predicted GDP Growth



Note: The figure shows the time series of the predicted GaR one year ahead for each country in the sample. The predicted GaR is shifted forward to align the predictions with the realization.

monetary policy instruments (Duprey and Ueberfeldt 2020; Franta and Gambacorta 2020; Galán 2020). Furthermore, by examining the impact of policy variables on the vulnerability of GDP growth, the GaR concept also can be used as a potential measure to calibrate the current stance of macroprudential policy to safeguard financial stability (ESRB 2019; Suarez 2022).

To facilitate the use of the GaR concept as a measure of systemic risk or macroprudential policy stance, a proper understanding of cross-country differences is crucial. While some papers take into account selected country properties in their estimations (e.g., Arbatli-Saxegaard, Gerdrup, and Johansen 2020) or discuss this issue as an important area of future research (O'Brien and Wosser 2021; Suarez 2022), structural country characteristics have not been examined systematically so far in the respective strand of the literature. Such an analysis appears warranted, as the empirical GaR measure typically not only fluctuates substantially in the time dimension but also across countries (see Figure 1).[1] Our study contributes to

[1]Figure 1 shows one-year-ahead forecasts of the 10th percentile of predicted GDP growth, a frequently used measure of GaR, conditional on standard measures of financial risk estimated country by country. For each country, we estimate

the existing literature by putting a particular emphasis on structural country characteristics and their impact on empirical GaR estimates in a sample of European Union (EU) countries. The EU provides a particularly interesting setting. While countries are subject to a common regulatory framework, they vary substantially with respect to structural[2] country characteristics.

In Figure 1, two observations stand out. First, GaR estimates fell markedly in the run-up to the global financial crisis, in line with the narrative of a high financial risk episode. Second, a substantial degree of variation can be observed in the cross-section, giving rise to the potentially important role of cross-country heterogeneity. We focus on the latter aspect by examining the role of structural country characteristics in the context of GaR. Structural country characteristics can play an important role in at least three dimensions (see also Suarez 2022). First, countries can differ in their "standard" GaR values, i.e., the average GaR over time. For instance, economies with a more dispersed distribution of GDP growth are likely to exhibit lower average values of GaR. While this *structural gap* could be accounted for by including country fixed effects, it is nevertheless important to understand the drivers behind the cross-country differences in GaR, particularly from a policy perspective. Second, the reaction of GaR to changes in financial risk indicators may differ across countries. Such a *risk sensitivity gap* would become apparent when GaR estimates in individual countries show different reactions to changes in the financial risk indicator due to structural country characteristics.[3] For instance, economies with a strong financial

the following quantile function: $\hat{Q}_{y_{i,t+h}}(\tau \mid X_{i,t}) = X_{i,t}\hat{\beta}_{i,\tau}$, where $X_{i,t}$ is a vector containing the country-level index of financial stress (CLIFS), country-specific credit growth, current GDP growth, and a constant. Figure 1 shows the predicted 10th percentile of four quarters ahead, hence $\tau = 0.1$ and $h = 4$.

[2]While the expression "structural" often refers to the identification of causal effects in structural models, we use the term in a different context, i.e., structural country characteristics in the context of "non-cyclical."

[3]The gap vulnerability to risk, as defined by Suarez (2022), is a similar concept. While the risk sensitivity gap refers to differences in the coefficients of the risk parameters, the gap vulnerability to risk describes the resulting change in the "target gap," i.e., the deviation of GaR from mean (or median) growth. As this is the logical consequence of varying coefficients of the risk parameter, the two definitions are basically two sides of the same coin.

sector are likely to be less dependent on financial inflows and therefore may be less vulnerable to tightening financial conditions than countries with a less developed financial sector. Finally, structural differences across countries in principle also could result from a different effect of policy measures on the respective GaR, which can be referred to as the *policy sensitivity gap*. For instance, the magnitude of the effect of higher capital requirements in the banking sector may depend on the size of the financial sector, with limited effects on downside risks to growth in countries where the financial sector is small.

A better understanding of structural country characteristics driving differences in GaR across countries is a prerequisite to extend the use of the GaR concept in the context of policy design and assessment, as it should be taken into account when comparing GaR estimates (and the corresponding policy reactions) across countries. Our paper aims to fill this gap in the literature by focusing on the former two issues, i.e., the structural gap and the risk sensitivity gap.[4]

Specifically, we employ panel quantile regressions in which cross-country variation is modeled by including country-specific characteristics as well as interaction terms with financial risk indicators. Therefore, we examine potential drivers of the structural gap across countries by including various structural country characteristics in the panel quantile regression. As a result, we are able to shed light on the drivers of GaR across countries, which are usually disguised in country-by-country or panel fixed-effects regressions. Furthermore, we examine the interactions between structural characteristics and the respective financial risk indicator. Therefore, we investigate the impact of varying structural characteristics on the sensitivity of the GaR value with respect to the financial risk indicator, thus quantifying the respective risk sensitivity gap due to specific structural country characteristics.[5]

[4]The impact of the policy sensitivity gap is evidently also a relevant issue. However, given our sample, a reliable analysis is not feasible at the current juncture, in light of measurement errors due to challenges in quantifying macroprudential policy across countries and data availability.

[5]The panel framework is warranted not only to be able to evaluate structural country characteristics across countries but also to be able to take them into account in common regulatory frameworks. While forecasting performance

In light of a lack of previous empirical work on potential drivers of GaR across countries, we consult two adjacent strands of the literature to establish a conceptual framework. First, various country characteristics were identified to play a crucial role in explaining differences in terms of output drops in the global financial crisis and cross-country variation in business cycle volatility (see, among others, Blanchard et al. 2010; Crucini, Kose, and Otrok 2011; Lane and Milesi-Ferretti 2011; Rose and Spiegel 2011). From an ex post perspective, the financial crisis was associated with high downside risks. Characteristics that explain the realized output decline in the financial crisis may therefore also drive GaR estimates. Second, factors that explain heterogeneity in observed business cycle volatility also might help to understand GaR across countries, as countries with higher business cycle volatility show a more dispersed growth distribution than countries with limited growth volatility. As a result, the respective GaR values also are expected to be lower, as the distribution of the quantile projections reflects the distribution of GDP growth.

Four factors stand out as particularly relevant in shaping both the downturn during the global financial crisis and business cycle volatility: trade openness, public spending ratio, financial sector size, and government effectiveness. With respect to trade openness, previous studies suggest a positive link to GDP volatility (see, for instance, Loayza and Raddatz 2007; di Giovanni and Levchenko 2009; Kim, Lin, and Suen 2016), also because higher trade openness is associated with higher degrees of specialization in an economy. Thus, previous literature suggests a negative effect of higher trade openness on GaR. In contrast, the impact of public expenditures on output volatility is discussed more controversially in the literature. Carmignani, Colombo, and Tirelli (2011) report a positive link between government size and volatility, while earlier studies find a negative effect of public expenditures or government size on GDP growth volatility (Galí 1994; Fatás and Mihov 2001). Therefore, the direction of the effect also may depend on the type of taxes (Posch 2011) as well as on the type of the shock (Collard,

is somewhat attenuated in an integrated cross-country approach through pooling, the strength of the approach lies in the accurate evaluation of the sources of cross-country heterogeneity that would otherwise be difficult to capture appropriately.

Dellas, and Tavlas 2017). Thus, the impact of the public spending ratio on GaR remains mostly unclear. Regarding the size of the financial sector, empirical studies point to a dampening effect of more developed financial sectors on the volatility of GDP, consumption, and investment (Denizer, Iyigun, and Owen 2002; Beck, Lundberg, and Majnoni 2006; Manganelli and Popov 2015), although the effect seems to be less pronounced compared with trade openness, and the transmission channel may work via other structural country characteristics (Loayza and Raddatz 2007). At very high levels of financial depth, however, the effect weakens or even reverses, with high financial depth amplifying consumption, and investment volatility (Dabla-Norris and Srivisal 2013). In the context of GaR, we therefore expect a positive effect on GaR, although this effect could be reversed at higher levels of financial development. Finally, government effectiveness is generally found to be negatively linked to GDP volatility (see, for instance, Evrensel 2010) and is therefore likely to be positively linked to GaR. In summary, previous literature suggests increasing growth vulnerabilities (i.e., lower GaR) with increasing trade openness and decreasing levels of government effectiveness. The empirical effect of the ratio of public expenditures remains ambiguous, and the impact of the financial sector size may depend on the respective level of financial development, potentially resulting in a non-linear relationship between the two variables.

Our empirical analysis not only sheds light on whether stabilizing factors in the global financial crisis and with respect to growth volatility also mitigate growth risks,[6] i.e., whether these factors significantly contribute to the structural gap in GaR, but we also are able to examine the risk sensitivity gap associated with structural country characteristics. We find that structural country characteristics indeed play an important role in shaping cross-country variations in GaR. Both the structural gap and the risk sensitivity gap contribute significantly to structural differences in GaR across countries, whereby the magnitude of the effect differs by the respective financial risk indicator (i.e., financial stress versus credit growth) as well as by the respective time horizon. Higher trade openness and larger financial sectors lead to a structurally lower GaR value,

[6] Throughout the paper, lower GaR implies higher growth risks, and vice versa.

particularly at longer time horizons. Higher levels of government effectiveness mitigate growth risks across all time horizons, while the stabilizing role of a high public spending ratio is limited to the short run. The risk sensitivity gap seems to be most pronounced with respect to public spending ratio and trade openness but plays a less significant role in the context of financial sector size and government effectiveness.[7] Overall, our study highlights the importance of structural country characteristics when estimating GaR at the individual country level. We show that both the structural gap and the risk sensitivity gap play an important role, with the impact of structural characteristics varying with different time horizons, i.e., the term structure of GaR also may be driven by structural country characteristics. Finally, model evaluation exercises reveal that taking into account structural country exercises enhances the accuracy of projected growth risks compared with panel quantile regressions with fixed effects only.

The paper is structured as follows. Section 2 explains our empirical methodology and introduces a framework to examine both the structural gap and the risk sensitivity gap in the context of panel quantile regressions. Section 3 shows our empirical results, including our panel quantile estimations and the impact of the structural characteristics on the GaR term structure. Section 4 presents our model evaluation exercises, while Section 5 draws conclusions and discusses the policy implications of our empirical results.

2. Empirical Approach

2.1 Data

Our analysis is based on a cross-country unbalanced panel data set using time series from 24 European economies[8] over the period 1999:Q1–2019:Q4. The sample includes all European economies for

[7]We also find evidence for non-linearities in how financial sector size and government effectiveness affect GaR, although the effects are relatively small in magnitude compared with the overall effects of the respective structural characteristics (i.e., the structural gap).

[8]Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden.

which a country-specific financial stress measure and the credit-to-GDP ratio are available. For these countries, we construct the annualized average GDP growth rates using the quarterly seasonally adjusted real GDP provided by Eurostat. The logarithm of these time series, $Y_{i,t}$, is then converted into the approximate annualized growth rates h periods ahead, $y_{i,t+h} = \frac{(Y_{i,t+h} - Y_{i,t})}{h/4}$.

In line with previous literature, we include a measure of financial stress as an explanatory variable. In our first model, we use the Composite Indicator of Systemic Stress (CISS) developed by Hollo, Kremer, and Lo Duca (2012) and published by the ECB as a measure of European-wide financial stress.[9] The CISS aggregates five market-specific subindices on the basis of weights reflecting their time-varying cross-correlation structure. Thus, the CISS takes into account both the level of individual subindices and the number of indicators suggesting high financial stress. As a result, the CISS reacts more strongly if more indicators show signs of financial stress simultaneously. In the second estimation, we follow a more traditional GaR framework and use country-specific financial stress measures, i.e., the Country-Level Index of Financial Stress (CLIFS), introduced by Duprey, Klaus, and Peltonen (2017). The construction of the index follows the approach of Hollo, Kremer, and Lo Duca (2012). Using both the CISS and the CLIFS allows us to check whether the impact of country characteristics on GaR is already implicitly captured by country-specific financial stress measures.

While financial stress measures are highly relevant for short-term GaR estimations, credit growth is frequently used as a signal for medium-term financial imbalances (see, e.g., Aikman et al. 2019; Galán 2020; Adrian et al. 2022). The Bank for International Settlements publishes credit-to-GDP ratios for a wide range of countries. Based on this data set, we use the two-year average of the log differences of the credit-to-GDP ratio as a measure of credit growth.

Finally, for each country, we collect time series of four different structural characteristics: trade openness, which we define as the ratio of exported goods to GDP; the size of the financial sector, defined as the ratio of gross value-added of the financial sector to

[9] While the CISS is a euro-area-wide indicator, we also replicate our analysis with the global financial stress index developed by Monin (2019). The results are very similar and can be seen in the appendix in Table A.1.

GDP; and the ratio of public expenditures to GDP[10] and government effectiveness, as measured by the Worldwide Governance Indicators (WGI) project (Kaufmann, Kraay, and Mastruzzi 2011).[11] To make the coefficients in our estimations comparable across all explanatory variables, all included factors are standardized with a mean of zero and a standard deviation of one.

2.2 Growth-at-Risk Methodology

Following Adrian, Boyarchenko, and Giannone (2019), we rely on quantile regressions, developed by Koenker and Bassett (1978), to estimate GaR. Because of the multicountry setup, we employ a panel quantile regression framework. A major concern when estimating panel quantile regression is the large number of fixed effects (α_i) for every cross-sectional unit, especially when N is large and T is relatively small (Koenker 2004). However, as T is much larger than N in our case, coefficients can be estimated consistently (Galvao and Montes-Rojas 2015; Adrian et al. 2022). We follow previous research and include fixed effects for each country, resulting in country-specific intercepts at each quantile (τ).[12]

Quantile regressions allow us to estimate the differential effects of the conditioning variables on the distribution of the dependent variable. In our study, we are interested in the effects on the lower part of the distribution of the dependent variable, i.e., the effects on GaR. In our model, the dependent variable, y_{t+h}, is the annualized average GDP growth 1 quarter to 16 quarters ahead ($h = 1, 2, 3, \ldots, 16$), and the vector of conditioning variables, X_t, includes a constant, current GDP growth, a measure of financial stress and credit growth, as well

[10]The data for the first three country characteristics are obtained from Eurostat.

[11]Government effectiveness captures "perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies" (Kaufmann, Kraay, and Mastruzzi 2011). Thus, this indicator captures not only the intention of the regulations but also how they are implemented and whether they are credibly enforced.

[12]For inference, we use the block-bootstrap method, as shown in Kapetanios (2008). We use a block size of four quarters; however, changing the block size does not alter the interpretation of our results (see also Lahiri 2003).

as the structural characteristics we are mainly interested in. For each projection horizon h, we estimate the quantile function

$$\hat{Q}_{y_{i,t+h}}(\tau \mid X_{i,t}, \alpha_i) = \hat{\alpha}_{i,\tau} + X_{i,t}\hat{\beta}_{\tau}, \tag{1}$$

where $\hat{\alpha}_{i,\tau}$ denotes the estimated country-specific fixed effects at quantile τ. To estimate $\hat{\alpha}_{i,\tau}$ and coefficients $\hat{\beta}_{\tau}$, the quantile weighted absolute value of errors is minimized:

$$(\hat{\beta}_{\tau}, \hat{\alpha}_{i,\tau}) = \arg\min_{\alpha_i,\beta_\tau} \sum_{i=1}^{n} \sum_{t=1}^{T-h} \rho_{\tau}(y_{i,t+h} - X_{i,t}\beta_{\tau} - \alpha_i), \tag{2}$$

where ρ_{τ} is the standard asymmetric absolute loss function. As a measure for GaR, we use the 10th percentile of projected growth (in line with, e.g., Figueres and Jarociński 2020), hence, $\tau = 0.1$.

To assess the effect of structural characteristics on GaR, $X_{i,t}$ includes structural country characteristics, which we evaluate in the panel quantile regression. As explanatory variables, we consider various structural country characteristics, such as trade openness, the size of the financial sector, the public spending ratio, and government effectiveness.

In variants of the model, we consider interactions between the financial risk indicators and the included structural characteristics to take into account possible non-linearities. It is well documented that high financial stress leads to a widening of the lower tails of the distribution of projected growth (Adrian, Boyarchenko, and Giannone 2019). We thus introduce interactions to evaluate whether this form of non-linearity is further reinforced through structural country characteristics. By interacting the structural characteristics with the financial risk indicators, we allow the effects of the structural country characteristics to vary depending on current financial stress and observed credit growth.

Note that the coefficients of the structural country characteristics help to detect structural gaps, indicating whether these structural characteristics are associated with generally lower or higher GaR. The extent to which non-linearities in the impact of financial risk indicators are prevalent is indicative of the existence of risk sensitivity gaps highlighting particular sensitivities (i.e., varying responsiveness of GaR) in the face of high financial stress or credit growth.

Including interaction terms, we estimate the following panel quantile regression model:

$$\hat{Q}_{y_{i,t+h}}(\tau \mid X_{i,t}, \alpha_i) = \hat{\alpha}_{i,\tau} + X_{i,t}\hat{\beta}_\tau + Z_{i,t} \times FS_{i,t}\hat{\nu}_\tau + Z_{i,t} \times Credit_{i,t}\hat{\gamma}_\tau, \quad (3)$$

where $\alpha_{i,\tau}$ denotes the fixed effects, $Z_{i,t}$ is a subset of vector $X_{i,t}$ comprising structural country characteristics, and $FS_{i,t}$ and $Credit_{i,t}$ denote financial stress and credit growth, respectively, which also are elements of $X_{i,t}$.

Relating the concepts of the structural gap and the risk sensitivity gap to Equation (3), one may think of the partial effects of the structural characteristics, i.e., first derivatives. The structural gap can be thought of as the total effect, i.e., the coefficient on the respective measure plus the interaction terms for a given level of the financial risk measures. The risk sensitivity gap is captured by the interaction terms, as the responsiveness of GaR to the respective financial risk indicator depends on structural country characteristics.

3. Results

3.1 Main Results

First, we consider the CISS measure (Hollo, Kremer, and Lo Duca 2012) as a financial stress indicator, which is an aggregate measure that does not vary across countries. The fact that we use one and the same financial risk indicator across countries permits us a direct interpretation of how the propagation of financial stress to growth vulnerabilities is linked to country-specific structural characteristics. In contrast, credit growth is country specific. All measures in the regression are standardized to facilitate a direct comparison of the various factors in terms of magnitude.

Table 1 shows the coefficient estimates for the conditional 10th percentile for different specifications of the panel quantile regression model in which we evaluate the structural determinants of GaR. Columns 1–2 show results from a parsimonious, linear specification for forecasting horizons $h = 4$ and $h = 12$. These horizons are typically considered to assess short- and medium-term growth

Table 1. Main Results—CISS and Credit Growth

	Model 1		Model 2	
	$h = 4$ (1)	$h = 12$ (2)	$h = 4$ (3)	$h = 12$ (4)
CISS	–2.145***	–0.144**	–2.364***	–0.040
	(0.279)	(0.060)	(0.247)	(0.065)
Credit Growth	–0.225	–0.680***	–0.351	–0.986***
	(0.380)	(0.184)	(0.344)	(0.150)
Current GDP Growth	0.047	–0.573***	0.071	–0.548***
	(0.093)	(0.045)	(0.075)	(0.048)
Openness	–1.545**	–1.074***	–2.290***	–1.169***
	(0.645)	(0.237)	(0.507)	(0.219)
Financial Sector	0.036	–2.376***	0.958	–2.823***
	(1.141)	(0.704)	(1.303)	(0.735)
Public Expenditure	1.032***	0.065	1.051***	0.162
	(0.300)	(0.108)	(0.337)	(0.145)
Government Effectiveness	3.002***	2.250***	3.939***	2.609***
	(0.675)	(0.458)	(0.703)	(0.403)
Openness × CISS			0.214	0.106
			(0.238)	(0.099)
Financial Sector × CISS			0.674***	0.011
			(0.249)	(0.095)
Public Expenditure × CISS			1.271***	–0.099
			(0.278)	(0.092)
Government Effectiveness × CISS			0.184	0.124
			(0.251)	(0.098)
Openness × Credit Growth			–0.487*	–0.759***
			(0.291)	(0.173)
Financial Sector × Credit Growth			0.097	0.203***
			(0.223)	(0.064)
Public Expenditure × Credit Growth			–0.179	–0.046
			(0.176)	(0.143)
Government Effectiveness × Credit Growth			–0.181***	–0.121
			(0.367)	(0.164)
Observations	1,744	1,576	1,744	1,576

Note: The table shows the estimated coefficients of the conditional 10 percent quantile. Columns 1–2 show the results from the regression model in Equation (1) for the horizons (h) 4 and 12. Columns 3–4 show the results from the regression model in Equation (3) for the horizons (h) 4 and 12. The measure of financial stress is the CISS. Bounds are computed using 1,000 bootstrap samples. The significance level is denoted as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

risks.[13] To gauge the role of non-linearities and to assess the prevalence of risk sensitivity gaps, we augment the model with interaction terms of structural characteristics and the two included financial risk indicators (columns 3–4).

Considering the effects of financial stress on the one hand, as measured by the CISS, and credit growth on the other, we observe that the impact of financial stress is particularly significant and pronounced over shorter horizons, while the role of credit growth becomes more important as h increases. This pattern is well documented in the literature (see, for instance, Adrian et al. 2022).

The coefficients on structural characteristics in the linear specification shown in columns 1–2 provide an intuition on the overall effects of openness, financial sector size, public expenditures, and government effectiveness. For $h = 4$, we document significant adverse effects of trade openness on the predicted 10th percentile of the conditional one-year-ahead forecast of GDP growth. By contrast, public expenditures and government effectiveness exert significant positive effects on short-term growth risks and tend to stabilize the economy. Government effectiveness appears to play a particularly important role: a one-standard-deviation surge in government effectiveness is associated with an increase in the 10th percentile of projected GDP growth in $h = 4$ by approximately 3 percentage points. The two effects broadly confirm the findings of previous literature focusing on the link between public spending ratio and output volatility (Galí 1994; Fatás and Mihov 2001) on the one hand and the effect of government effectiveness on the other (Evrensel 2010). The coefficient on financial sector size is not significant for $h = 4$.

As h increases, we observe significantly adverse effects of openness and financial sector size. While both characteristics are associated with higher growth risks (i.e., lower GaR), larger financial sectors are particularly detrimental. An increase in financial sector size by one standard deviation is associated with a decrease in the lower tail of projected GDP growth by more than 2 percentage points. While the effect of trade openness is well in line with the findings of previous literature, which suggests a positive link between GDP volatility and openness (see, for instance, di Giovanni

[13] Below, we elaborate on the term structure of GaR, discussing coefficients from $h = 1, \ldots, 16$.

and Levchenko 2009), the role of large financial sectors is somewhat more surprising, as most empirical studies indicate a dampening effect of more developed financial sectors on GDP volatility (e.g., Manganelli and Popov 2015). Previous literature also suggests, however, that this effect weakens or even reverses at high levels of financial depth, as large financial sectors may amplify consumption and investment volatility (Dabla-Norris and Srivisal 2013). Earlier studies thus point to a non-linear link between financial sector size and GDP volatility, which is also consistent with recent findings in the finance-growth nexus literature (see, for instance, Breitenlechner, Gachter, and Sinderman 2015). According to our findings, the negative effect of financial sector size seems to dominate in the GaR framework, although we will argue below that the link between the two variables is ambiguous depending on the forecasting horizon (see Section 3.2). With an increasing forecasting horizon, the effect of the public spending ratio becomes insignificant, suggesting that the stabilizing role of higher public expenditures works only in the short term. Furthermore, the effect of government effectiveness appears to diminish somewhat but nevertheless plays an important role for a forecasting horizon of three years ($h = 12$).

Next, we consider the interaction terms of the structural characteristics in the regression model to account for non-linearities in the effects of the explanatory variables on GaR (columns 3–4). For $h = 4$, we observe significant and positive coefficients on interactions with financial stress for financial sector size and public expenditures, indicating that these factors mitigate the adverse effects of financial stress on projected growth vulnerabilities to some extent as risks increase. We also observe significant and negative coefficients of openness and government effectiveness interacted with credit growth. This is to some extent surprising, as credit growth usually plays a secondary role in shaping short-term growth vulnerabilities. This finding suggests an overall negative effect of openness on short-term vulnerabilities, at least for countries with buoyant credit growth. A possible explanation for this effect is that more open economies typically also exhibit higher levels of financial openness, with high rates of credit growth possibly depending on cross-border wholesale funding. On the other hand, the negative interaction term for government effectiveness and credit growth indicates that the effect of higher levels of government effectiveness is less pronounced in the face of excessive credit growth.

Regarding the role of interactions in shaping medium-term projected growth risks, we observe significantly negative coefficients of the interactions between credit growth and openness as well as financial sector size. While the detrimental effects of openness on growth vulnerabilities become more pronounced with higher credit growth, probably for the same reasons explained above, the negative effect of financial sector size is somewhat mitigated with higher credit growth. In this context, a larger financial sector could be associated with lower dependencies on cross-border funding, thereby mitigating risks linked to higher credit growth. From this perspective, the stabilizing role of more developed financial sectors, as suggested in the literature (e.g., Beck, Lundberg, and Majnoni 2006), becomes more relevant in an environment of high credit growth. The coefficient on the interaction term is, however, relatively small in magnitude, suggesting a limited role of non-linearities associated with financial sector size.

In Table 2, we replicate the estimations from above using the CLIFS instead of the CISS as a measure of financial stress. In contrast to the CISS, which is an aggregate measure of financial stress, the CLIFS is country specific (Duprey, Klaus, and Peltonen 2017). We consider the CLIFS to take into account that structural characteristics may affect not only the transmission of financial stress but also its country-specific emergence.

Considering columns 1–2, it appears that the overall effects of structural characteristics on projected growth vulnerabilities are not sensitive to the financial stress measure used. Allowing for multiplicative terms in 3–4, however, we observe some differences in how financial stress and structural country characteristics interact in shaping short-term risks. While we have observed that the effects of financial sector size and public expenditure are mitigated in instances of high financial stress using the CISS, this effect becomes insignificant once we consider the CLIFS for $h = 4$. Considering the CLIFS, the interaction with openness becomes significant for $h = 12$, thus indicating that the adverse effects of trade openness diminish to some extent with increasing levels of financial stress. Estimates shown in Table 2 suggest that structural characteristics also affect the transmission of country-specific financial stress and

Table 2. Main Results—CLIFS and Credit Growth

	Model 1		Model 2	
	$h = 4$ (1)	**$h = 12$ (2)**	**$h = 4$ (3)**	**$h = 12$ (4)**
CLIFS	–1.082***	–0.036	–1.222***	–0.096
	(0.256)	(0.056)	(0.310)	(0.082)
Credit Growth	–0.559	–0.729***	–0.724**	–0.999***
	(0.365)	(0.188)	(0.368)	(0.140)
Current GDP Growth	0.046	–0.577***	0.062	–0.558***
	(0.074)	(0.046)	(0.084)	(0.043)
Openness	–1.588***	–0.885***	–2.028***	–1.208***
	(0.581)	(0.291)	(0.700)	(0.231)
Financial Sector	–1.220	–2.856***	0.093	–2.919***
	(1.293)	(0.787)	(1.596)	(0.714)
Public Expenditure	1.142***	0.083	1.201***	0.105
	(0.294)	(0.129)	(0.387)	(0.129)
Government Effectiveness	5.224***	2.254***	6.039***	2.632***
	(0.710)	(0.409)	(0.905)	(0.353)
Openness × CLIFS			0.340	0.214**
			(0.264)	(0.098)
Financial Sector × CLIFS			0.012	0.021
			(0.367)	(0.069)
Public Expenditure × CLIFS			0.346	0.052
			(0.252)	(0.076)
Government Effectiveness × CLIFS			0.341	0.084
			(0.267)	(0.071)
Openness × Credit Growth			–0.589*	–0.814***
			(0.310)	(0.141)
Financial Sector × Credit Growth			0.303	0.201***
			(0.214)	(0.067)
Public Expenditure × Credit Growth			–0.187	–0.125
			(0.206)	(0.140)
Government Effectiveness × Credit Growth			–1.221***	–0.097
			(0.431)	(0.146)
Observations	1,740	1,572	1,740	1,572

Note: The table shows the estimated coefficients of the conditional 10 percent quantile. Columns 1–2 show the results from the regression model in Equation (1) for the horizons (h) 4 and 12. Columns 3–4 show the results from the regression model in Equation (3) for the horizons (h) 4 and 12. The measure of financial stress is the CLIFS. Bounds are computed using 1,000 bootstrap samples. The significance level is denoted as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

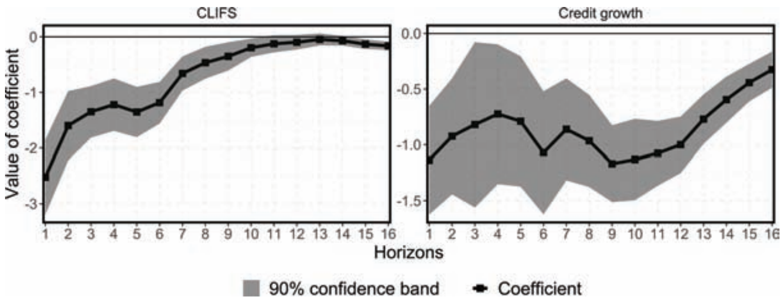
are generally robust to the variants of financial stress measures used in the analysis.

Overall, our findings clearly suggest that structural country characteristics play an important role in shaping variations in GaR. Over short-term horizons, we observe the stabilizing effects of public spending ratio and government effectiveness, with the latter being particularly pronounced. Considering interaction terms with financial stress, we observe that the stabilizing effect of public expenditures is particularly important when financial stress is high, whereas government effectiveness has a predominately linear effect on short-term GDP growth risks. Regarding medium-term growth risks, financial sector size and trade openness play an important and negative role in shaping growth vulnerabilities, while high levels of government effectiveness are still associated with higher GaR levels. Considering interactions with credit growth, we show that the adverse effects of larger financial sectors somewhat diminish with higher credit growth, while the negative effects of openness are further reinforced by increasing levels of credit growth.

The significant effects of structural characteristics, both with respect to GaR levels and the sensitivity of GaR to the underlying financial risk indicators, point to the prevalence of both structural and risk sensitivity gaps. In turn, our results have important macroprudential policy implications. Variations in the structural gap suggest that the appropriate macroprudential policy stance may, among other things, depend on structural characteristics, at least in an environment of homogeneous risk preferences across countries. Risk sensitivity gaps, as revealed by non-linearities in the effect of the included financial risk indicators depending on structural country characteristics, suggest that growth risks in some countries react more sensitively to increasing financial risks than in others. Thus, the appropriate reaction of macroprudential policy to variations in financial stress and credit growth also may depend on the respective (structural) country characteristics, as already suggested in theoretical considerations related to the GaR framework (Suarez 2022).

In the following sections, we focus on country-specific measures of financial stress (i.e., the CLIFS), primarily for two reasons. First, using country-specific financial stress measures is more common in previous literature (see, for instance, Aikman et al. 2019; Galán 2020; Adrian et al. 2022), thus facilitating a comparison of our empirical

Figure 2. Estimated Coefficients of the Financial Risk Indicators from 1 to 16 Quarters Ahead, Using the CLIFS as the Financial Stress Measure



Note: The figure shows the estimated coefficients of the financial risk indicators in the GaR estimation ($\tau = 0.1$) 1 to 16 quarters ahead. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples.

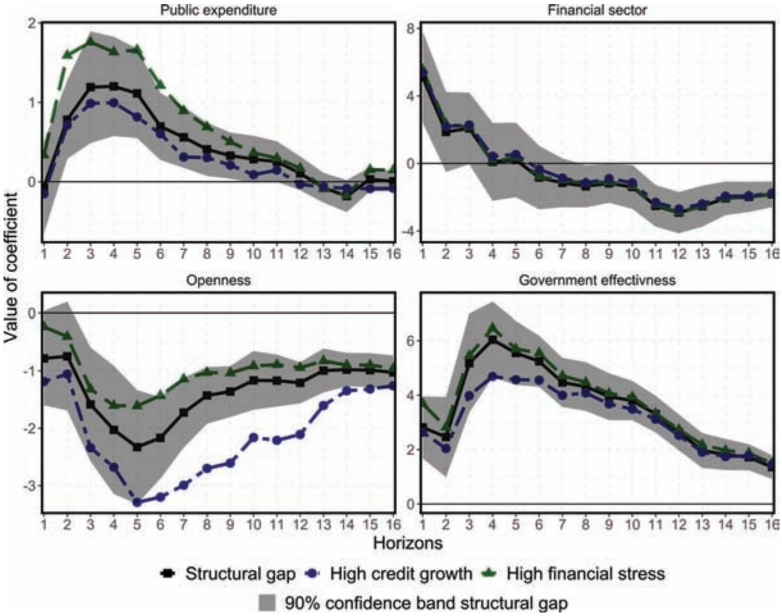
results to other studies. Second, using the CLIFS instead of the CISS is a more conservative approach to evaluate the effect of structural country characteristics on GaR, as those same factors may be associated with differences in financial stress across countries (i.e., more favorable structural country characteristics could be associated with lower contagion or higher resilience, thus resulting in more favorable financial stress at the individual country level).

3.2 Term Structure of GaR and Structural Characteristics

While the focus above is on the distribution of projected GDP growth one year ($h = 4$) and three years ahead ($h = 12$), we now extend our analysis to $h = 1, \ldots, 16$ quarters. Considering the effects of structural country characteristics on GaR for a series of forecasting horizons gives us an indication of how structural characteristics affect the term structure of GDP growth risks. Therefore, we extend the analysis by Adrian et al. (2022), who examine how financial conditions affect the term structure of GaR, to structural country characteristics.

We first evaluate how the two financial risk indicators affect the term structure of GaR. Figure 2 shows the evolution of the estimated coefficients of the CLIFS and credit growth $h = 1, \ldots, 16$ quarters

Figure 3. Estimated Coefficients for Structural Characteristics from 1 to 16 Quarters Ahead, Using the CLIFS as the Financial Stress Measure



Note: The figure shows the estimated coefficients of the structural characteristics in the GaR estimation ($\tau = 0.1$) 1 to 16 quarters ahead. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples. The green and blue lines show the linear combination of the coefficients on the structural characteristics and the interaction terms with financial stress and credit growth (each evaluated at the 90th percentile).

ahead, based on the estimation of regression model (3). While we discuss these in more detail below, estimates using the CISS are shown in Figures A.1 and A.2 in the appendix. The gray area indicates the 90 percent confidence intervals. Consistent with previous literature (see, for instance, Aikman et al. 2019; Adrian et al. 2022), the CLIFS has the most adverse effects in the short term, while the negative impact of credit growth is economically and statistically significant for all time horizons.

In a similar vein, Figure 3 presents the evolution of the structural characteristics' coefficients for 1 to 16 quarters ahead. The black line shows the coefficients of the respective structural country characteristics. In addition, we show the coefficients of the structural characteristics plus the interaction term with financial stress (green line) and credit growth (blue line) evaluated at the 90th percentile of financial stress and credit growth, respectively. While the black (solid) line can be interpreted as a measure of the structural gap, the green and blue (dashed) lines point to the additional existence of risk sensitivity gaps in the case of strong deviations from the black line.

As already discussed above, higher public expenditures mitigate growth risks in the short run, as the respective coefficients are significantly positive from $h = 2$ to $h = 9$ (upper left panel in Figure 3). While we do not observe a risk sensitivity gap associated with increasing credit growth, higher financial stress can be mitigated to some extent by a high public spending ratio, once again pointing to a stabilizing role of larger public sectors in the short run.

Interestingly, the effect of the size of the financial sector strongly depends on the forecasting horizon, as evident in the upper right panel. In the very short run, larger financial sectors are associated with lower growth vulnerabilities but exercise strong detrimental effects on GaR in the medium run. Non-linearities therefore seem to play an important role not only in the finance-volatility nexus, as suggested by the literature (Dabla-Norris and Srivisal 2013), but also with respect to the GaR term structure. Interestingly, interactions with financial stress and credit growth do not play an important role in quantitative terms,[14] indicating that financial sector size is an important determinant of the structural gap but less so of the risk sensitivity gap.

The effects of openness are shown in the lower left panel of Figure 3. Non-linearities associated with increasing financial risk indicators are most pronounced with respect to openness. Notably, however, the impact of the two financial risk indicators, i.e., financial stress and credit growth, go in opposite directions. While openness mitigates growth risks in the face of high financial stress, growth risks

[14] As shown in Table 2, the interaction term is still statistically significant. Due to the large structural gap driven by financial sector size, however, the relatively small coefficient on the interaction term (i.e., the risk sensitivity gap) is hardly visible in this graphical illustration.

are amplified when credit growth is high. The figure clearly shows that trade openness is an important factor for both the structural and risk sensitivity gaps.

Finally, for government effectiveness, shown in the lower right panel, we see that this variable is a stabilizing factor for projected GDP growth, irrespective of the forecasting horizon. Interaction terms play an important role mostly with respect to high credit growth, and in particular for $h = 3, \ldots, 7$, giving rise to a risk sensitivity gap. Clearly, higher levels of government effectiveness are associated with a marked positive structural gap throughout the forecasting horizon.

Overall, considering a series of forecasting horizons, we document that structural country characteristics do strongly affect the term structure of GaR from the short to the medium run. However, the effects of structural characteristics across different forecasting horizons draw a rather heterogeneous picture. While public expenditures tend to affect projected growth risks in the short run, openness is more important at higher forecasting horizons. Government effectiveness has pronounced effects over forecasting horizons of at least three years, while a larger financial sector has mitigating effects over the short run but amplifies growth risks in the medium run.

3.3 Sensitivity Analyses

From the analysis above, it becomes evident that the structural characteristics of the public and the financial sector are important determinants of GaR. We now assess the sensitivity of our results by including different measures for public and financial sector characteristics.[15]

To capture financial system characteristics and potential systemic risk factors, we have focused so far on indicators of financial sector size. Evaluating a further aspect that has been identified as a potentially important aspect of the financial system (see also ESRB 2021) and complementing the analysis above, we now turn to banking sector concentration. Market concentration might be of particular interest from a policy perspective, as the related risks can be more readily addressed than in the case of a large financial sector.

[15] The corresponding Figures A.3, A.4, and A.5, are shown in the appendix.

Specifically, we study the effect of bank concentration measured by the Herfindahl-Hirschman Index (HHI). In the panel quantile regression, financial sector size is replaced by the HHI. As expected, we find that higher banking sector concentration is associated with higher growth risk. This is evident through negative coefficients on GaR (black line), at least over a forecasting horizon of one year, where we observe significant effects. In addition, the inclusion of interaction terms with both financial stress and credit growth points to the prevalence of a risk sensitivity gap, at least for some forecasting horizons. In line with previous findings documented by the ESRB (2021), countries with highly concentrated banking sectors exhibit higher growth risks and are especially vulnerable in the event of high credit growth.

In addition, we evaluate whether the effects of financial sector size are potentially driven by specific segments of the financial sector by considering subsectoral aggregates. Specifically, we replace total financial sector size with the ratio of other financial intermediaries' assets (excluding monetary institutions, pension funds, and insurance companies) to GDP. While the effects in the short run are consistent, medium-run effects turn insignificant when considering the relative size of the non-bank financial sector, indicating that mainly the relative size of the banking and insurance sector drives medium-run growth risks.

Instead of considering the public spending ratio, we also replicate our analysis with debt-to-GDP ratios. We find very similar effects, i.e., higher levels of debt are associated with lower growth risks, even though we do not observe a pronounced risk sensitivity gap associated with public debt. While this result may sound counterintuitive, one has to take into account that public expenditures and public debt are correlated (the correlation coefficient amounts to 0.44 in our sample). In other words, the (stabilizing) effect of flows seems to exceed the (potentially destabilizing) impact of stocks, i.e., high debt levels. This is not truly surprising, as GaR measures cyclical risks, and higher levels of public expenditures are likely associated with stronger automatic stabilizers on the one hand and also may enable the respective government to enact more effective countercyclical fiscal policies in a crisis, leading to lower cyclical downside risks. Against this background, it is conceivable that variations in public debt mainly reflect the variation in public expenditures rather than fiscal sustainability or fiscal space issues.

Overall, it appears that the relevance of country characteristics does not depend on the specific measure, confirming the importance of structural country characteristics in the GaR framework.

4. Model Evaluation

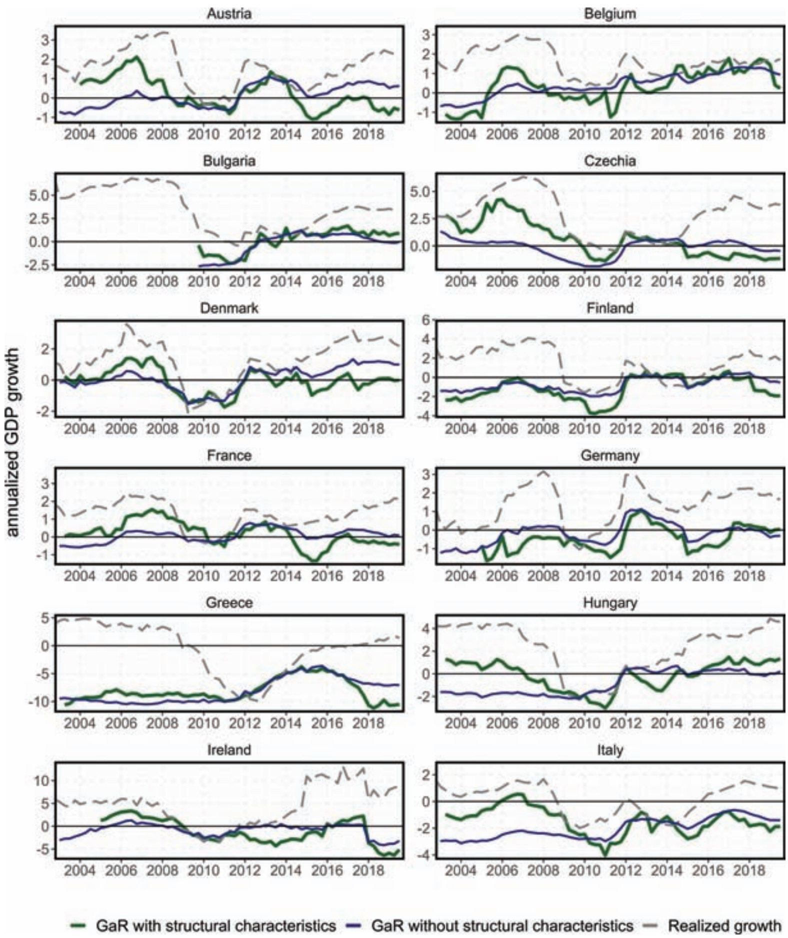
To evaluate the implications of the inclusion of structural characteristics for GaR, we next discuss the predicted values of the 10th percentile of projected GDP growth with and without structural characteristics. Moreover, building on predicted GaR, we examine potential forecasting gains by taking structural characteristics into account and consider model evaluation exercises.

Figures 4 and 5 show the predicted GaR three years ahead, estimated with and without country characteristics.[16] The gray (dashed) line is the realized annualized growth rate, the blue line represents the predicted GaR without taking into account structural characteristics, and the green line specifically considers structural characteristics in the form of Equation (3). Since we show the 10th percentile of projected GDP growth, realized GDP growth should be above the predicted GaR values approximately 90 percent of the time. To facilitate the interpretation of the figures, the predicted GaR is shifted forward to align the growth predictions with realizations for the respective quarters. Depending on data availability, the series of predicted GaR starts later for some countries.

While Figures 4 and 5 reveal the importance of structural country characteristics when estimating GaR, a detailed discussion of individual countries would clearly go beyond the scope of the paper. Generally, the effect of structural characteristics is both country and time specific. While, e.g., in Sweden, GaR values tend to be lower

[16]For the sake of brevity, we focus only on the GaR with a time horizon of three years. This perspective is probably more interesting for policymakers, as such a medium-term view may allow for a specific and appropriate policy reaction to increased systemic risks. We repeat the same analysis for GaR estimates one year ahead in the appendix, also confirming that structural country characteristics are important determinants of GaR, both with respect to the structural gap and the risk sensitivity gap.

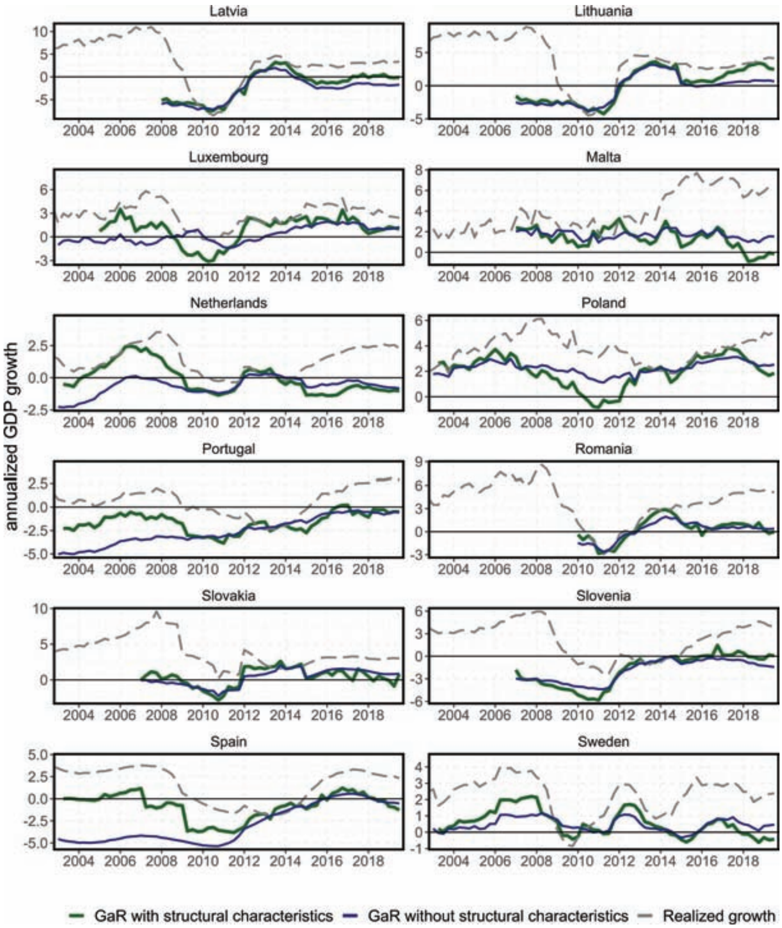
Figure 4. Predicted GaR Three Years Ahead with and without Structural Characteristics



Note: The figure shows the predicted GaR ($\tau = 0.1$) for a three-year forecasting horizon, estimated with and without the structural characteristics, together with realized GDP growth.

when structural characteristics are taken into account, the opposite holds true for, e.g., Malta. Moreover, it appears that in several countries, models incorporating structural characteristics predict higher values of GaR (e.g., Austria, Czech Republic, Hungary, Italy, Netherlands, Luxembourg, Portugal, Spain, Sweden) in the early

Figure 5. Predicted GaR Three Years Ahead with and without Structural Characteristics

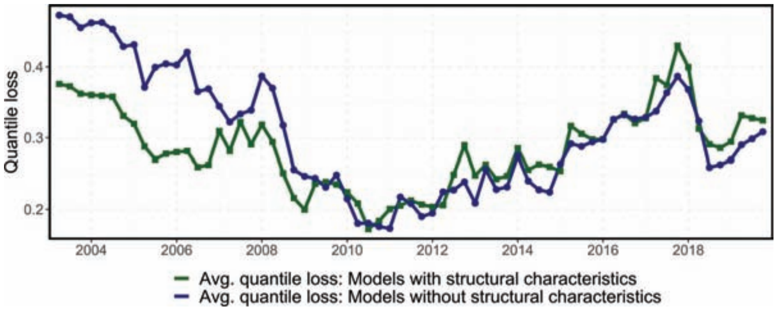


Note: The figure shows the predicted GaR ($\tau = 0.1$) for a three-year forecasting horizon, estimated with and without the structural characteristics, together with realized GDP growth.

2000s. However, after the global financial crisis, the wedge between predictions from models with and without country characteristics appears to shrink, indicating that both models perform similarly after the global financial crisis.

The fact that predicted GaR with and without structural characteristics deviates substantially, in particular in the run-up to the

Figure 6. Quantile Loss over Time



Note: This figure shows the average quantile loss of the panel model with and without structural characteristics for the forecasting horizon $h = 12$ over time.

financial crisis, begs the question of which model would have been more useful in identifying growth risks during that period. Considering in-sample average quantile loss across countries as an indication for the goodness of fit, it appears that the model with structural characteristics performs considerably better until the financial crisis.[17] Figure 6 shows the quantile loss over the sample period for $h = 12$. Especially in the run-up to the financial crisis, we observe substantially larger quantile loss for the model without structural characteristics, suggesting that a model incorporating structural characteristics is more accurate for this period.[18]

To evaluate the forecasting performance of GaR models that utilize country characteristics, we run several model evaluation exercises. We backtest the specification of the panel quantile regression model including country characteristics and interaction terms against two benchmarks using backtesting tools used in previous literature for forecasting horizons 1, 4, and 12 quarters (see, e.g., Brownlees and Souza 2021). As benchmarks, we consider a simple country-by-country quantile regression (BM 1), as shown in Figure 1,

[17]The overall quantile loss is evaluated below in further model evaluation exercises.

[18]Figure A.8 shows the average quantile loss across countries for $h = 4$. Even though quantile loss tends to be higher for the model without structural characteristics, differences in forecasting accuracy are overall less pronounced.

and a fixed-effects panel quantile regression without structural characteristics and interaction terms (BM 2).

First, we consider the unconditional coverage as the actual-over-expected ratio (AE ratio), i.e., incidences in which the actual GDP growth rate falls short of the respective GaR values (so-called hits) compared with the expected incidences implied by the quantile τ. A ratio below one means that the respective GaR model is too conservative and overestimates growth risks, while a ratio above one implies the opposite. Second, to further assess the in-sample goodness of fit, we use the dynamic quantile test (DQ test) of Engle and Manganelli (2004). The DQ test allows us to check for independence of hits in addition to the evaluation of the correct coverage.[19] Finally, we evaluate the average in-sample predictions based on the quantile loss function as an indication for forecasting accuracy, which also is frequently done in the context of value-at-risk evaluations (see, e.g., Gonzalez-Rivera, Lee, and Mishra 2004; Giacomini and Komunjer 2005; Brownlees and Souza 2021).

Table 3 reports the in-sample model evaluation, showing the three backtesting methods for forecasting horizons 1, 4, and 12 quarters for the two benchmark models and the panel specification with country characteristics (CC model). Generally, the CC model lies between the two benchmarks. Starting with the AE ratio, it becomes obvious that all models are too conservative and overestimate growth risks, except for the BM 1 model for $h = 1$, where it slightly underestimates growth risks. Over all predicted horizons, the AE ratio of the country-by-country model (BM 1) is closest to 1, whereas the fixed-effects panel quantile regression model overestimates GaR to the largest degree (BM 2). The specification with country characteristics also is too conservative but to a lesser extent than BM 2, indicating that taking country characteristics into account increases forecasting accuracy. Next, Table 3 shows the percentage of countries where the DQ test is not rejected at the 5 percent significance level. Generally, we see that the null hypothesis of an accurate model is rejected more often with increasing horizons. This means that the number of countries where GaR models are considered optimal by the DQ test shrinks with the forecasting horizon. While there is no difference

[19]Following Brownlees and Souza (2021), we use four lags of the hit sequence.

Table 3. In-Sample Model Evaluation

	AE Ratio			**DQ Test**			**Average Quantile Loss**		
	BM 1	**BM 2**	**CC Model**	**BM 1**	**BM 2**	**CC Model**	**BM 1**	**BM 2**	**CC Model**
$h = 1$	1.03	0.75	0.91	87.5%	87.5%	87.5%	0.68	0.82	0.76
$h = 4$	0.76	0.67	0.69	37.5%	29.2%	45.8%	0.57	0.63	0.61
$h - 12$	0.91	0.82	0.86	62.5%	20.8%	29.2%	0.22	0.30	0.28

Note: This table reports the in-sample model evaluation for the forecast horizons of 1, 2, and 12 quarters ahead and three models: the actual over expected ratio; the percentage of series for which the dynamic quantile test, based on the last four lags of the hit sequence, does not reject the null of model optimality at the 5 percent significance level; and the average quantile loss.

for $h = 1$, for $h = 4$, the specification with country characteristics performs best and is adequate for more countries than the two benchmark models. However, for the 12-quarters-ahead predictions, BM 1 is rejected to the lowest extent, while BM 2 is rejected most often. Finally, we compare the performance of each model according to the average quantile loss. We see that the BM 1 model performs 11 percent, 7 percent, and 22 percent better than the CC model, while the CC model improves the average quantile loss compared with BM 2 by 8 percent, 3 percent, and 7 percent, respectively. Hence, the CC model once again lies between the two benchmarks.

Our sample of 24 European countries is subject to considerable heterogeneity. As a result, it is not surprising that the panel regressions cannot keep pace with the country-by-country models in terms of forecasting accuracy, as the panel regression framework operates under the assumption that the countries load similarly on the financial risk measures employed. While this is important to document, we are mainly interested in the extent to which structural country characteristics affect growth risks. Against this background, the panel regression framework is warranted, especially in the context of a common regulatory framework across countries to implement an integrated modeling approach. Notably, the loss in accuracy can be reduced considerably when country characteristics are modeled explicitly.

5. Conclusion

The analysis in this paper aimed to understand the cross-country variation in growth vulnerabilities associated with financial stress and credit growth by putting a particular focus on the role of structural country characteristics. Our findings document that structural differences across countries play an important role in how financial risk indicators affect the projected distribution of future growth outcomes. By focusing on differences in trade openness, financial sector size, public spending ratio, and a measure of government effectiveness, we show that these structural characteristics not only lead to structural differences in GaR at the individual country level but also give rise to different reactions to varying levels of financial risk. Thus, our findings suggest the existence of both a structural gap in GaR due to structural country characteristics and a risk sensitivity gap, with structural differences across countries also leading to different degrees of responsiveness to varying financial risk indicators. Furthermore, our empirical results also show that structural country characteristics play a significant role in the context of the term structure of GaR, with the impact of the structural characteristics varying with the respective time horizons.

Our findings have important policy implications, particularly for macroprudential surveillance and the calibration of the respective policy tools. Since both the level of systemic risks, as measured by the structural gaps, and the responsiveness of systemic risk to changes in the financial risk indicators, as measured by the risk sensitivity gap, crucially depend on structural country characteristics, such cross-country differences should be explicitly considered both in the risk assessment and in the design of macroprudential policy. For example, a larger financial sector is, ceteris paribus, associated with generally higher growth risks. Thus, countries with large financial sectors may need a tighter macroprudential policy stance to mitigate possible downside risks to the same extent. However, as the negative effects of financial sector size diminish with higher financial stress (short term) and credit growth (medium term), growth risks in these countries will react less sensitively to surges in the respective financial risk indicators. Similar reflections can be made with regard to the remaining structural country characteristics that were examined in this paper. Furthermore, taking into account structural country characteristics in the transmission of financial risks, both in terms of GaR levels and sensitivity to the examined financial risk indicators, also may facilitate the use of the concept to assess the macroprudential policy stance at the individual country level. In fact, model evaluation exercises show that taking into account country characteristics helps to accurately identify and predict growth risks.

To make the GaR framework more readily applicable in a policy context, further research is necessary both in examining other potentially important structural determinants of GaR and concerning cross-country differences with regard to the sensitivity of GaR to policy measures, i.e., the policy sensitivity gap. The latter task is particularly challenging, as macroprudential policy is difficult to measure due to the multidimensional nature of the respective toolbox, and experience in applying many of those instruments is still limited.

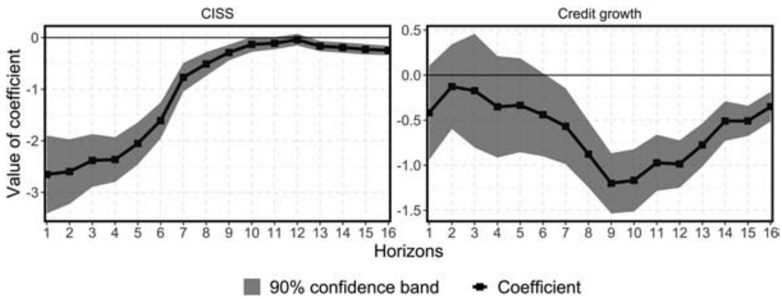
Appendix. Additional Table and Figures

Table A.1. OFR FSI and Credit Growth

	Model 1		Model 2	
	$h = 4$ (1)	$h = 12$ (2)	$h = 4$ (3)	$h = 12$ (4)
OFR FSI	–2.326***	0.081	–2.415***	0.051
	(0.199)	(0.058)	(0.165)	(0.061)
Credit Growth	0.041	–0.819***	0.163	–1.034***
	(0.351)	(0.185)	(0.348)	(0.166)
Current GDP Growth	0.070	–0.576***	0.083	–0.539***
	(0.052)	(0.054)	(0.072)	(0.051)
Openness	–2.974***	–0.738***	–2.885***	–1.149***
	(0.482)	(0.273)	(0.429)	(0.241)
Financial Sector	–1.162	–2.672***	–0.756	–2.714***
	(1.012)	(0.809)	(1.166)	(0.649)
Public Expenditure	0.645***	0.025	0.835***	0.109
	(0.215)	(0.142)	(0.307)	(0.127)
Government Effectiveness	3.862***	2.373***	4.600***	2.415***
	(0.615)	(0.414)	(0.633)	(0.390)
Openness × OFR FSI			–0.069	0.032
			(0.182)	(0.068)
Financial Sector × OFR FSI			0.191	0.022
			(0.223)	(0.084)
Public Expenditure × OFR FSI			0.871***	–0.012
			(0.236)	(0.082)
Government Effectiveness × OFR FSI			0.232	0.111**
			(0.159)	(0.055)
Openness × Credit Growth			–0.480*	–0.618***
			(0.267)	(0.159)
Financial Sector × Credit Growth			0.164	0.200***
			(0.175)	(0.060)
Public Expenditure × Credit Growth			0.007	–0.078
			(0.131)	(0.150)
Government Effectiveness × Credit Growth			–0.938**	–0.059
			(0.399)	(0.139)
Observations	1,744	1,576	1,744	1,576

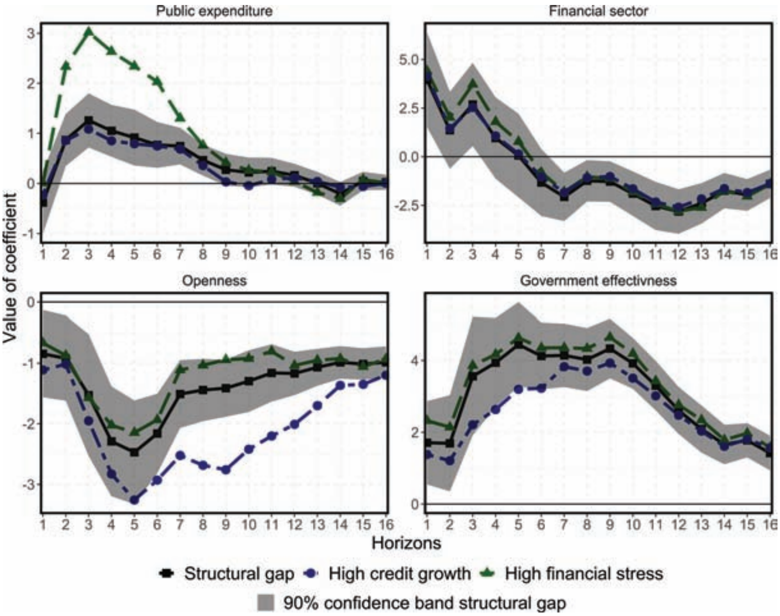
Note: The table shows the estimated coefficients of the conditional 10 percent quantile. Columns 1–2 show the results from the regression model in Equation (1) for the horizons (h) 4 and 12. Columns 3–4 show the results from the regression model in Equation (3) for the horizons (h) 4 and 12. The measure of financial stress is the Office of Financial Research Financial Stress Index (OFR FSI). Bounds are computed using 1,000 bootstrap samples. The significance level is denoted as follows: *p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01.

Figure A.1. Estimated Coefficients of the Financial Risk Indicators from 1 to 16 Quarters Ahead, Using the CISS as a Financial Stress Measure



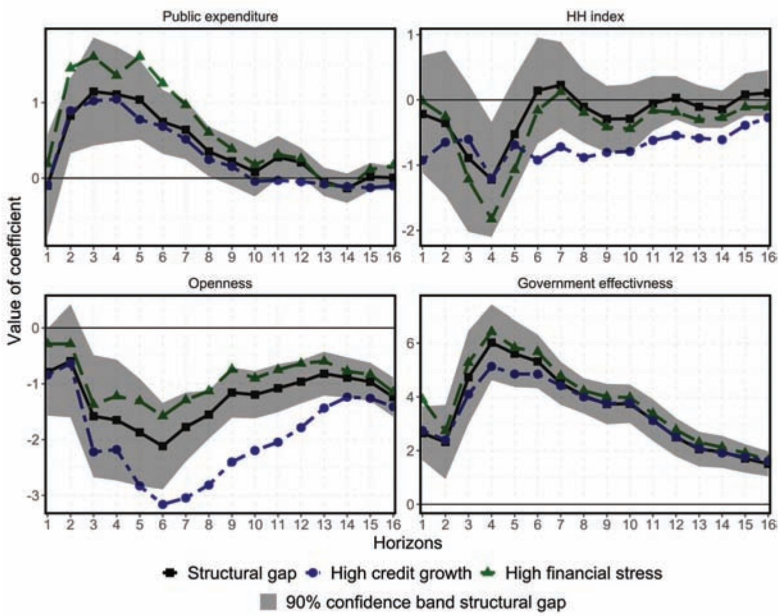
Note: The figure shows the estimated coefficients of the financial risk indicators in the GaR estimation ($\tau = 0.1$) 1 to 16 quarters ahead. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples.

Figure A.2. Estimated Coefficients of the Structural Characteristics from 1 to 16 Quarters Ahead, Using the CISS as a Financial Stress Measure



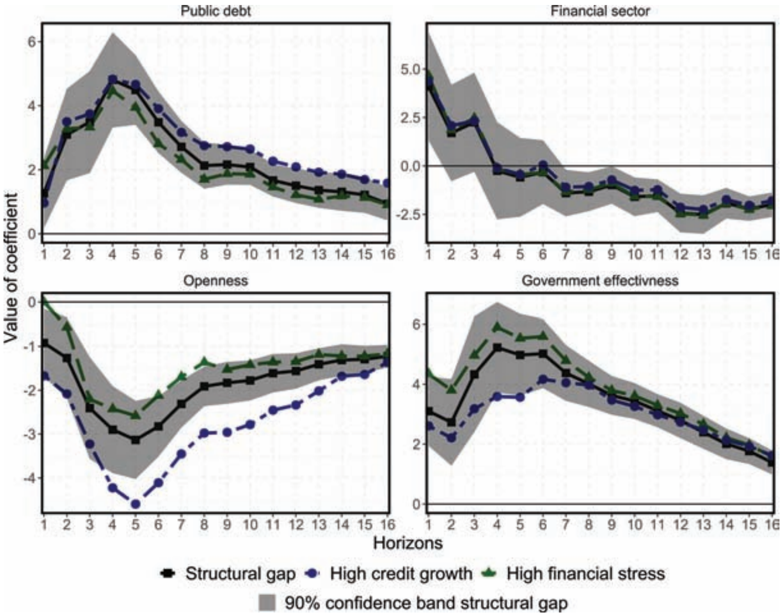
Note: The figure shows the estimated coefficients of the structural characteristics of the GaR ($\tau = 0.1$) 1 to 16 quarters ahead. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples. The green and blue lines show the linear combination of the coefficients on the structural characteristics and the interaction terms with financial stress and credit growth (each evaluated at the 90th percentile).

Figure A.3. Estimated Coefficients of the Structural Characteristics from 1 to 16 Quarters Ahead, Using the CLIFS as the Financial Stress Measure



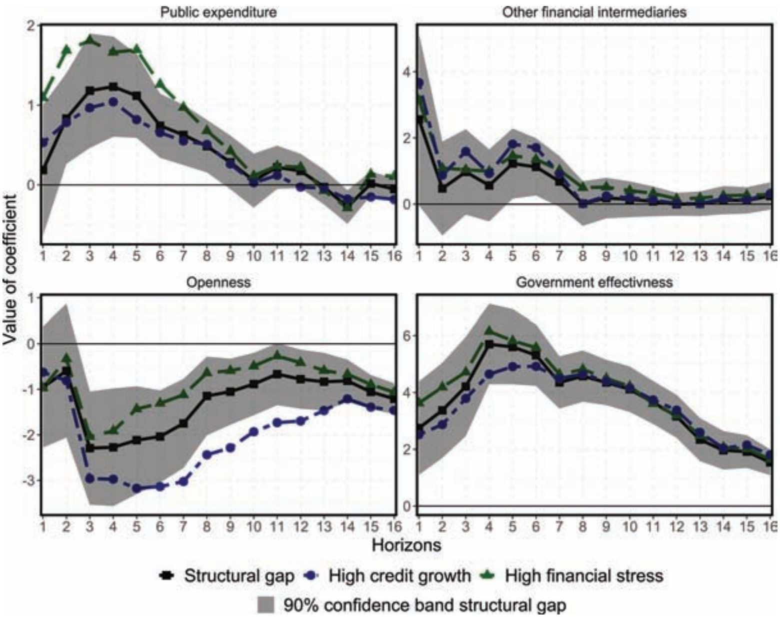
Note: The figure shows the estimated coefficients of the structural characteristics of the GaR ($\tau = 0.1$) 1 to 16 quarters ahead. Financial sector size is substituted with the HH index. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples. The green and blue lines show the linear combination of the coefficients on the structural characteristics and the interaction terms with financial stress and credit growth (each evaluated at the 90th percentile).

Figure A.4. Estimated Coefficients of the Structural Characteristics from 1 to 16 Quarters Ahead, Using the CLIFS as the Financial Stress Measure



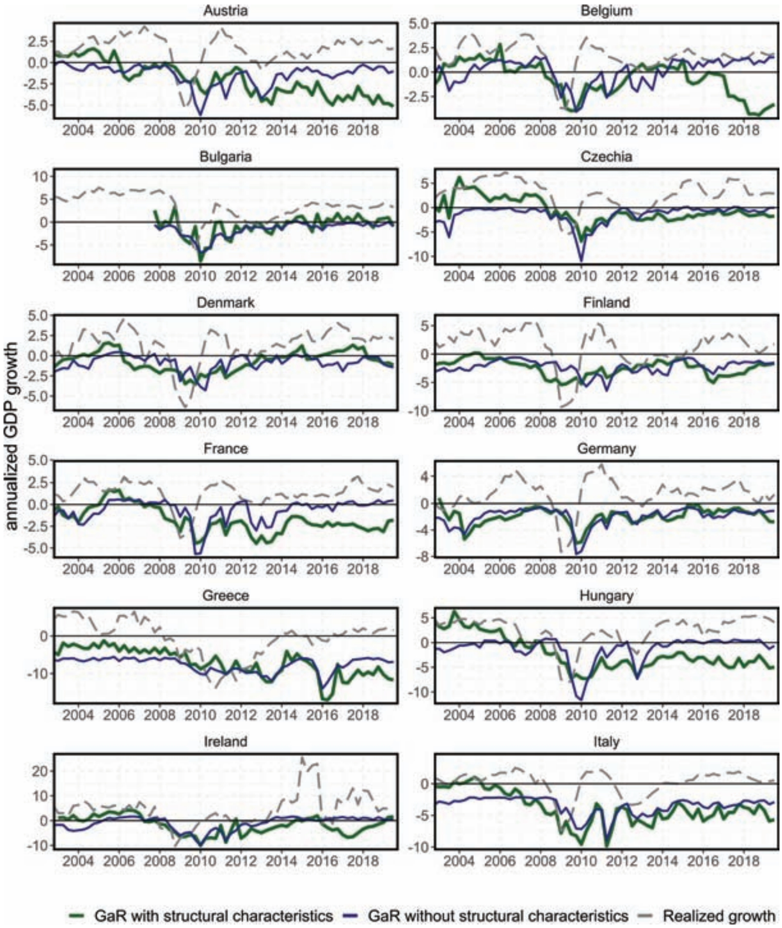
Note: The figure shows the estimated coefficients of the structural characteristics of the GaR ($\tau = 0.1$) 1 to 16 quarters ahead. Public expenditure is substituted with public debt. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples. The green and blue lines show the linear combination of the coefficients on the structural characteristics and the interaction terms with financial stress and credit growth (each evaluated at the 90th percentile).

Figure A.5. Estimated Coefficients of the Structural Characteristics from 1 to 16 Quarters Ahead, Using the CLIFS as the Financial Stress Measure



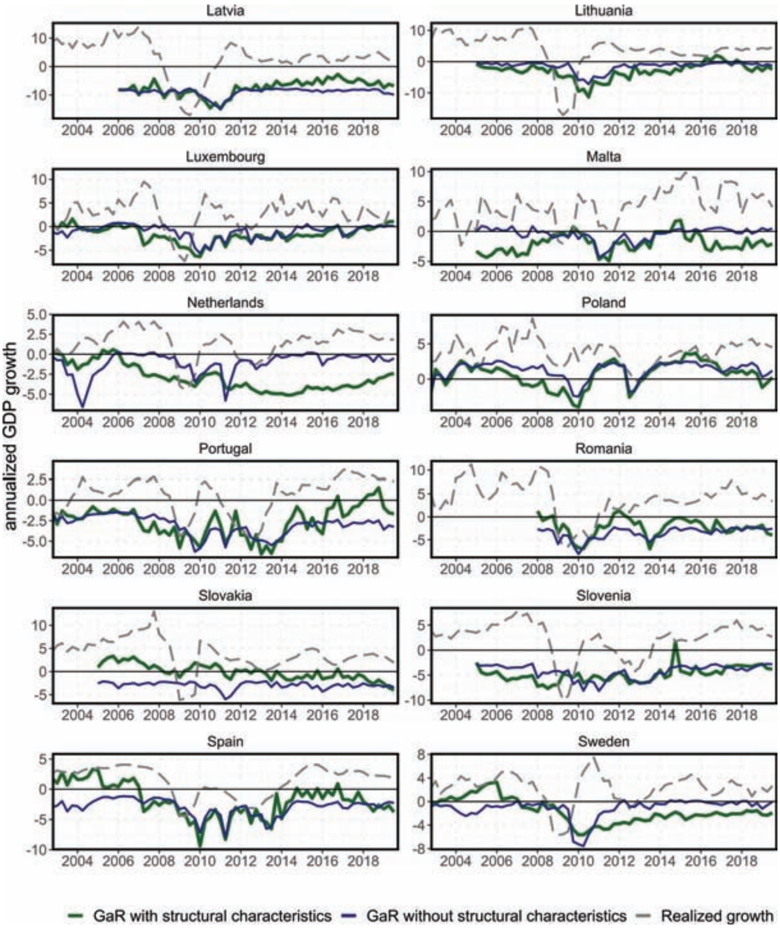
Note: The figure shows the estimated coefficients of the structural characteristics of the GaR ($\tau = 0.1$) 1 to 16 quarters ahead. Financial sector size is substituted with the ratio of assets of other financial intermediaries (excluding monetary institutions, pension funds, and insurance companies) to GDP. The black line represents the estimated coefficients, and the gray area shows the 90 percent confidence intervals; bounds are computed using 1,000 bootstrap samples. The green and blue lines show the linear combination of the coefficients on the structural characteristics and the interaction terms with financial stress and credit growth (each evaluated at the 90th percentile).

Figure A.6. Predicted GaR One Year Ahead with and without Structural Characteristics



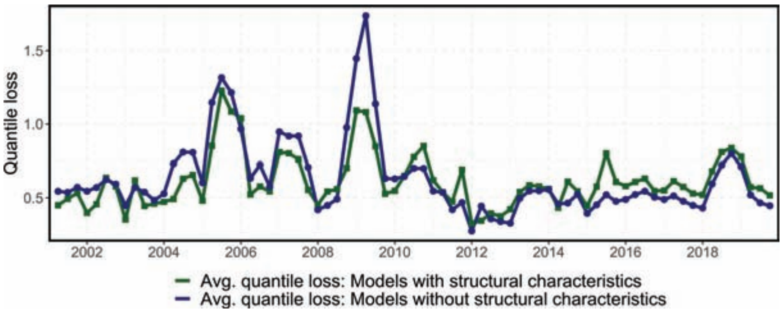
Note: The figure shows the predicted GaR ($\tau = 0.1$) for a one-year forecasting horizon, estimated with and without the structural factors, together with realized GDP growth.

Figure A.7. Predicted GaR One Year Ahead with and without Structural Characteristics



Note: The figure shows the predicted GaR ($\tau = 0.1$) for a one-year forecasting horizon, estimated with and without the structural factors, together with realized GDP growth.

Figure A.8. Quantile Loss over Time



Note: This figure shows the average quantile loss of the panel model with and without structural characteristics for the forecasting horizon $h = 4$ over time.

References

Adrian, T., N. Boyarchenko, and D. Giannone. 2019. "Vulnerable Growth." *American Economic Review* 109 (4): 1263–89.

Adrian, T., F. Grinberg, N. Liang, S. Malik, and J. Yu. 2022. "The Term Structure of Growth-at-Risk." *American Economic Journal: Macroeconomics* 14 (3): 283–323.

Adrian, T., D. He, N. Liang, and F. M. Natalucci. 2019. "A Monitoring Framework for Global Financial Stability." IMF Staff Discussion Note No. 2019/006.

Aikman, D., J. Bridges, S. Hacioglu Hoke, C. O'Neill, and A. Raja. 2019. "Credit, Capital and Crises: A GDP-at-Risk Approach." Working Paper No. 824, Bank of England.

Arbatli-Saxegaard, E. C., K. R. Gerdrup, and R. M. Johansen. 2020. "Financial Imbalances and Medium-Term Growth-at-Risk in Norway." Staff Memo No. 5, Norges Bank.

Beck, T., M. Lundberg, and G. Majnoni. 2006. "Financial Intermediary Development and Growth Volatility: Do Intermediaries Dampen or Magnify Shocks?" *Journal of International Money and Finance* 25 (7): 1146–67.

Blanchard, O. J., H. Faruqee, M. Das, K. J. Forbes, and L. L. Tesar. 2010. "The Initial Impact of the Crisis on Emerging Market Countries [with comments and discussion]." *Brookings Papers on Economic Activity* (Spring): 263–323.

Breitenlechner, M., M. Gachter, and F. Sindermann. 2015. “The Finance–Growth Nexus in Crisis.” *Economics Letters* 132 (July): 31–33.

Brownlees, C., and A. B. Souza. 2021. “Backtesting Global Growth-at-Risk.” *Journal of Monetary Economics* 118 (March): 312–30.

Carmignani, F., E. Colombo, and P. Tirelli. 2011. “Macroeconomic Risk and the (de)stabilising Role of Government Size.” *European Journal of Political Economy* 27 (4): 781–90.

Collard, F., H. Dellas, and G. Tavlas. 2017. “Government Size and Macroeconomic Volatility.” *Economica* 84 (336): 797–819.

Crucini, M. J., M. A. Kose, and C. Otrok. 2011. “What Are the Driving Forces of International Business Cycles?” *Review of Economic Dynamics* 14 (1): 156–75.

Dabla-Norris, E., and N. Srivisal. 2013. “Revisiting the Link Between Finance and Macroeconomic Volatility.” IMF Working Paper No. 13/29.

Denizer, C. A., M. F. Iyigun, and A. Owen. 2002. “Finance and Macroeconomic Volatility.” *B.E. Journal of Macroeconomics* 2 (1): 1–32.

di Giovanni, J., and A. A. Levchenko. 2009. “Trade Openness and Volatility.” *Review of Economics and Statistics* 91 (3): 558–85.

Duprey, T., B. Klaus, and T. Peltonen. 2017. “Dating Systemic Financial Stress Episodes in the EU Countries.” *Journal of Financial Stability* 32 (October): 30–56.

Duprey, T., and A. Ueberfeldt. 2020. “Managing GDP Tail Risk.” Staff Working Paper No. 20-3, Bank of Canada.

Engle, R. F., and S. Manganelli. 2004. “Caviar: Conditional Autoregressive Value at Risk by Regression Quantiles.” *Journal of Business and Economic Statistics* 22 (4): 367–81.

European Systemic Risk Board. 2019. “Features of a Macroprudential Stance: Initial Considerations.” ESRB Report.

———. 2021. “A Framework for Assessing Macroprudential Stance.” ESRB Report.

Evrensel, A. Y. 2010. “Corruption, Growth, and Growth Volatility.” *International Review of Economics and Finance* 19 (3): 501–14.

Fatás, A., and I. Mihov. 2001. “Government Size and Automatic Stabilizers: International and Intranational Evidence.” *Journal of International Economics* 55 (1): 3–28.

Figueres, J. M., and M. Jarociński. 2020. "Vulnerable Growth in the Euro Area: Measuring the Financial Conditions." *Economics Letters* 191 (June): Article 109126.

Franta, M., and L. Gambacorta. 2020. "On the Effects of Macroprudential Policies on Growth-at-Risk." *Economics Letters* 196 (November): Article 109501.

Galán, J. E. 2020. "The Benefits Are at the Tail: Uncovering the Impact of Macroprudential Policy on Growth-at-Risk." Forthcoming in *Journal of Financial Stability*.

Galí, J. 1994. "Government Size and Macroeconomic Stability." *European Economic Review* 38 (1): 117–32.

Galvao, A. F., and G. Montes-Rojas. 2015. "On Bootstrap Inference for Quantile Regression Panel Data: A Monte Carlo Study." *Econometrics* 3 (3): 654–66.

Giacomini, R., and I. Komunjer. 2005. "Evaluation and Combination of Conditional Quantile Forecasts." *Journal of Business and Economic Statistics* 23 (4): 416–31.

González-Rivera, G., T.-H. Lee, and S. Mishra. 2004. "Forecasting Volatility: A Reality Check Based on Option Pricing, Utility Function, Value-at-Risk, and Predictive Likelihood." *International Journal of Forecasting* 20 (4): 629–45.

Hollo, D., M. Kremer, and M. Lo Duca. 2012. "CISS—A Composite Indicator of Systemic Stress in the Financial System." ECB Working Paper No. 1426.

Kapetanios, G. 2008. "A Bootstrap Procedure for Panel Data Sets with Many Cross-Sectional Units." *Econometrics Journal* 11 (2): 377–95.

Kaufmann, D., A. Kraay, and M. Mastruzzi. 2011. "The Worldwide Governance Indicators: Methodology and Analytical Issues 1." *Hague Journal on the Rule of Law* 3 (2): 220–46.

Kim, D.-H., S.-C. Lin, and Y.-B. Suen. 2016. "Trade, Growth and Growth Volatility: New Panel Evidence." *International Review of Economics and Finance* 45 (September): 384–99.

Koenker, R. 2004. "Quantile Regression for Longitudinal Data." *Journal of Multivariate Analysis* 91 (1): 74–89.

Koenker, R., and G. Bassett. 1978. "Regression Quantiles." *Econometrica* 46: 33–50.

Lahiri, S. 2003. *Resampling Methods for Dependent Data*. Springer.

Lane, P. R., and G. M. Milesi-Ferretti. 2011. "The Cross-Country Incidence of the Global Crisis." *IMF Economic Review* 59 (1): 77–110.

Loayza, N. V., and C. Raddatz. 2007. "The Structural Determinants of External Vulnerability." *World Bank Economic Review* 21 (3): 359–87.

Manganelli, S., and A. Popov. 2015. "Financial Development, Sectoral Reallocation, and Volatility: International Evidence." *Journal of International Economics* 96 (2): 323–37.

Monin, P. J. 2019. "The OFR Financial Stress Index." *Risks* 7 (1): 25.

O'Brien, M., and M. Wosser. 2021. "Growth at Risk & Financial Stability." Financial Stability Note No. 2/FS/21, Central Bank of Ireland.

Posch, O. 2011. "Explaining Output Volatility: The Case of Taxation." *Journal of Public Economics* 95 (11): 1589–1606.

Prasad, A., S. Elekdag, P. Jeasakul, R. Lafarguette, A. Alter, A. X. Feng, and C. Wang. 2019. "Growth at Risk: Concept and Application in IMF Country Surveillance." IMF Working Paper No. 2019/036.

Rose, A. K., and M. M. Spiegel. 2011. "Cross-Country Causes and Consequences of the Crisis: An Update." *European Economic Review* 55 (3): 309–24.

Suarez, J. 2022. "Growth-at-Risk and Macroprudential Policy Design." *Journal of Financial Stability* 60 (June): Article 101008.