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Medium-term growth-at-risk in the euro area

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Abstract

Financial stability indicators can be grouped into financial stress indicators that reflect heightened spreads and market volatility, and financial vulnerability indicators that reflect credit and asset price imbalances. Based on a panel of euro area countries, we show that both types of indicators contain information about downside risks to real GDP growth (growth-at-risk) in the short-term (1-year ahead). However, only vulnerability indicators contain information about growth-at-risk in the medium-term (3-years ahead and beyond). Among various vulnerability indicators suggested in the literature, the Systemic Risk Indicator (SRI) proposed by Lang et al. (2019) outperforms in terms of in-sample explanatory power and out-of-sample predictive ability for medium-term growth-at-risk in euro area countries. Shocks to the SRI induce a rich "term structure" for growth-at-risk: downside risks to real GDP growth are reduced in the short-term, but over the medium-term the effect reverses and downside risks to real GDP growth go up considerably. We also show that using cross-country information from the panel of euro area countries can improve the out-of-sample forecasting performance of growth-at-risk for the euro area aggregate.

Keywords: Growth-at-risk, financial stress, financial vulnerabilities, quantile regression, local projections

JEL classification: E37, E44, G01, G17, C22

Non-Technical Summary

Growth-at-risk, i.e. linking current macro-financial conditions to future tail risks to real GDP growth, has become a central approach in financial stability analysis. The approach was pioneered by Adrian et al. (2019) who showed for US data that deteriorating financial conditions significantly lower the left tail of the 1-year ahead real GDP growth distribution. There is a growing body of literature building on these insights, but most papers have focused on financial conditions or financial stress indicators, and short-term prediction horizons. However, for countercyclical macroprudential policy it is crucial to identify risks with a sufficient lead time, to allow for potential mitigating action such as increasing bank capital buffers or implementing borrower-based measures.

With this background in mind, we study the information content of various financial stability indicators for growth-at-risk in euro area countries at various projection horizons, but with a special focus on the medium-term (3-years ahead). In particular, we distinguish between financial stress indicators that reflect heightened spreads and market volatility, and financial vulnerability indicators that reflect the build-up of credit and asset price imbalances. The rationale for distinguishing between these two groups of indicators is that the early warning literature for financial crises has found that mainly vulnerability indicators are useful for issuing warning signals with long lead times. A large set of indicators is compared in terms of their in-sample explanatory power and out-of-sample predictive ability for tail risk (5th percentile) to future real GDP growth. Based on the best performing indicators, a multivariate model is constructed to measure both short-term and medium-term growth-at-risk for the euro area aggregate and euro area countries.

The main finding of our paper is that financial stress and vulnerability indicators both contain information for growth-at-risk in the short-term (1-year ahead), but only vulnerability indicators contain information about growth-at-risk in the medium-term (3-years ahead and beyond). Among various vulnerability indicators suggested in the literature, such as the Basel credit-to-GDP gap or composite financial cycle measures, the Systemic Risk Indicator (SRI) developed by Lang et al. (2019) outperforms in terms of in-sample explanatory power and out-of-sample predictive ability for medium-term growth-at-risk, improving the tick loss by around 30% compared to a model that only conditions on current real GDP growth. We also show that the inclusion of lags and non-linear interaction terms for vulnerability indicators is important to enhance model fit and predictive power.

A second key finding of our paper is that financial vulnerabilities, as measured by the SRI, induce a rich "term structure" for growth-at-risk, which is different to the "term structure" identified by Adrian et al. (2022) for financial conditions. In particular, a positive shock to the SRI leads to a reduction in downside risks to real GDP growth in the short-term, but over the medium-term the effect reverses and downside risks to real GDP growth go up considerably. In addition, the magnitude of the growth-at-risk term structure differs depending on whether the SRI is positive (vulnerabilities are above average) or negative (vulnerabilities are below average). In particular, when vulnerabilities are already elevated, the short-term reduction in GDP tail risk induced by shocks to the SRI is half as large as when vulnerabilities are subdued, while the medium-term increase in GDP tail risk is almost 50% higher. We also show that the impact of SRI shocks on GDP tail risk is much larger than on upper quantiles, in particular for medium-term horizons (3 to 4 years ahead). This contrasts with financial stress indicators, which have an asymmetric impact on the real GDP growth distribution mainly for short-term horizons (1 to 2 years).

A third key finding of our paper is that the use of cross-country information from the panel of euro area countries can improve the out-of-sample forecasting performance of growth-at-risk for the euro area aggregate. This is most likely due to the fact that we are looking at rare events when trying to predict tail risk. For example, for a single country with 30 years of quarterly data, focusing on the 5th percentile means zooming in on the six most extreme quarterly observations. To the extent that the true underlying distribution has a fat left tail, estimation uncertainty could be very large. Pooling extreme observations across countries can potentially alleviate this estimation uncertainty to some extent, leading to more robust out-of-sample predictions. Exploring this topic in greater detail is left for future research.

Compared to the existing growth-at-risk literature, we make the following contributions. First, we focus on identifying drivers of medium-term growth-at-risk instead of short-term growth-at-risk, which is crucial for macroprudential policy purposes. Second, we compare the information content for growth-at-risk of various financial stress and vulnerability indicators and show which ones work best for medium-term horizons. Third, we show that financial vulnerabilities induce a very different "term structure" for growth-at-risk than financial conditions. Fourth, we focus both on the panel of euro area countries and the euro area aggregate, whereas most other papers have focused either on the US, the euro area aggregate, or a panel of international countries. Finally, to our knowledge we are the first to highlight the potential usefulness of cross-country data for improving out-of-sample predictions of growth-at-risk for a single jurisdiction.

1 Introduction

Growth-at-risk, i.e. the use of quantile local projections to measure tail risk to future real GDP growth, has become a central approach in financial stability analysis to link current macro-financial conditions to future risks to the real economy.[1] The approach was pioneered by Adrian et al. (2019) who showed for US data that deteriorating financial conditions significantly lower the left tail of the 1-year ahead real GDP growth distribution. There is a growing body of literature building on these insights, but most papers have focused on financial conditions or financial stress indicators, and short-term prediction horizons.[2] However, for countercyclical macroprudential policy it is crucial to identify risks with a sufficient lead time, to allow for potential mitigating action such as increasing bank capital buffers or implementing borrower-based measures.

With this background in mind, we study the information content of various financial stability indicators for growth-at-risk in euro area countries at various projection horizons, but with a special focus on the medium-term (3-years ahead). In particular, we distinguish between financial stress indicators that reflect heightened spreads and market volatility, and financial vulnerability indicators that reflect the build-up of credit and asset price imbalances. The rationale for distinguishing between these two groups of indicators is that the early warning literature for financial crises has found that mainly vulnerability indicators are useful for issuing warning signals with long lead times.[3] Using the tick loss function, a large set of indicators is compared in terms of their in-sample explanatory power and out-of-sample predictive ability for tail risk (5th percentile) to future real GDP growth. Based on the best performing indicators, a multivariate model is constructed to measure both short-term and medium-term growth-at-risk for the euro area aggregate and euro area countries.

The main finding of our paper is that financial stress and vulnerability indicators both contain information for growth-at-risk in the short-term (1-year ahead), but only vulnerability indicators contain information about growth-at-risk in the medium-term (3-years ahead and beyond). Among various vulnerability indicators suggested in the literature, such as the Basel credit-to-GDP gap or composite financial cycle measures, the Systemic Risk Indicator (SRI) developed by Lang et al. (2019) outperforms in terms of in-sample explanatory power and out-of-sample

[1] See for example IMF (2017) or ECB (2021) for recent policy applications.

[2] For an overview of the literature, see the discussion further below.

[3] See for example Borio and Lowe (2002), Borio and Drehmann (2009), Alessi and Detken (2011), Detken et al. (2014), or Lang et al. (2019).

predictive ability for medium-term growth-at-risk, improving the tick loss by around 30% compared to a model that only conditions on current real GDP growth. We also show that the inclusion of lags and non-linear interaction terms for vulnerability indicators is important to enhance model fit and predictive power.

A second key finding of our paper is that financial vulnerabilities, as measured by the SRI, induce a rich "term structure" for growth-at-risk, which is different to the "term structure" identified by Adrian et al. (2022) for financial conditions. A positive shock to the SRI leads to a reduction in downside risks to real GDP growth in the short-term, but over the medium-term the effect reverses and downside risks to real GDP growth go up considerably. In addition, the magnitude of the growth-at-risk term structure differs depending on whether the SRI is positive (vulnerabilities are above average) or negative (vulnerabilities are below average). In particular, when vulnerabilities are already elevated, the short-term reduction in GDP tail risk induced by shocks to the SRI is half as large as when vulnerabilities are subdued, while the medium-term increase in GDP tail risk is almost 50% higher. We also show that the impact of SRI shocks on GDP tail risk is much larger than on upper quantiles, in particular for medium-term horizons (3 to 4 years ahead), but that the entire GDP growth distribution is shifted. This contrasts with financial conditions and financial stress indicators, which have an impact mainly on lower quantiles of the real GDP growth distribution at short-term horizons (1 to 2 years).

A third key finding of our paper is that the use of cross-country information from the panel of euro area countries can improve the out-of-sample forecasting performance of growth-at-risk for the euro area aggregate. This is most likely due to the fact that we are looking at rare events when trying to predict tail risk. For example, for a single country with 30 years of quarterly data, focusing on the 5th percentile means zooming in on the six most extreme quarterly observations. To the extent that the true underlying distribution has a fat left tail, estimation uncertainty could be very large. Pooling extreme observations across countries can potentially alleviate this estimation uncertainty to some extent, leading to more robust out-of-sample predictions. Exploring this topic in greater detail is left for future research.

Compared to the existing growth-at-risk literature, we make the following contributions. First, we focus on identifying drivers of medium-term growth-at-risk instead of short-term growth-at-risk, which is crucial for macroprudential policy purposes. Second, we compare the information content for growth-at-risk of various financial stress and vulnerability indicators and show which ones work best for medium-term horizons. Third, we focus both on the panel of euro area countries and the euro area aggregate, whereas most other papers have focused either on the US, the euro area aggregate, or a panel of international countries. Finally, to our knowledge we are the first to highlight the potential usefulness of cross-country data for improving out-of-sample predictions of growth-at-risk for a single jurisdiction.

Our paper builds on and contributes to the quickly expanding growth-at-risk literature. Based on the pioneering work of Adrian et al. (2019) for the US, many papers have focused on the role of financial conditions or financial stress in predicting GDP tail risk over short horizons. E.g. Figueres and Jarocinski (2020) compare the information content of different financial conditions measures for predicting 1-year ahead GDP tail risk for the euro area aggregate. De Santis and Van der Veken (2020) look at the information content of various survey indicators, spread measures, and financial stress indicators for 1-quarter and 1-year ahead GDP tail risk in the US. Falconio and Manganelli (2020) use a quantile vector autoregression (QVAR) to study how the excess bond premium affects the 1-month ahead distribution of industrial production in the US. Carriero et al. (2021) study the nowcasting ability of different indicators and modelling techniques for economic tail risk in the US. Finally, Plagborg-Moller et al. (2020) study the potentially non-linear nexus between financial indicators and the 1-quarter and 1-year ahead distribution of GDP growth for 13 advanced economies.

A few papers have focused on financial vulnerabilities and medium-term prediction horizons, but none has looked explicitly at the euro area (countries) or has systematically compared the in-sample and out-of-sample information content of different vulnerability indicators. For example, Aikman et al. (2018) study how three composite measures of leverage, asset valuations, and credit terms affect the GDP growth distribution in the UK 1-quarter, 1-year, and 3-years ahead. Aikman et al. (2019) study how indicators of credit booms, property price booms and current account deficits affect growth-at-risk over the medium term (3 to 5 years) for a panel dataset of 16 advanced economies. Hartwig et al. (2021) compare the in-sample early warning and growth-at-risk properties of different vulnerability indicators at the country level across 45 advanced and emerging economies. Galán (2020) studies how credit, house prices, financial conditions, and macroprudential policy affect the GDP growth distribution between 1 and 16 quarters into the future based on a panel of 36 advanced and emerging economies. Finally, Chavleishvili et al. (2021) use a QVAR of order one to study the interaction of financial stress and the financial cycle in the euro area, but their focus is more on the short- rather than the medium-term.

The remainder of the paper is structured as follows. Section 2 presents the econometric modelling framework and data. Section 3 studies in detail the information content of various financial stability indicators for growth-at-risk at various horizons, with a special focus on the medium-term. Section 4 performs quantile impulse response analysis for the key variables and discusses the different term structures of growth-at-risk. Section 5 presents the evolution of estimated growth-at-risk across the euro area based on the full model specification containing financial stress and vulnerability indicators. Section 6 shows the importance of using cross-country information for out-of-sample predictions of growth-at-risk for the euro area aggregate. Section 7 concludes.

2 Modelling framework and data

2.1 Modelling framework

To analyze the impact of financial stress and vulnerability indicators on tails of the future real GDP growth distribution, we employ panel quantile local projections following Adrian et al. (2022). In particular, we estimate quarterly panel quantile regression models for each projection horizon $h = 1, ..., 16$ where the conditional quantile of the real GDP growth distribution at the given horizon is modelled as:

$$Q_{y_{i,t+h+4,\tau}} = \alpha_i^{h,\tau} + \rho^{h,\tau} y_{i,t} + \beta^{h,\tau} \mathbf{X'_{i,t}} + \varepsilon_{i,t+h+4,\tau}, \tag{1}$$

where $y_{i,t+h+4}$ is the year-on-year real GDP growth rate for a country i in a quarter $t+h+4$, and $\mathbf{X'_{i,t}}$ is a vector of explanatory variables capturing the state of the macro-financial environment, financial stress and financial vulnerabilities, while $\alpha_i^{h,\tau}$ are country fixed effects, and $\varepsilon_{i,t+h+4,\tau}$ denotes an error term. The coefficients of interest for our analysis are $\beta^{h,\tau}$ for different horizons $h = 1, ..., 16$ and different quantiles $\tau = 0.05, \ldots, 0.5, \ldots, 0.9$, which trace out the quantile local projection impulse response function (QIRF) of annual real GDP growth to a one unit increase in the respective explanatory variable.

We use a two-step estimation procedure for panel quantile regressions following Canay (2011), where in the first step unobserved fixed effects are estimated using the within-estimator (i.e. assuming country fixed effects remain the same across different quantiles), and in the second step a standard conditional quantile regression is estimated using the dependent variable adjusted for the fixed effect from the first step (see Canay (2011) for more details). Following the recommendation of Besstremyannaya and Golovan (2019) for panels with small n/T, we bootstrap the standard errors for the vector of coefficients before conducting significance tests.

2.2 Data

For our empirical analysis, we use a quarterly panel dataset starting in 1970 Q1 covering 19 euro area countries, Denmark, Sweden and Great Britain.[4] The variables of interest cover real GDP growth, a measure of economic sentiment, the debt service ratio, a financial stress indicator, and various financial vulnerability indicators (see further details below). The panel dataset is unbalanced as data availability across indicators and countries differs (see Table B1 in Annex B). For most of the larger Western European countries (e.g. DE, IT, ES, FR, GB) data availability starts in the 1970s or 1980s. For some smaller countries (e.g. AT, PT, GR) some of the indicators only start being available towards the end of the 1990s. For many of the Eastern European or very small countries (e.g. CY, EE, LT, LV, LU, MT) data availability for some of the indicators only starts during the 2000s.

Real GDP growth is taken from Eurostat and is back-casted with data obtained from national statistics to obtain longer time series. The economic sentiment indicator (ESI) is obtained from the European Commission. The debt service ratio (DSR) is calculated based on data from the ECB, Eurostat and the BIS according to the methodology proposed by Drehmann et al. (2015). Real total credit growth is computed based on Eurostat data and back-casted with BIS data to obtain longer time series. The country-level indicator of financial stress (CLIFS) is obtained from Duprey et al. (2017) via the ECB's statistical data warehouse. For the euro area aggregate the composite indicator of systemic stress (CISS) by Kremer et al. (2012) is used. In terms of vulnerability indicators, the Basel credit-to-GDP gap (see e.g. Drehmann et al. (2010)), the bank credit-to-GDP gap, the cyclical systemic risk indicator (SRI) by Lang et al. (2019), and the financial cycle by Schüler et al. (2015) are used.[5] These vulnerability indicators have been found useful in the context of

[4]We include Denmark, Sweden and Great Britain in the estimation sample as these countries have long time series available with relevant GDP tail risk events and are sufficiently similar to many euro area countries. For simplicity we will refer to euro area countries throughout the remainder of this paper.

[5]Credit gaps are computed as deviations from a recursive HP-filter with a smoothing parameter of 400,000. The SRI is constructed as a weighted average of six early warning indicators: (i) the two-year change in the bank credit-to-GDP ratio (with 36% weight); (ii) the two-year growth rate of real total credit (5%); (iii) the two-year change in the debt service ratio (5%); (iv) the three-year change in the residential real estate price-to-income ratio (17%); (v) the three-year growth

early warning models for financial crises, which motivates their potential inclusion in growth-at-risk models, especially when considering longer projection horizons. Table 1 provides an overview of key descriptive statistics for the different indicators across the panel of countries.

Table 1: Summary statistics for key indicators

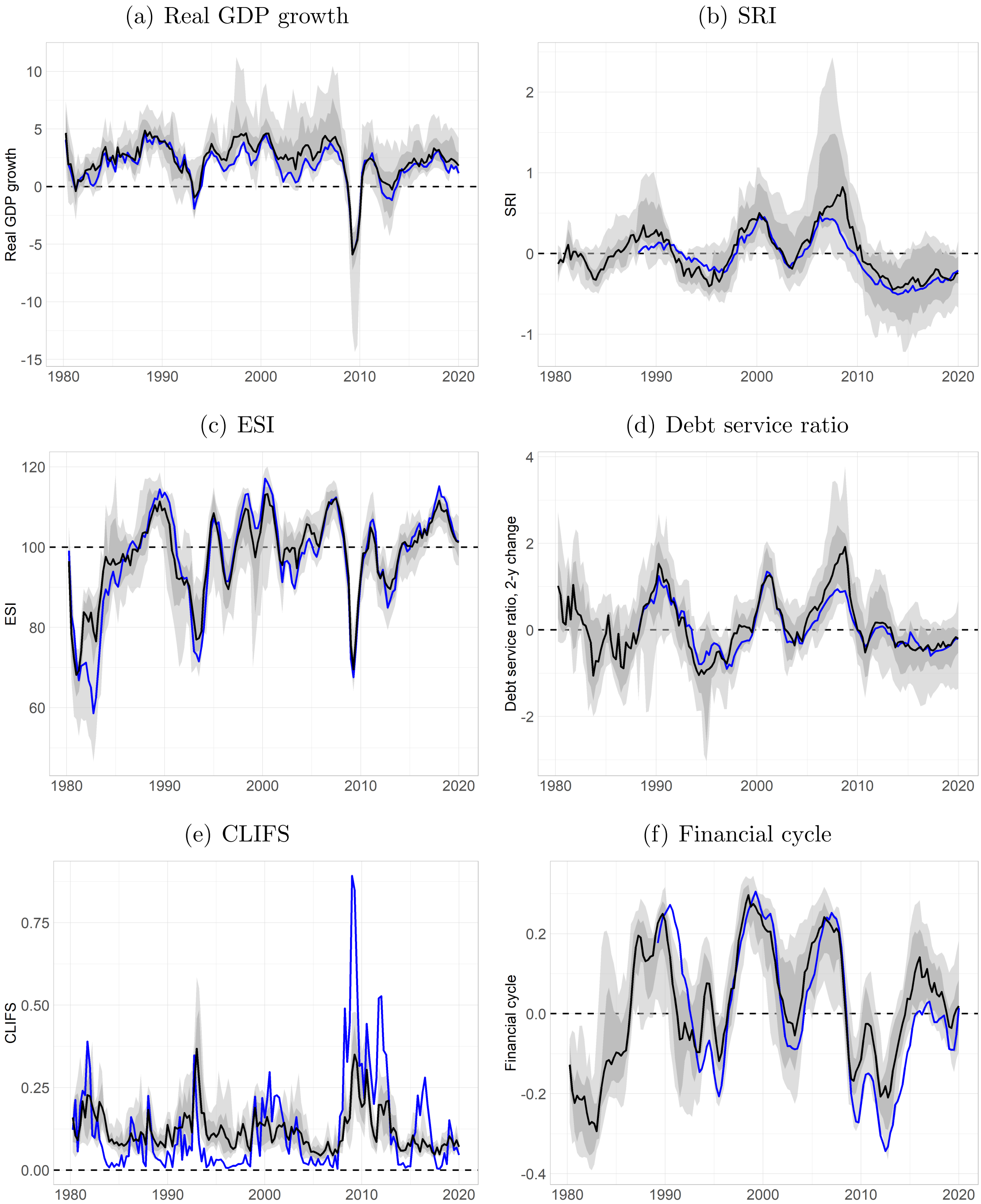
Variable	Obs.	Mean	Std. Dev.	Median	Q05	Q25	Q75	Q95
Real GDP growth	3492	2.70	3.32	2.67	-2.40	1.15	4.33	7.91
SRI	2279	-0.01	0.61	-0.03	-0.89	-0.36	0.27	1.01
Financial cycle	2830	0.01	0.17	0.01	-0.29	-0.12	0.14	0.28
Bank credit-to-GDP gap	3165	-1.48	13.14	-0.36	-24.50	-4.75	3.55	15.90
Total credit-to-GDP gap	3185	-0.35	17.08	-0.39	-28.38	-6.56	6.96	27.77
Real total credit 2-y growth	3255	4.83	6.59	3.79	-3.27	0.71	7.72	15.77
Debt service ratio, 2-y change	2770	0.06	1.40	0.02	-1.80	-0.59	0.71	2.04
CLIFS	3165	0.13	0.10	0.10	0.04	0.07	0.17	0.34
ESI	2909	98.58	12.03	100.70	75.60	92.40	107.00	114.10

Notes: Summary statistics computed for the sample of EA countries and DK, GB, and SE on the sample up to 2019 Q4. Q05, Q25, Q75, Q95 denote 5th, 25th, 75th, and 95th percentiles, respectively.

As shown in Figure 1, there were two main episodes when most euro area countries experienced very low or even negative real GDP growth: at the beginning of the 1990s and during the global financial crisis in 2008/2009. During the euro area sovereign debt crisis of 2011/2012 real GDP growth was also highly negative in some countries, but this episode of tail risk for real GDP growth was confined to Cyprus, Finland, Greece, Ireland, Italy, The Netherlands, Portugal, Slovenia, and Spain. From Figure 1 one can see that the CLIFS tended to shoot up to elevated levels just before these episodes, indicating the potential short-term leading properties of financial stress indicators also highlighted by Figueres and Jarocinski (2020). From Figure 1 one can see that the economic sentiment indicator follows similar dynamics to those of real GDP growth. The SRI and the financial cycle display clear cyclical patterns, with the former vulnerability indicator showing somewhat longer cycle lengths. Both vulnerability indicators reached elevated levels across countries well in advance of the episodes with low real GDP growth indicated above, suggesting potential leading information for growth-at-risk over the medium term.

rate of real equity prices (17%); and (vi) the current account-to-GDP ratio (20%). The financial cycle is constructed as a time-varying weighted average of the percentile ranks of four indicators: percentage change in total credit, percentage change in house prices, percentage change in equity prices and percentage point change in bond yields. The time-varying aggregation weights are based on the cross-correlations among the indicators.

Figure 1: Cross country distribution plots for key indicators



Notes: The blue line denotes the Euro Area aggregate, the black line the median across countries and the shaded areas represent the interquartile range and the 90th to 10th percentile range across countries.

3 Identifying drivers of medium-term growth-at-risk

3.1 Comparison of different indicators

Most of the existing growth-at-risk literature has focused on financial conditions or financial stress indices as key explanatory variables (Adrian et al., 2022, 2019; Figueres and Jarocinski, 2020; De Santis and Van der Veken, 2020). While financial condition indices typically contain information about financial stress and financial vulnerabilities, they are generally closer to stress indicators. In our analysis, we follow Aikman et al. (2019) and Galán (2020) and delineate financial stress from indicators capturing the build-up of financial vulnerabilities. Since the focus of our analysis is on medium-term horizons, we evaluate multiple competing measures of cyclical vulnerabilities. In particular, we consider the SRI, the Financial cycle, the total credit-to-GDP gap (Basel gap), the bank credit-to-GDP gap, the 2-year growth rate of real total credit, and the 2-year change in the debt service ratio. Financial stress is captured by the country level index of financial stress ($CLIFS$). For details on the different indicators, recall the description of data in Section 2.

To identify key drivers of medium-term growth-at-risk, we evaluate both the in-sample explanatory power and the out-of-sample predictive power of individual indicators described in subsection 2.2 for tail risk to real GDP growth. In order to compare indicator performance, we use the tick loss as a measure of model fit, which is commonly used to evaluate the accuracy of value-at-risk models[6]. The tick loss is the value of the objective function that is minimized by the quantile regression. More precisely, it is computed as follows: $TL_{h,\tau} = (\tau - \mathbf{1}(\widehat{\varepsilon}_{h,\tau} < 0))\widehat{\varepsilon}_{h,\tau}$, where $\mathbf{1}()$ denotes the indicator function. We select $\tau = 0.05$ for the exercise, in line with the existing growth-at-risk literature. As a benchmark model, we estimate for each horizon a panel quantile regression with current real GDP growth as the only explanatory variable. We then add each of the potential indicators to this benchmark model one at a time. In addition, we also consider models with an additional lag of the potential indicators (indicated as $+lag$), models that allow for a different impact when the indicator is larger than zero (denoted by $+int$), and models that

[6] Most papers that use a formal metric for model evaluation employ either the tick loss function (Brownlees and Souza, 2021; Carriero et al., 2020; Figueres and Jarocinski, 2020; Giacomini and Komunjer, 2005) or predictive scores (Adams et al., 2021; Adrian et al., 2019; De Santis and Van der Veken, 2020). Since our focus is not on density forecasts, we follow the literature and use the tick loss approach in our in-sample and out-of-sample exercises.

include an interaction term of the indicator with respect to the level of financial stress (denoted by $+$*CLIFS*). We run the exercise for horizons $h = 1, 4, 8, 12, 16$, with particular emphasis on the medium-term horizon $h = 8$, i.e. the real GDP growth rate between year 2 and year 3 into the future.

To make the in-sample results comparable, we balance observations across all models. We then rank models according to their in-sample improvement in the tick loss compared to the benchmark model at horizon $h = 8$. The out-of-sample exercise is designed as follows. We estimate the models on a balanced sample across indicators for countries with sufficiently long time series availability[7], starting from the earliest available date up until 1999 Q4. The resulting coefficient estimates are used to produce predictions and the associated out-of-sample tick loss for the period 2000 Q1 - 2019 Q4, without re-estimating parameters during the out-of-sample period. Table 2 reports the improvement in the tick loss function for both in-sample and out-of-sample exercises for models with fixed effects. Tick losses are averaged over all observations in the estimation sample for the in-sample exercise and over all observations in the evaluation sample for the out-of-sample exercise.

We start with the discussion of results for the medium-term horizon ($h = 8$), i.e. the main horizon of interest. Looking at the in-sample results, the SRI delivers consistently the largest improvements in the tick loss over the baseline model. The model with the SRI improves over the baseline model by 24%. This is much higher than for other vulnerability indicators considered: the 2-year growth rate of real total credit improves over the baseline model by 15.3%, the 2-year change in the debt service ratio improves by 11.7%, and the bank and total credit-to-GDP gaps by 10.6% and 9.6% respectively. The financial cycle fares the worst from the vulnerability indicators, improving the tick loss only by 6.8%, less than a third of the improvement associated with the SRI. Interestingly, indicators capturing financial stress ($CLIFS$) and economic sentiment (ESI) have only marginal improvements over the baseline model at the medium-term horizon (0% and 3% improvement respectively).

In addition to including just current values of the indicators, we also evaluate models augmented by a lag and interaction terms. In case of the SRI, adding a lag ($+lag$) or interaction with financial stress ($+ * CLIFS$) does not result in further improvements of the in-sample tick loss function for the medium-term horizon $h = 8$. However, allowing for different effects when the SRI is larger than zero (i.e.

[7]Countries included in the out-of-sample exercise: BE, DE, DK, ES, FI, FR, GB, IE, IT, NL, SE.

Table 2: Improvement in tick loss function (5th percentile, fixed effects)

	In sample					Out of sample				
Horizon (h)	1	4	8	12	16	1	4	8	12	16
SRI, +lag, +int	20.7	27.4	30.4	16.9	4.4	15.7	19.3	27.6	10.7	17.2
SRI, +lag, +*CLIFS	16.4	23.1	24.0	13.8	4.3	13.7	4.3	-5.3	-4.9	11.7
SRI, +lag	16.5	22.6	24.0	13.6	3.7	14.6	5.0	11.8	11 .0	15.1
SRI	9.79	19.8	23.7	11.4	2.5	5.9	-5.5	12.0	10.3	15.4
Real total credit (2y-gr.), +lag	13.7	16.4	15.8	9.3	2.5	11.0	4.8	6.8	1.4	18.4
Real total credit (2y-gr.)	12.7	15.1	15.3	9.0	2.0	7.9	4.4	6.6	1.9	18.2
Bank credit gap, +lag, +int	9.2	13.7	15.0	14.5	7.3	-19.1	-59.1	-14.8	-42.5	-3.3
DSR (2y-change), +lag	16.2	14.7	12.4	8.4	1.7	20.2	16.7	11.4	4.5	-0.2
DSR (2y-change)	16.2	14.2	11.7	8.4	1.5	30.4	14.5	6.5	1.2	-0.3
Financial Cycle, +lag, +*CLIFS	14.6	5.9	10.8	11.4	7.1	24.3	4.2	11.8	12.0	3.7
Bank credit gap	5.3	10.0	10.6	8.4	4.9	-8.1	-37.9	0.7	-0.4	3.8
Bank credit gap, +lag	6.1	10.4	10.5	9.9	5.9	-6.8	-35.4	1.0	-0.9	3.9
Total credit gap, +lag, +int	8.8	11.8	10.0	7.6	3.3	14.9	14.4	-17.4	-23.1	-20.9
Total credit gap, +lag	8.6	11.4	9.8	7.7	3.2	11.3	-5.7	11.6	-1.2	-0.1
Total credit gap	8.5	11.4	9.6	6.0	2.6	11.3	-7.8	11.7	-1.8	-0.5
Financial Cycle, +lag , +int	14.7	5.4	8.6	10.2	6.0	23.7	-0.5	10.3	0.7	3.6
Financial Cycle, +lag	14.4	4.8	8.1	9.6	5.9	24.4	2.9	1.3	4.4	2.9
Financial Cycle	0.8	0.0	6.8	9.3	4.8	9.6	-2.3	5.4	7.4	2.6
ESI, +lag	7.6	3.1	2.8	2.7	2.2	-12.7	-9.4	-1.8	4.1	5.0
ESI	0.6	0.9	2.7	0.9	2.2	-19.4	-17.8	3.3	4.5	5.0
CLIFS, +lag	6.5	1.6	0.0	2.4	2.1	-0.4	-4.5	-1.6	1.3	-3.9
CLIFS	5.5	1.0	0.0	0.9	2.0	-0.7	-3.8	-1.9	-1.0	-3.9
Baseline	0.39	0.39	0.38	0.34	0.34	0.46	0.48	0.61	0.76	0.63

Notes: Improvements in tick loss function are in percentage relative to the model with GDP only (See row "Baseline" for the tick loss). The models are ordered by the in-sample performance for $h = 8$. *+lag* indicates models with an additional lag of the indicator. *+int* indicates models that allow for a different impact when the indicator is positive compared to when it is negative. *+*CLIFS* indicates models that include an interaction term of the indicator with respect to the level of financial stress.

when vulnerabilities are above average) compared to when it is below zero (i.e. vulnerabilities are below average) improves the in-sample performance by a quarter, delivering an overall tick loss improvement of 30.4% (see model $SRI, {+lag}, {+int}$). This indicates interesting state dependence, where shocks to financial vulnerabilities have different effects on future GDP tail risk depending on whether vulnerabilities are already elevated or not (See also the discussion in Section 4). For other indicators the inclusion of a lag also does not result in huge improvements in the in-sample fit for $h = 8$: the largest improvement is by only 1.3 percentage points from 6.8% to 8.1% in case of the financial cycle. However, state dependence also seems to matter for the bank credit gap (+4.4pp for the model with int) and the interaction with financial stress seems to be relevant for the financial cycle (+2.7pp for model with $+*CLIFS$). But none of the models comes close in terms of model fit to the best-performing SRI model.

The out-of-sample results for the medium-term horizon ($h = 8$) corroborate the good performance of the SRI for predicting GDP tail risk. While the model with only the current SRI improves over the baseline model by 12%, adding a lag and interaction term for when the SRI is positive ($+lag, +int$) improves the out-of-sample performance substantially by almost 16 percentage points to 27.6%. This is roughly similar to the improvement in the in-sample exercise (30.4%). Importantly, the out-of-sample performance of the full SRI model is around two and a half times the performance of the second best performing model that does not include the SRI: the model with the financial cycle, its lag, and an interaction with the CLIFS improves over the baseline model by 11.8% in the out-of-sample exercise at horizon $h = 8$. Other vulnerability indicators fare similarly to the best financial cycle model for the medium-term horizon: the model with the *debt service ratio* and its lag and the model with the total credit gap improve over the baseline model by 11.4% and 11.7%. The out-of-sample performance of economic sentiment (ESI) and financial stress ($CLIFS$) is very poor for the medium term horizon - similar to the findings from the in-sample exercise.

When looking at other horizons, a number of additional results emerge. First, models including the SRI deliver mostly the largest or among the largest improvements in the tick loss over the baseline model, both in-sample and out-of-sample.[8] Second, the importance of other indicators varies across horizons. Models including the debt service ratio or the financial cycle rank among the best at very short horizons ($h = 1$), but the relative improvement decreases at longer horizons. Third, accounting for the dynamics of the indicators (by including a lag) is important for the SRI, the financial cycle, and ESI. For example, at the short horizon ($h = 1$) the in-sample performance of the SRI increases by almost 7 p.p. to 16.5% after adding a lag, while the improvement from 0.8% to 14.4% for the financial cycle is even larger. Similar improvements hold in the out-of-sample exercise. This points to the importance of capturing the dynamics of these indicators for short-term prediction horizons. For longer horizons, the value added of lags is much smaller for all variables. Fourth, in general, most indicators rank similarly in the in-sample and out-of-sample exercises, with a few exceptions where adding a lag or interaction term worsens the out-of-sample performance. For example, this is the case for the bank and total credit gaps. Finally, measures of economic sentiment and financial stress do not appear to add much information over the baseline model except for short horizons in the in-sample exercise.

Overall, among vulnerability indicators the models including the SRI outperform the models with other vulnerability indicators like the credit gaps or the fi-

[8] The main exception is the out-of-sample performance for $h = 1$, where the DSR and the financial cycle are better. In addition, for $h = 16$ real credit growth does marginally better out-of-sample than the SRI, 18.4% improvement vs. 17.2% improvement, but does worse in-sample, 2.5% improvement vs. 4.4% improvement.

nancial cycle. This generally points to the importance of including the SRI in euro area growth-at-risk models. Our results also suggest that commonly used financial stress indicators do not perform well beyond the 1-year horizon. In contrast, for the medium-term horizon only vulnerability indicators capturing the build-up of credit and asset price imbalances manage to improve over the baseline model with GDP growth only. The results for the medium-term horizon are generally in line with the literature (Aikman et al., 2019; Arbatli-Saxegaard et al., 2020; Duprey and Ueberfeldt, 2020; Galán, 2020; Gächter et al., 2022; O'Brien and Wosser, 2021) who find that vulnerability indicators are important for capturing medium-term growth-at-risk. Nevertheless, none of the papers performs a proper empirical exercise comparing the out-of-sample performance of the various vulnerability measures.

The existing literature points to the importance of financial conditions/financial stress for GDP tail risk at short horizons, mostly 1-4 quarters ahead (Adrian et al., 2022, 2019; Chavleishvili and Manganelli, 2019; Ferrara et al., 2022; Figueres and Jarocinski, 2020; Giglio et al., 2016; De Santis and Van der Veken, 2020). Our results, however, point to a rather less important role of financial stress indicators at the 1-year horizon. This is in line with Reichlin et al. (2020) who perform an out-of sample evaluation and show that financial conditions contain little timely information on downturn events beyond what is already available in real economic indicators. Our results confirm that while the performance of $CLIFS$ is better at short-term horizons than at medium horizons, the marginal added information content is still much lower than what vulnerability indicators provide, even at short-term horizons (see the discussion above).[9] This finding highlights the importance of taking into consideration various indicators of vulnerability in addition to financial stress or financial conditions, even for shorter projection horizons.

We also repeated the same exercises for models without country fixed effects. The results corroborate the findings from the models with fixed effects and are reported in Table B2 in Annex B.

3.2 Performance of the full model

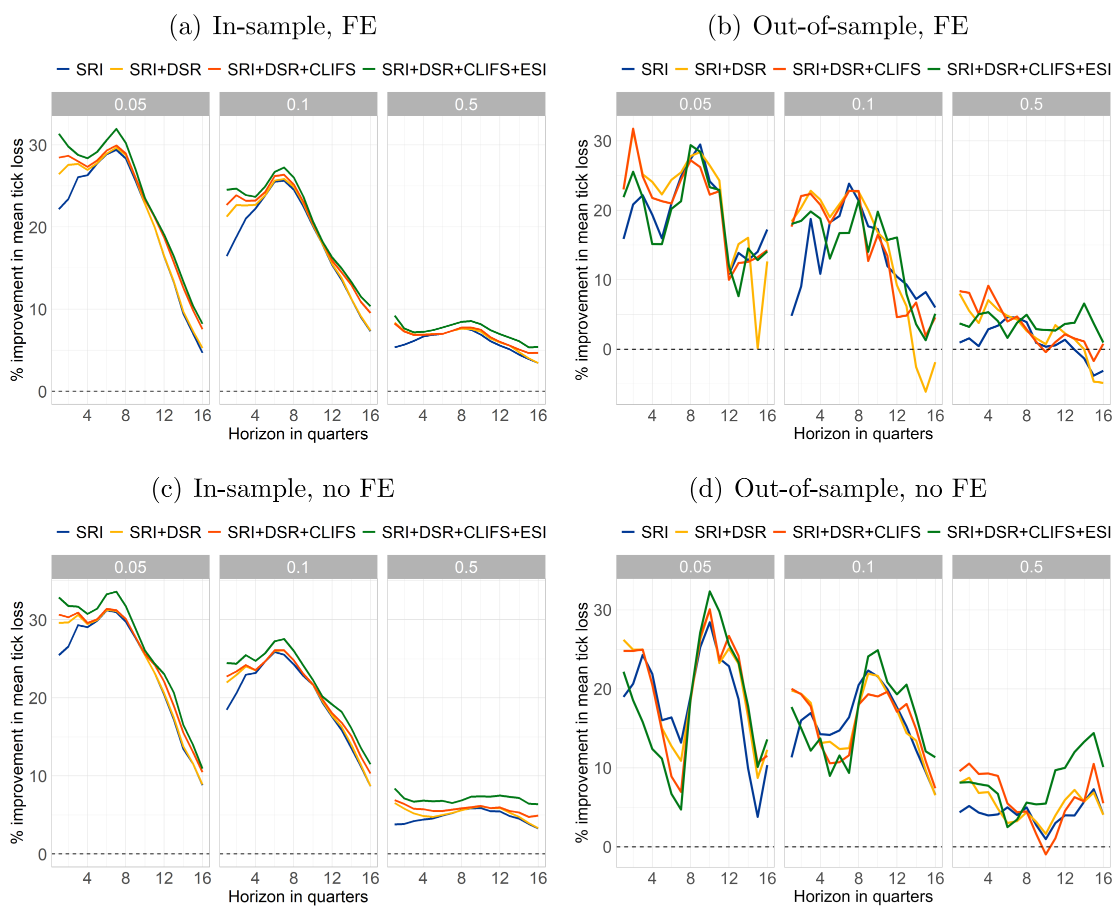
As various indicators contain information about GDP tail risk (see discussion above in subsection 3.1), we now consider a multivariate model by adding selected indi-

[9]Our shortest prediction horizon corresponds to the annual GDP growth rate five quarters ahead. As financial stress indicators contain mainly information for very near-term horizons, e.g. 1-2 quarters ahead, this can partly explain why the CLIFS has lower information content at $h = 1$ than the SRI.

cators one at a time to the best-performing single-indicator model based on the SRI. We focus on variables that performed well and where the information content overlapping with the SRI is expected to be low (DSR, financial stress, economic sentiment).

The improvement in the tick loss compared to the baseline model (with GDP growth as the only explanatory variable) across selected horizons and quantiles are presented in Figure 2 and Table B3. We start with a model including only the SRI $(+lag, +int)$, as it performed best among all indicators tested (blue line in Figure 2). We then add the *debt service ratio* since it performed well at shorter horizons (yellow line). Next, we add the $CLIFS$ to capture the level of financial stress, as this indicator can also be potentially important for short horizons (red line). Finally, we also add the economic sentiment indicator, resulting in a full model that includes the SRI, the *Debt service ratio*, the $CLIFS$, and the ESI and its lag (green line in Figure 2).

Figure 2: Improvements in tick loss for various models



Notes: Improvement in tick loss is relative to the model that only conditions on current real GDP growth. Panel headings indicate the quantile of the model ($\tau = 0.05, 0.1, 0.5$).

Overall, the results of the in-sample exercise suggest that the largest marginal improvement at all horizons is due to the inclusion of the SRI, which improves over the baseline model by around 22.2% for $h = 1$ and by 28.4% for $h = 8$.[10] Augmenting the model with indicators in addition to the SRI is only important for horizons up to $h = 4$. The biggest marginal improvements for $h = 1$ come from the addition of the *Debt service ratio*, which increases the improvement in tick loss by 4 p.p to 26.5%, and ESI which increases the performance by almost 3 p.p. to 31.4 %. For the medium-term horizon ($h = 8$), the largest improvements on top of the SRI come from the addition of ESI, which improves the tick loss by 1.3 p.p. to 30.2%. In general, improvements over the baseline model are largest for the 5-th and 10-th percentile, while they are more modest for the median model. This points to the importance of the SRI, and to a smaller extent also the *debt service ratio*, $CLIFS$ and ESI, especially for the quantification of downside risks to growth, compared to median predictions.

The out-of-sample exercise generally confirms the results of the in-sample exercise. The largest marginal improvement is due to the inclusion of the SRI, which improves over the baseline model by around 15.9% for $h = 1$ and by 27.4% for $h = 8$. This suggests that the medium-term forecasting improvement compared to the benchmark model is larger than the improvement over the short-term horizon. Compared to the in-sample exercise, the importance of including the *Debt service ratio* is greater as it improves the performance by an additional 8 p.p. to 23% at $h = 1$. Adding $CLIFS$ does not improve the out-of-sample performance further, while adding ESI decreases it again. At the medium term horizon ($h = 8$), the inclusion of the *Debt service ratio* and the $CLIFS$ does not add to the out-of-sample performance of the model, while adding ESI improves it only marginally, by 2 p.p. to 29.4%. Overall, the results described are similar when estimating the model with and without country fixed effects.

Table 3 reports the regression coefficients for the 5-th percentile model, once with country fixed effects and once without fixed effects. For easier comparison of effect sizes, Figure 3 also presents the standardized coefficients for different horizons. In terms of statistical significance, most variables are significant at shorter-horizons (up to $h = 4$). At longer horizons, however, some variables lose statistical significance. In terms of magnitude, the largest standardised coefficients are generally those related to the SRI. At $h = 1$, the standardized coefficient for the SRI is about 5, the interaction term $SRI > 0$ is about half of that and negative, while

[10]Numbers differ slightly to the ones reported in section 3.1, due to different balancing of the sample across variables.

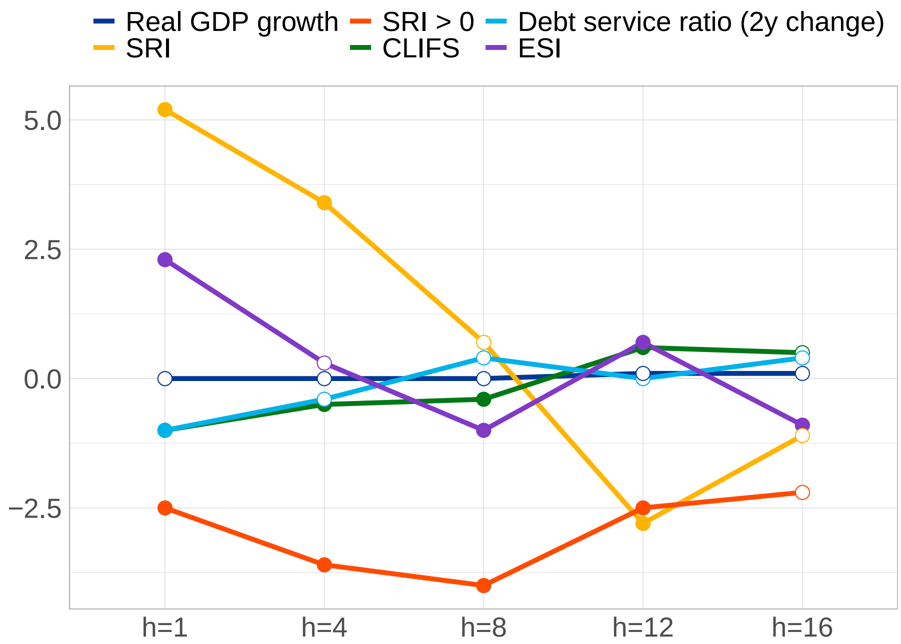
Table 3: Regression results (5th percentile)

	Fixed effects				
	h = 1	h = 4	h = 8	h = 12	h = 16
(Intercept)	−0.96**	−0.38	0.16	−0.67	−1.74**
	(0.41)	(0.43)	(0.48)	(0.51)	(0.58)
Real GDP growth	0.04	−0.02	−0.04	0.09	0.06
	(0.10)	(0.09)	(0.07)	(0.08)	(0.12)
SRI	5.16***	3.35**	0.67	−2.85**	−1.14
	(1.23)	(1.54)	(0.93)	(1.28)	(1.22)
SRI lag	−4.49***	−3.84***	−1.21	2.63	1.41
	(1.25)	(1.49)	(0.94)	(1.45)	(1.46)
SRI>0	−2.5***	−3.60***	−4.04***	−2.48**	−2.17
	(0.83)	(0.86)	(0.84)	(1.08)	(1.57)
DSR (2y-change)	−0.68***	−0.31	0.32	0.01	0.25
	(0.15)	(0.28)	(0.25)	(0.24)	(0.40)
CLIFS	−0.96**	−0.50*	−0.37**	0.57***	0.51
	(0.33)	(0.27)	(0.16)	(0.15)	(0.40)
ESI	2.34***	0.27	−1.03***	0.69*	−0.89**
	(0.39)	(0.37)	(0.31)	(0.42)	(0.36)
ESI lag	−2.17***	−0.85**	0.53*	−0.55	0.42
	(0.36)	(0.37)	(0.37)	(0.39)	(0.41)
	No fixed effects				
	h = 1	h = 4	h = 8	h = 12	h = 16
(Intercept)	−1.65***	−1.21***	−0.92***	−1.27***	−1.48***
	(0.15)	(0.28)	(0.19)	(0.26)	(0.37)
Real GDP growth	0.23***	−0.05	0.12**	0.2***	0.65***
	(0.04)	(0.07)	(0.05)	(0.06)	(0.09)
SRI	5.35***	2.48**	−0.55	−3.61***	−3.83***
	(0.52)	(0.97)	(0.65)	(0.93)	(1.26)
SRI lag	−5.70***	−3.59***	−0.93	2.89***	3.60**
	(0.51)	(0.93)	(0.62)	(0.89)	(1.20)
SRI>0	−2.23***	−2.49***	−2.82***	−2.12***	−2.09**
	(0.28)	(0.52)	(0.35)	(0.51)	(0.70)
DSR (2y-change)	−0.59***	−0.20	0.37***	−0.17	−0.14
	(0.10)	(0.18)	(0.12)	(0.17)	(0.24)
CLIFS	−0.69***	−0.35*	−0.22*	0.43**	0.64**
	(0.11)	(0.20)	(0.13)	(0.18)	(0.24)
ESI	2.06***	0.10	−0.85**	0.74*	−0.64
	(0.24)	(0.44)	(0.29)	(0.41)	(0.54)
ESI lag	−2.13***	−0.70*	0.15	−1.04**	0.36
	(0.24)	(0.43)	(0.29)	(0.4)	(0.54)

Notes: SE in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

ESI is also relatively large at 2.5. The standardised coefficients for $CLIFS$ and the *Debt service ratio* are smaller at around -1.25. At longer horizons, standardised coefficients generally decrease in absolute value, except for the interaction term $SRI > 0$, which is around -4 for $h = 8$, while the rest of the coefficients are smaller than 1 in absolute value. Interestingly, for several variables we can observe sign reversals across the different horizons. The coefficient on the SRI changes from 5.2 at $h = 1$ to -2.9 at $h = 12$. The coefficient on $CLIFS$ changes from -1 at $h = 1$ to 0.6 at $h = 12$. Similar reversals occur also for ESI and the *Debt service ratio*, from 2.3 and -0.7 at $h = 1$ to -1 and 0.3 at $h = 8$, respectively. These coefficient reversals give rise to a term structure of growth-at-risk, which can differ to the term structure for financial conditions highlighted by Adrian et al. (2022). The next section discusses the dynamic effects of shocks to each of the variables and the term structures of growth-at-risk in more detail.

Figure 3: Standardized coefficients - 5th percentile - FE



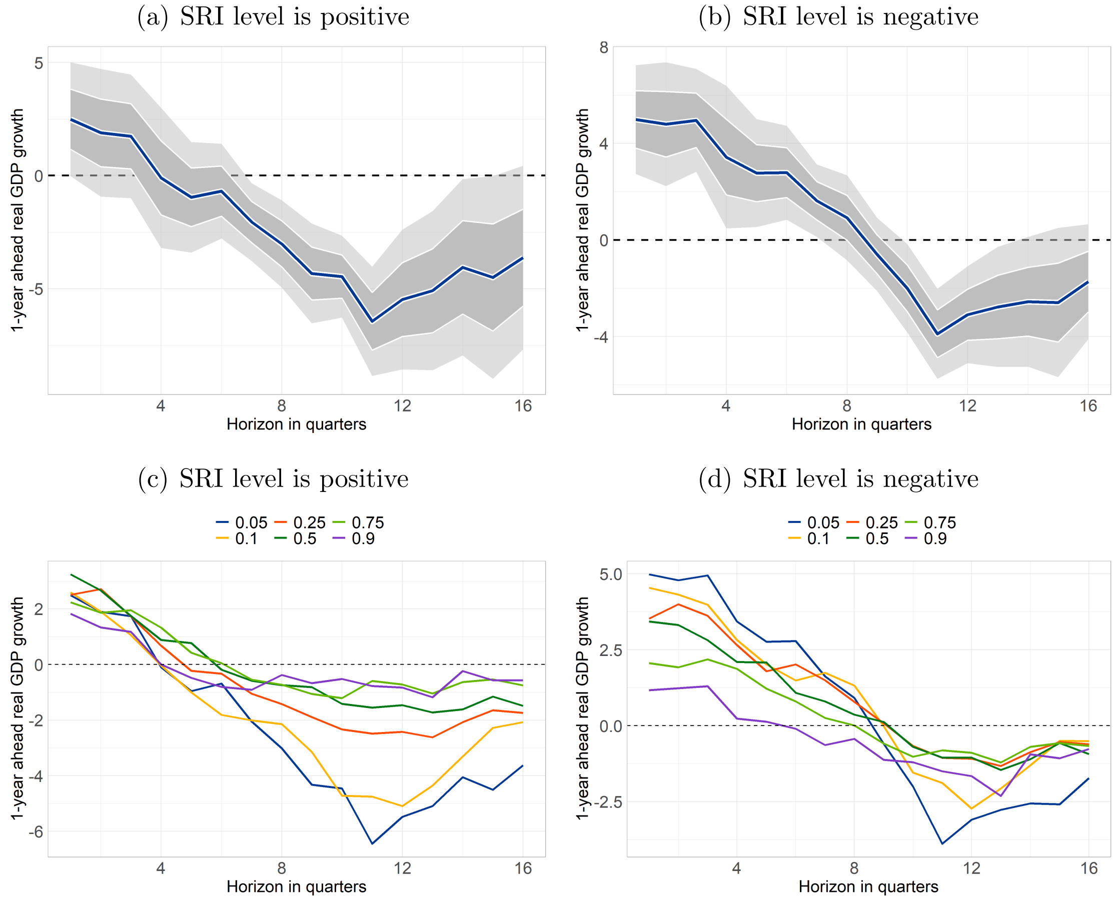
Notes: The filled circles indicate statistical significance at the 10% level. Hollow circles indicate that the coefficient is statistically insignificant.

4 Impulse response analysis for key drivers of tail risk

Now that we have identified the most important drivers of short- and medium-term tail risk to real GDP growth in euro area countries, we zoom in on the dynamic effects of shocks to each of the drivers and how the impact differs across percentiles of the real GDP growth distribution. More specifically, we trace out the quantile local projection impulse response functions (QIRFs) for different parts of the real GDP growth distribution by estimating our full model from section 3.2 for different quantiles and projection horizons $h = 1, ..., 16$. To study the impact of shocks on GDP tail risks over time we plot the QIRFs for the 5th percentile model with confidence bands. To study the potentially heterogeneous effects of shocks across the distribution of real GDP growth we plot the QIRFs for the set of quantiles $\tau \in \{0.05, 0.1, 0.25, 0.5, 0.75, 0.9\}$. To ensure comparability of the different QIRFs, we standardize all variables by subtracting the mean and dividing by the standard deviation across countries and time. Results are presented for the model with country fixed effects, but findings are robust to using a model without fixed effects (See Figures A1 to A4 in Appendix A).

We start with a detailed discussion of the dynamic effects of shocks to the SRI, as this is the most important driver of medium-term tail risk to GDP growth in euro area countries as shown in section 3.1. The first key insight is that shocks to the SRI induce a term structure for tail risk to real GDP growth, which is different to the term structure identified by Adrian et al. (2022) for financial conditions (panels (a) and (b) in Figure 4): A positive shock to the SRI leads to a reduction in downside risks to real GDP growth in the short-term, but over the medium-term the effect reverses and downside risks to real GDP growth go up considerably. In contrast, a tightening of financial conditions (or an increase in financial stress) tends to lead to an increase in short-term downside risks and a reduction in medium-term downside risks. The economic intuition behind the SRI term structure is as follows: increases in the SRI reflect strong growth in credit and asset prices, which can support demand and economic activity initially and reduce the likelihood of large GDP contractions in the short-term. However, sustained increases in credit and asset prices lead to more fragility in household and NFC balance sheets. Hence, over the medium-term downside risks to real GDP growth increase, as potentially small shocks to income or asset prices can induce large adjustments in consumption and investment due to financial accelerator effects (Bernanke et al., 1999).

Figure 4: QIRFs for SRI shocks (full model, fixed effects)



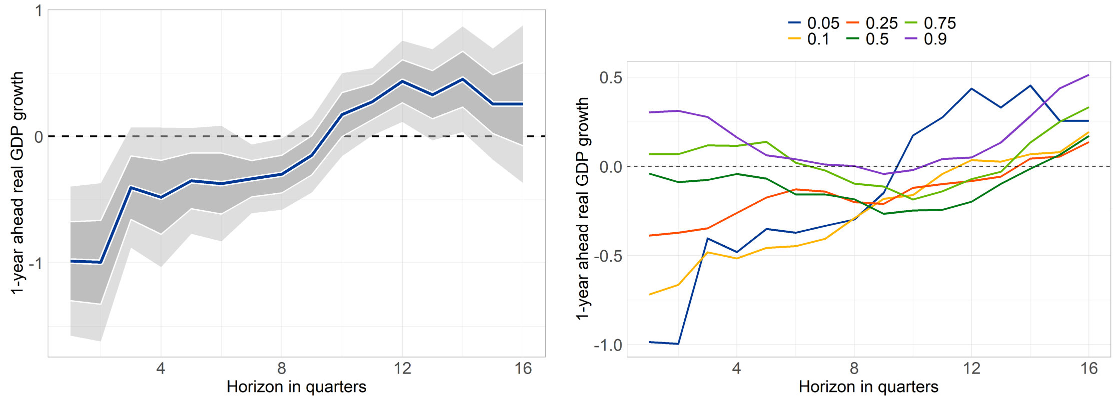
Notes: Panels (a) and (b) show the IRFs for the 5th percentile model with one and two standard error bands.

The second key insight is that the magnitude of the growth-at-risk term structure induced by shocks to the SRI differs depending on whether the SRI is positive (vulnerabilities are above average) or negative (vulnerabilities are below average). In particular, as shown in panels (a) and (b) in Figure 4, the short-term reduction in GDP tail risk induced by shocks to the SRI is almost twice as large when vulnerabilities are subdued (+5pp GDP growth tail risk) compared to situations where vulnerabilities are already elevated (+2.5pp GDP growth tail risk). In addition, the medium-term increase in GDP tail risk induced by shocks to the SRI is almost 50% lower when vulnerabilities are subdued (-4pp) compared to situations where vulnerabilities are already elevated (-6pp). These results again have an intuitive economic explanation: when credit and asset price growth are low (negative SRI), an increase in these growth rates can alleviate borrowing constraints in the short-term and support economic activity without necessarily causing stretched balance sheets of borrowers that create risks in the medium-term. On the other hand, when credit and asset price growth are already high (positive SRI), an increase in these growth rates might not add much to consumption or investment demand in the short-term, but mainly leads to further stretch in borrower balance sheets which increases fragility and downside economic risks in the medium-term.

The third insight is that the impact of SRI shocks varies considerably in magnitude across different quantiles of the real GDP growth distribution. In particular, when vulnerabilities are already elevated, shocks to the SRI have a highly asymmetric impact on the GDP growth distribution mainly in the medium-term (8-12 quarters ahead): tail risk as measured by the 5th percentile is impacted around four times more than the median (-6pp vs. -1.5pp) for horizon $h = 11$ as shown in panel (c) of Figure 4. When vulnerabilities are subdued, shocks to the SRI still cause an asymmetric impact over the medium-term, but slightly less pronounced: tail risk is now impacted around three times more than the median (-4pp vs. -1.25pp) for horizon $h = 11$ as shown in panel (d) of Figure 4. In addition, when vulnerabilities are low, shocks to the SRI also induce a large asymmetric impact on the real GDP growth distribution in the short-term (1-6 quarters ahead): the 5th percentile is impacted around four times more than the 90th percentile. In general, upper quantiles of the real GDP growth distribution are much less responsive to SRI shocks than lower quantiles, although the entire distribution of real GDP growth is affected by SRI shocks. This is again different to the impact of financial conditions.

The dynamic impact of shocks to the CLIFS (financial stress) on GDP tail risk is qualitatively similar to the term structure of growth-at-risk induced by shocks to financial conditions as documented by Adrian et al. (2022). As shown in figure 5, in the short-term an increase in financial stress leads to heightened downside risks to real GDP growth (-1pp), which is statistically significant, while in the long-term downside risks to real GDP growth are reduced (+0.5pp), but this is barely significant statistically. Asymmetry in the impact of shocks to the CLIFS across different quantiles of the GDP growth distribution is mainly present in the shorter term (1-6 quarters ahead): for horizon $h = 1$ the 5th percentile is affected twice as much as the 25th percentile (-1pp vs. -0.5pp), while the median of the GDP growth distribution is not affected at all. Overall, shocks to the CLIFS mainly impact on GDP tail risk, while higher quantiles are barely moved, which is similar to the findings for financial conditions as shown in Adrian et al. (2019).

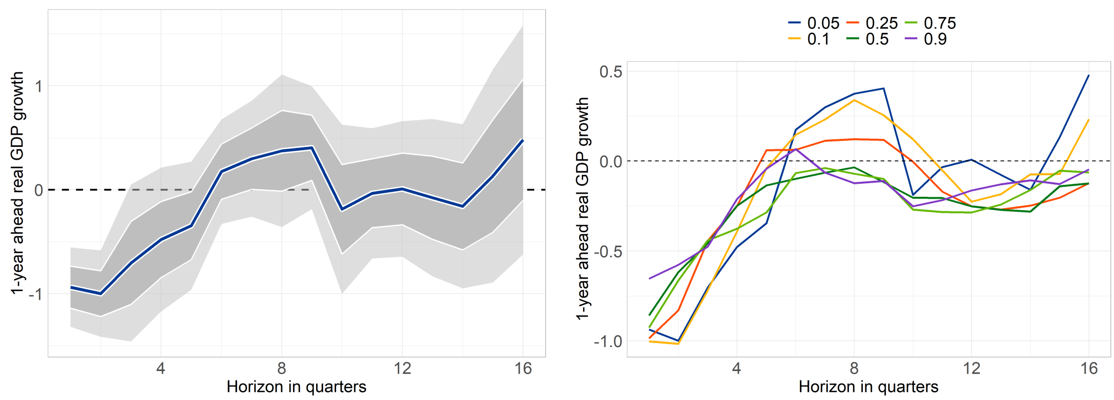
Figure 5: QIRFs for CLIFS (full model, fixed effects)



Notes: The left panels shows the IRFs for the 5th percentile model with one and two standard error bands.

Shocks to the DSR do not induce a term structure for GDP tail risk: while increases in the DSR heighten short-term GDP tail risk (-1pp), there is no reversal and in the medium-term the impact is close to zero and statistically insignificant (Figure 6). Moreover, the impact of a DSR shock does not differ much across quantiles. In the short-term, all quantiles are reduced by a similar magnitude through DSR shocks (-0.6pp to -1pp), while in the medium-term there is hardly any impact. These findings can be explained as follows: increases in the debt service ratio of the non-financial private sector imply less disposable income to be spent on goods and services and therefore less aggregate demand. Hence, increases in the DSR push down the entire distribution of real GDP growth in the short-term.

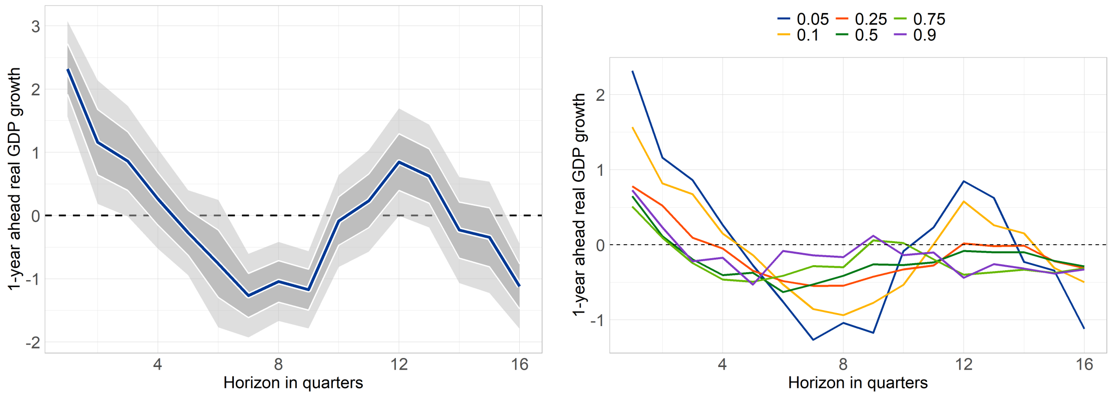
Figure 6: QIRFs for Debt Service Ratio (full model, fixed effects)



Notes: The left panels shows the IRFs for the 5th percentile model with one and two standard error bands.

Finally, shocks to economic sentiment[11] lead to a complex cyclical term structure for GDP tail risk (Figure 7): higher economic sentiment reduces tail risk in the short-term (+2pp), increases it for horizon $h = 8$ (-1pp), and then again reduces (+1pp) and increases (-1pp) tail risk for horizons $h = 12$ and $h = 16$ respectively. Asymmetry in the impact across different percentiles of the GDP growth distribution can be found throughout: the impact on tail risk (5th and 10th percentile) is always much larger in absolute magnitude than the impact on higher quantiles. In fact, the upper quantiles are barely affected throughout the projection horizon. The economic mechanism behind these findings could be as follows: sentiment is itself a highly cyclical variable, where periods of positive sentiment are followed naturally by periods of negative sentiment, and therefore sentiment shocks lead to a complex oscillating impact on GDP tail risk over time.

Figure 7: QIRFs for ESI (full model, fixed effects)



Notes: The left panels shows the IRFs for the 5th percentile model with one and two standard error bands.

5 Evolution of growth-at-risk in the euro area

Now that we are equipped with a full model for explaining short- and medium-term downside risks to real GDP growth in the euro area, we can analyse model output and model dynamics in more detail.

The first observation is that estimated downside risks to real GDP growth vary considerably over time, both at short- and medium-term prediction horizons as

[11] The role of sentiment for GDP is theoretically underpinned by the existence of *irrational* and self-fulling animal spirits (Acharya et al., 2021; Di Giovinazzo, 2011) or the effects of *news* (Blanchard et al., 2013). Recently, Nowzohour and Stracca (2020) surveyed the literature on confidence and macroeconomic fluctuations and found evidence of contemporaneous and forward looking correlations suggesting that economic sentiment could be a driver of economic activity.

shown in Figure 8.[12] There were benign episodes, e.g. in 1997, 2004 or 2015, when growth-at-risk was close to 0% for both prediction horizons. At other times, e.g. at the beginning of the 2000s or during the global financial crisis, short- and medium-term growth-at-risk stood as high as -5% to -15%.

The second observation is that the magnitude and dynamics of downside risks to real GDP growth can differ considerably depending on the prediction horizon, as shown in Figure 8. This is not surprising given that the information content of the various growth-at-risk drivers also differs across prediction horizons. For example, short-term growth-at-risk for the euro area was elevated in 1993 and 2012 at -5% and -4%, whereas medium-term growth-at-risk was much more muted. These were episodes when financial stress indicators spiked and economic sentiment collapsed (see panels (c) and (e) in Figure 1). On the other hand, medium-term growth-at-risk started to increase well ahead of the global financial crisis, in line with increases in the SRI as shown in panel (b) of Figure 1, and reached its peak already in mid-2006 at -5%. Short-term growth-at-risk started rising somewhat later and peaked only in 2009 at -10%, during the height of economic and financial stress. These dynamics illustrate the varying information content of vulnerability and stress indicators, the former driving in particular medium-term tail risks, and the latter driving mainly short-term tail risks.

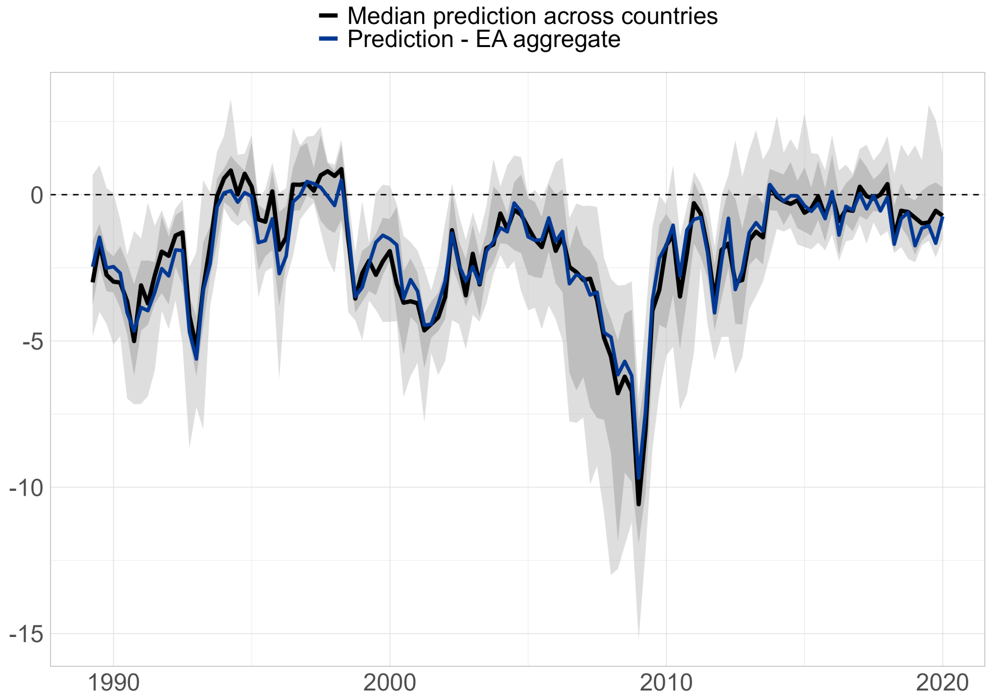
The third observation is that the level of growth-at-risk at a given point in time can differ substantially across euro area countries, as illustrated by the wide grey shaded areas in Figure 8. Dispersion in short- and medium-term downside risks to GDP growth were particularly pronounced ahead of and during the global financial crisis, with the 90th to 10th percentile range across countries being -3% to -12% and -2% to -15% respectively. The wide range of medium-term downside risks across countries was driven by large dispersion in the build-up of financial vulnerabilities ahead of the global financial crisis, as represented by the SRI (see panel (b) of Figure 1). During more benign time periods the 90th and 10th percentile of growth-at-risk across countries usually only differed by 2 to 3 percentage points.

The medium-term growth-at-risk model captures well the heterogeneous downside risks to GDP growth that prevailed across euro area countries ahead of the global financial crisis. This is illustrated by the high positive correlation between

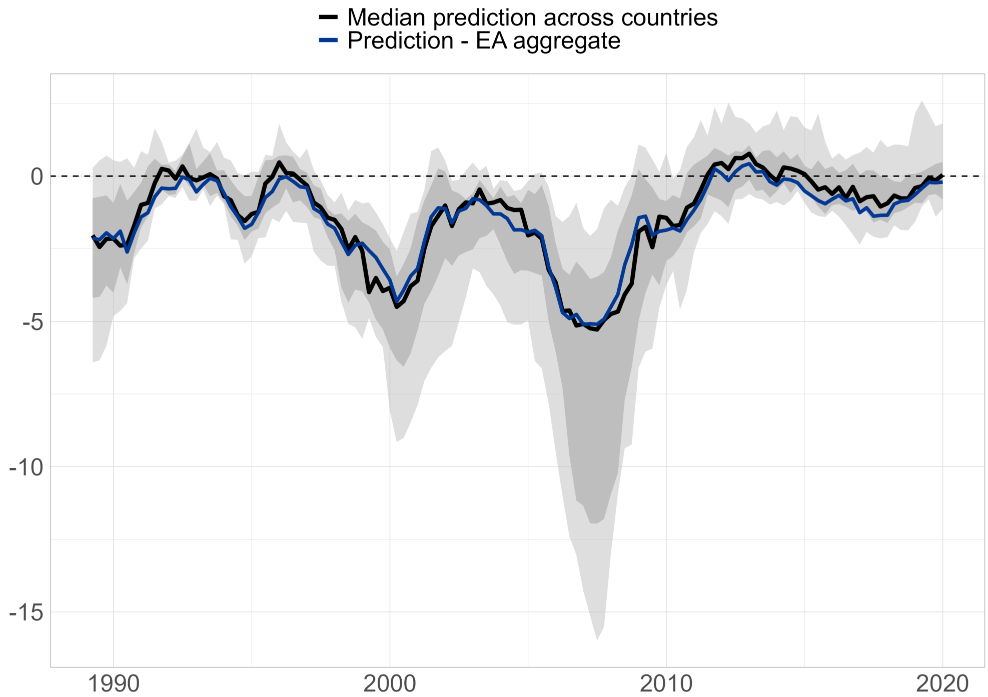
[12]The short-term horizon refers to the model using h=1, i.e. the 1-year ahead real GDP growth rate in the next quarter. Given publication lags of around 1 quarter for some of the explanatory variables, such a model specification seems appropriate for real-time monitoring of 1-year ahead growth-at-risk. The medium-term horizon refers to the model using h=8, i.e. the 1-year ahead real GDP growth rate in 2 years time, or in other words the real GDP growth rate between year 2 and year 3 into the future.

Figure 8: One-year (h=1) and three-year (h=8) ahead predicted tail risk

(a) 1-year horizon



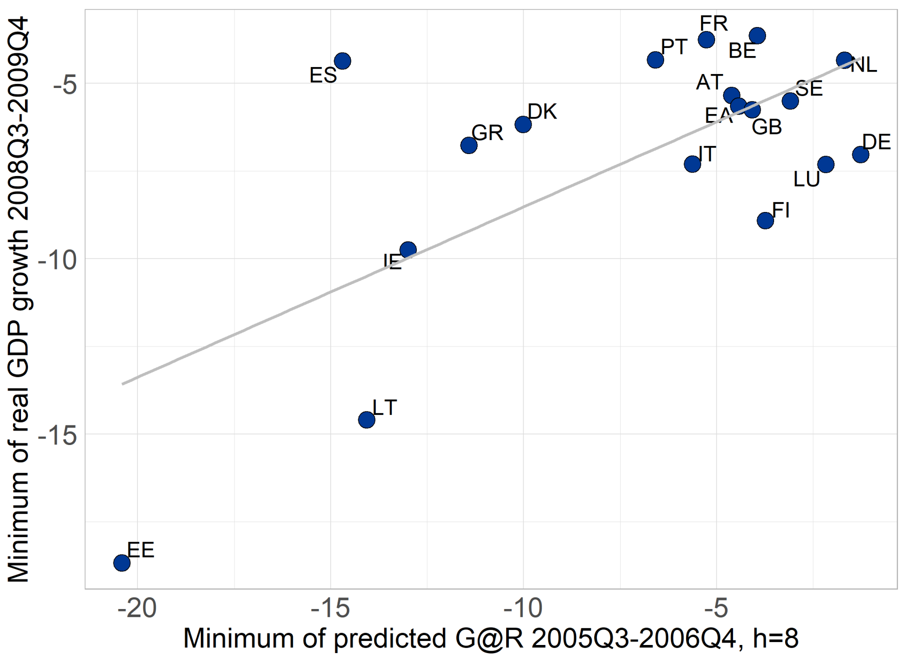
(b) 3-year horizon



Notes: The blue line denotes the Euro Area aggregate, the black line the median across countries and the shaded areas represent the interquartile range and the 90th to 10th percentile range across countries. Outcomes shown represent at each point in time the prediction of GDP tail risk one-year and three-years into the future.

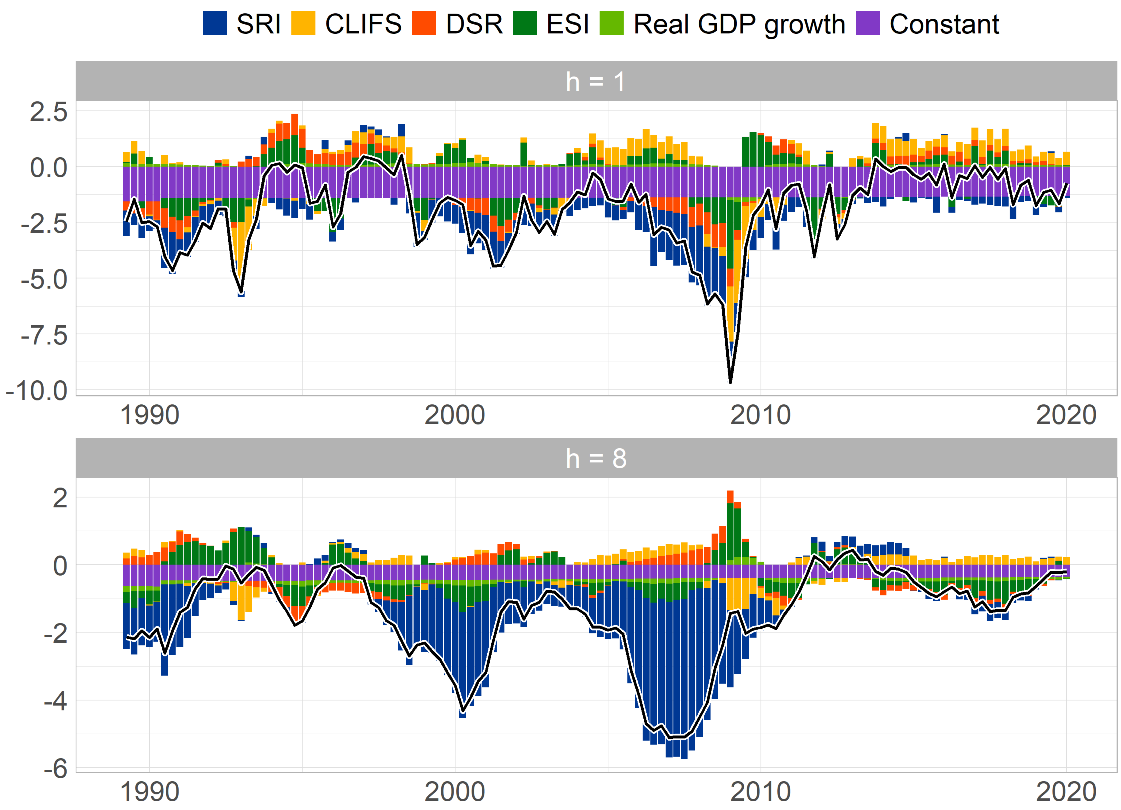
the predicted medium-term (i.e. 3-year ahead) downside risks in 2005/2006 and subsequent realised real GDP growth in 2008/2009 (Figure 9). Countries like Austria, Belgium, and the Netherlands, which did not experience a major build-up of financial vulnerabilities ahead of the global financial crisis, had more benign medium-term growth-at-risk predictions and real GDP growth realisations in relative terms. In contrast, countries like Estonia, Ireland, and Lithuania experienced large credit-fuelled asset price booms as reflected by the SRI, leading to much higher growth-at-risk predictions in 2005/2006 and more severe drops in real GDP growth during 2008/2009. This heterogeneity in growth-at-risk estimates highlights the importance of monitoring country-level dynamics in the euro area in addition to euro area aggregates.

Figure 9: Medium-term tail risk predictions ahead of the GFC and subsequent realized GDP growth



The linear nature of the estimated quantile local projections also allows for a straightforward decomposition of tail risk into driving factors, which facilitates building an economic narrative around estimated downside risks to GDP growth. For example, the initial slight increases in short-term growth-at-risk for the euro area during 2006 and 2007 were driven primarily by the build-up of financial vulnerabilities represented by the SRI, while the sharp spikes in short-term growth-at-risk during 2008 and 2009 were mainly driven by deteriorating economic sentiment and spikes in financial stress which risked impairments to large parts of the financial system at that time (see Figure 10 upper panel). Similar drivers were behind the spikes in short-term growth-at-risk for the euro area in 2011/2012 during the sovereign debt crisis. In contrast, the early and gradual build-up of medium-term growth-at-risk for the euro area during the late 1990s and the mid 2000s was primarily driven by sustained increases in underlying vulnerabilities, such as increased non-financial private sector leverage and exuberant asset price appreciation, as captured by the SRI (see Figure 10 lower panel). The rather muted medium-term growth-at-risk estimates in recent years are in turn due to low levels of the SRI, which reflect the subdued credit dynamics and deleveraging process following the global financial crisis.

Figure 10: Decomposition of EA aggregate tail risk, horizon h=1 and h=8



6 Importance of using cross-country information

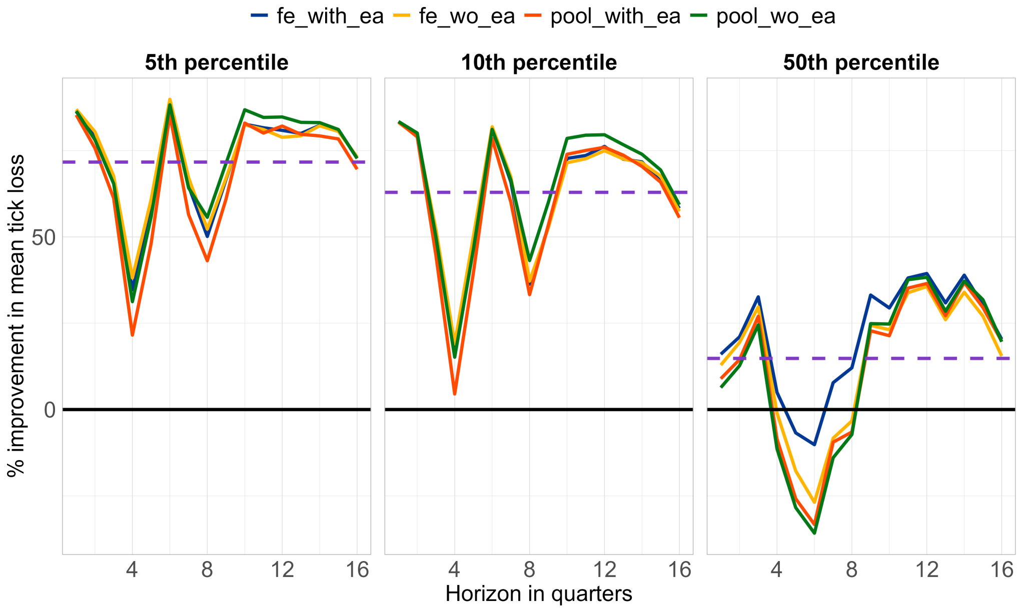
The existing growth-at-risk literature typically uses one of two approaches when it comes to data. The first approach estimates growth-at-risk models using single-country data (Adrian et al., 2019; Figueres and Jarocinski, 2020). The second approach makes use of panel data for model estimation (Adrian et al., 2022; Galán, 2020). While both approaches might be justified a-priori, they are rarely compared empirically. To fill this gap, we compare the out-of-sample model performance for the euro area aggregate based on two different parameter estimates: one based on panel data and one based on euro area aggregate data. Naturally, the in-sample fit for the model based on euro area aggregate data will be better than for the model based on panel model. This is because we are estimating k parameters and trying to fit one series, while in the panel approach we are estimating k parameters while trying to fit around 20 series. Nonetheless, there might be over-fitting to rare events in case of the model based on euro area aggregate data, which should show up in the out-of-sample performance.

We design the exercise for the empirical comparison of the two approaches as follows. First, we estimate our model in a panel setting and compute the predictions for the euro area aggregate using a weighted average of individual euro area countries. Next, we estimate our model using data for the euro area aggregate only. Similar to the out-of-sample exercise in section 3.1, we only use data up to 1999 Q4 to estimate model coefficients and keep them constant for the predictions during the period 2000 Q1 - 2019 Q4.[13] Prediction accuracy for tail risk is evaluated using the out-of-sample tick loss. We conduct the exercise for our parsimonious model specification that includes current *Real GDP growth*, the *SRI*, *SRI lag*, and the *SRI interaction (SRI>0)*. To see how robust the panel results are, we estimate four different versions with and without country fixed effects and also with and without the inclusion of the euro area aggregate as a separate unit in the panel.

The results for the parsimonious models with only SRI variables are presented in Figure 11. They show large performance gains for predicting lower tails of the euro area real GDP growth distribution (5th and 10th percentiles) when using panel information for estimation. Although the relative performance of the panel model over the single country model in terms of mean tick loss tends to fluctuate depending on the prediction horizon, the improvements are generally large and above 50%. Interestingly, the improvements in tick loss for lower tails are much larger than for the median. For the median model there are also prediction horizons where the panel model performs worse than the euro area aggregate model. The results also suggest that the relative improvement of the panel model over the single country model for predicting tail risks does not depend on the inclusion of fixed effects or the euro area as a separate unit in the panel: the relative improvements in out-of-sample tick loss are very similar for all model variants.

[13]Data availability to estimate the euro area aggregate model starts in 1988.

Figure 11: Comparison of out-of-sample prediction performance for the euro area aggregate based on a panel model compared to a euro area aggregate model



Notes: The charts shows the improvement in out-of-sample tick loss of the panel models relative to the euro area aggregate model. Purple dashed line denotes the average across specifications and horizons for a given percentile. Model specifications are denoted as follows: *fe_with_ea* denotes a fixed effects panel model which includes the euro area aggregate as a unit in the panel, *fe_wo_ea* denotes a fixed effects panel model which excludes the euro area aggregate as unit in the panel, *pool_with_ea* denotes a panel model without fixed effects which includes the euro area aggregate as unit in the panel, *pool_wo_ea* denotes a panel model without fixed effects which excludes the euro area aggregate as a unit in the panel.

One potential explanation for these results could be that we are looking at rare events when trying to predict tail risk. For example, for a single country with 30 years of quarterly data, focusing on the 5th percentile means zooming in on the six most extreme quarterly observations. To the extent that the true underlying distribution has a fat left tail, estimation uncertainty could be very large, and there could be the risk of overfitting to very few events. Pooling extreme observations across countries can potentially alleviate this estimation uncertainty to some extent, due to an increased number of rare event realisations, leading to more robust out-of-sample predictions.

To shed more light on the differences in model performance, Figure 12 zooms in on the predictions for the 5th percentile of the real GDP growth distribution at horizon $h = 8$ from both the euro area aggregate model and from the panel model. The figure shows that the aggregate model has been more imprecise in most periods except three quarters around the global financial crisis. In particular, it has underestimated tail risks during the 2011 sovereign debt crisis and the 5th percentile prediction from the aggregate model has been consistently above the actual real GDP growth rate since 2011. Comparison of the coefficients from the two approaches suggests that the worse out-of-sample performance of the euro area aggregate model might stem from the fact that the coefficients could be overestimated in size compared to the panel model, possibly due to the low number of rare events available for estimation (Figure 13).

Figure 12: Euro area out-of-sample predictions and tick loss, 5th percentile, $h = 8$

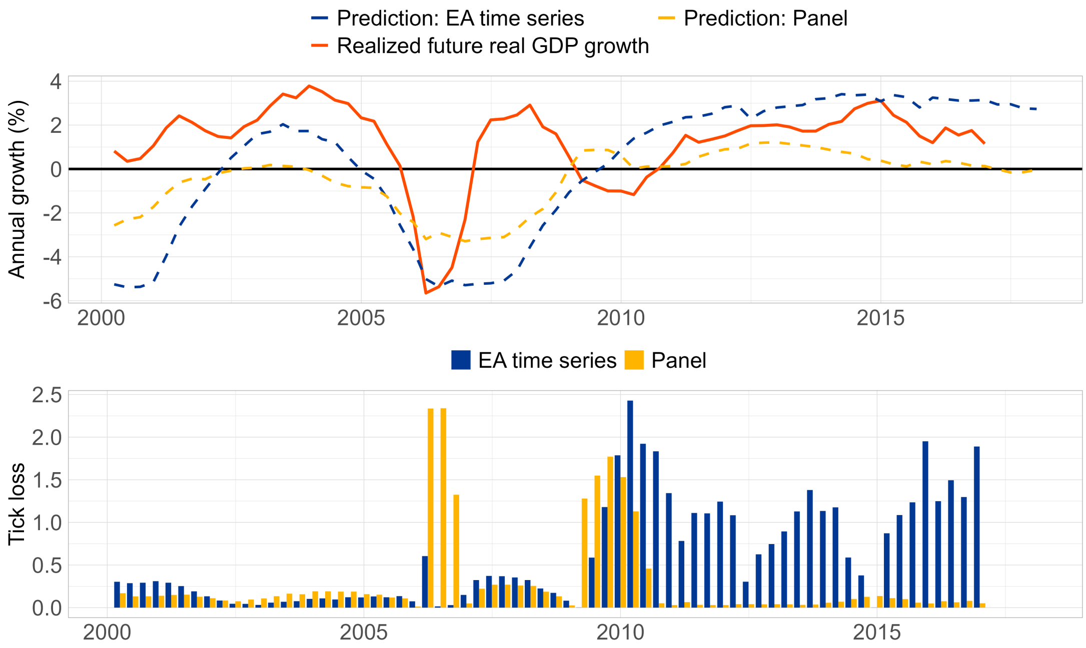
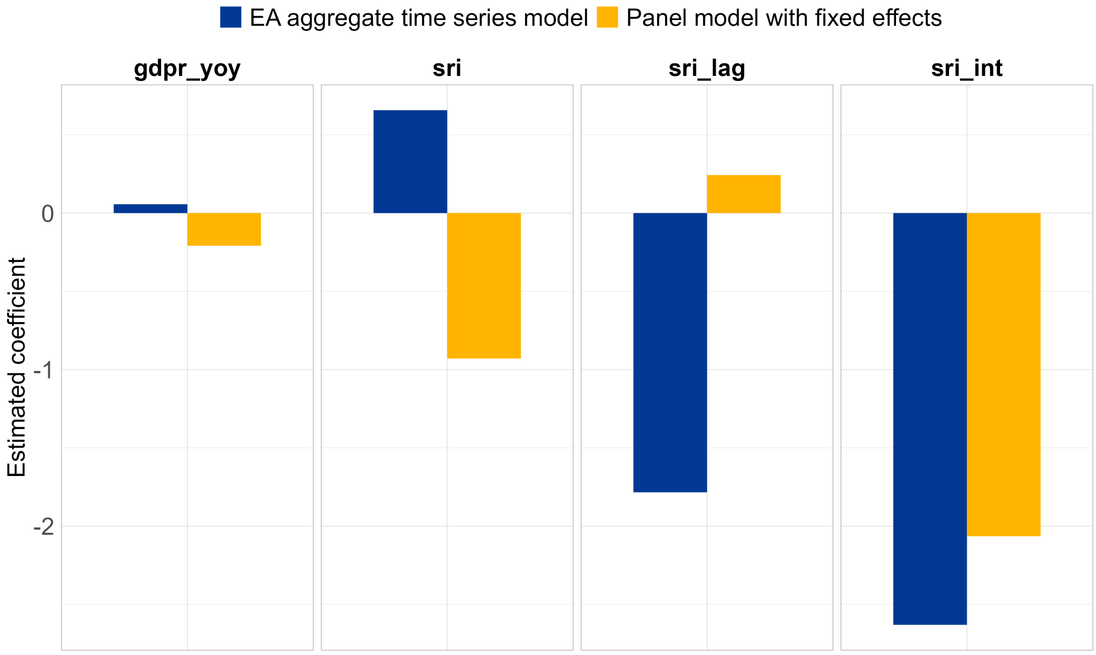


Figure 13: Comparison of coefficients in the panel and aggregate euro area models, 5th percentile



7 Conclusion

In this paper, we studied the information content of various financial stress and vulnerability indicators for growth-at-risk in euro area countries at various projection horizons, but with a special focus on the medium-term (3-years ahead). A focus on the medium-term is crucial to allow macroprudential policy to potentially mitigate emerging risks, as long implementation and transmission lags apply.

The main finding of our paper is that financial stress and vulnerability indicators both contain information for growth-at-risk in the short-term (1-year ahead), but only vulnerability indicators contain information about growth-at-risk in the medium-term (3-years ahead and beyond). Among various vulnerability indicators suggested in the literature, such as the Basel credit-to-GDP gap or composite financial cycle measures, the Systemic Risk Indicator (SRI) developed by Lang et al. (2019) outperforms in terms of in-sample explanatory power and out-of-sample predictive ability for medium-term growth-at-risk.

We also showed that financial vulnerabilities, as measured by the SRI, induce a rich "term structure" for growth-at-risk, which if different to the term structure induced by financial conditions or financial stress. A positive shock to the SRI leads to a reduction in downside risks to real GDP growth in the short-term, but over the medium-term the effect reverses and downside risks to real GDP growth go up considerably. In addition, interesting non-linearities emerged: the magnitude of the growth-at-risk term structure differs depending on whether the SRI is positive (vulnerabilities are above average) or negative (vulnerabilities are below average). In particular, when vulnerabilities are subdued the short-term reduction in GDP tail risk induced by shocks to the SRI is almost twice as large as when vulnerabilities are elevated, while the medium-term increase in GDP tail risk is almost 50% lower.

Finally, we showed that the impact of SRI shocks on GDP tail risk is much larger than on upper quantiles, in particular for medium-term horizons (3 to 4 years ahead). This pattern contrasts with financial conditions or stress indicators, which have an asymmetric impact on the real GDP growth distribution mainly for short-term horizons (1 to 2 years).

The multivariate model that we developed in this paper, which features the best-performing financial stress and vulnerability indicators, can be used to monitor short- and medium-term risks to real GDP growth for the euro area aggregate and individual euro area countries.

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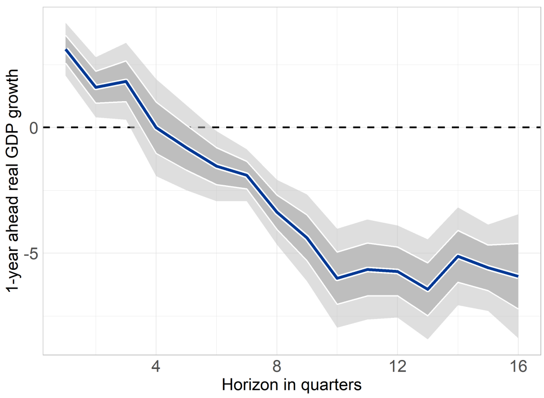
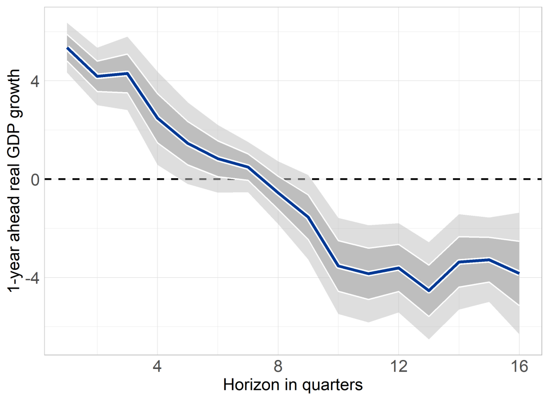
Appendix A: Additional figures

Figure A1: QIRFs for SRI (full model, no fixed effects)

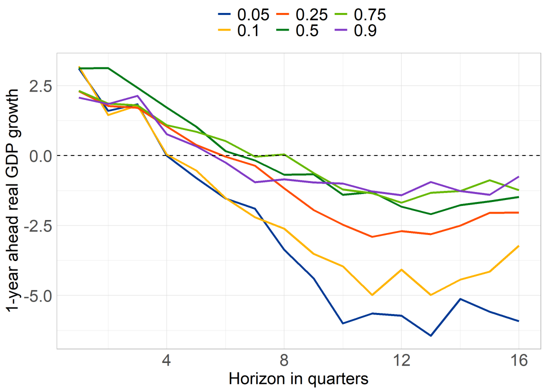
(a) SRI level is positive



(b) SRI level is negative



(c) SRI level is positive



(d) SRI level is negative

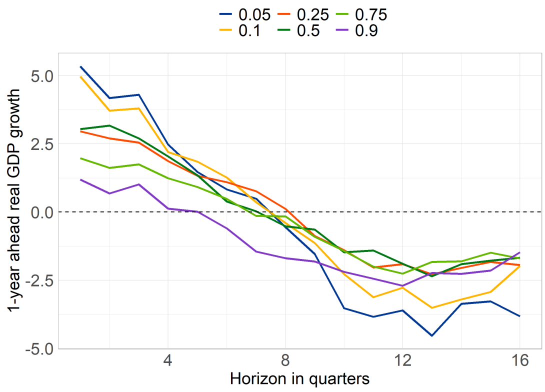
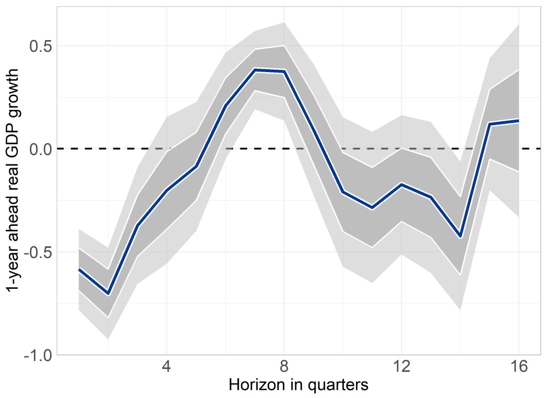


Figure A2: QIRFs for Debt Service Ratio (full model, no fixed effects)



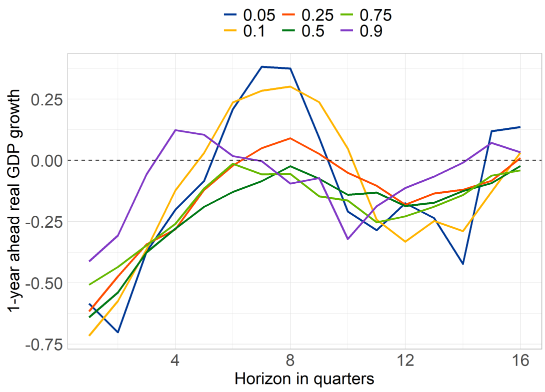


Figure A3: QIRFs for CLIFS (full model, no fixed effects)

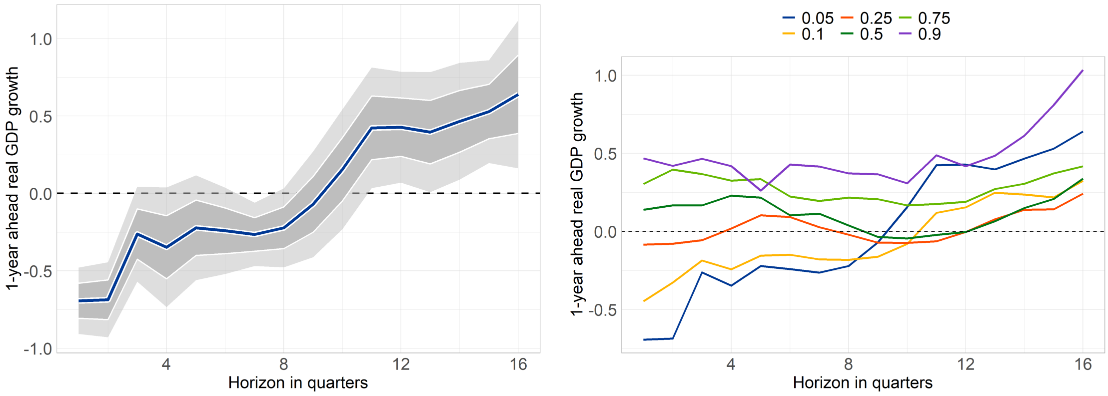
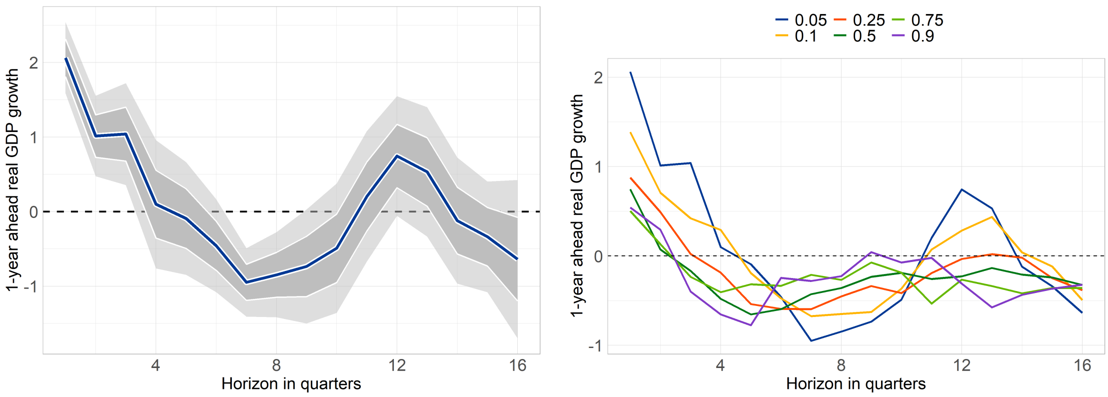


Figure A4: QIRFs for ESI (full model, no fixed effects)



Appendix B: Additional tables

Table B1: Data availability for key indicators

Country	Real GDP growth	SRI	Financial cycle	CLIFS	Debt Service Ratio	ESI
AT	1971-03-31	1999-03-31	1988-12-31	1970-03-31	1982-03-31	1985-03-31
BE	1971-03-31	1976-03-31	1973-03-31	1990-03-31	1975-03-31	1980-03-31
CY	1996-03-31	2010-03-31	2006-06-30	1998-03-31	2010-03-31	2001-06-30
DE	1971-03-31	1983-03-31	1972-06-30	1970-03-31	1975-03-31	1980-03-31
DK	1971-03-31	1984-03-31	1972-06-30	1970-03-31	1975-03-31	1980-03-31
EE	1996-03-31	2006-03-31	2006-03-31	1999-03-31	2006-03-31	1992-06-30
ES	1971-03-31	1988-03-31	1973-06-30	1970-03-31	1982-03-31	1987-06-30
FI	1971-03-31	1982-03-31	1973-03-31	1970-03-31	1982-03-31	1985-03-31
FR	1971-03-31	1981-03-31	1972-06-30	1970-03-31	1975-03-31	1980-03-31
GB	1971-03-31	1990-03-31	1971-06-30	1970-03-31	1975-03-31	1980-03-31
GR	1996-03-31	2000-03-31	1996-03-31	1992-12-31	1982-03-31	1982-03-31
IE	1971-03-31	1981-12-31	1973-09-30	1983-06-30	1976-06-30	1985-03-31
IT	1971-03-31	1976-12-31	1972-06-30	1970-03-31	1975-03-31	1980-03-31
LT	1996-03-31	2006-06-30	2003-06-30	2003-06-30	2005-12-31	1993-06-30
LU	1971-03-31	2005-03-31	2009-06-30	1994-06-30	2005-03-31	1980-03-31
LV	1996-03-31	2009-03-31	2002-09-30	2005-03-31	2009-03-31	1993-06-30
MT	2001-03-31	2008-03-31	2007-06-30	1998-12-31	2006-03-31	2002-12-31
NL	1971-03-31	1983-03-31	1972-06-30	1970-03-31	1975-03-31	1980-03-31
PT	1971-03-31	1998-03-31	1990-06-30	1977-06-30	1975-03-31	1987-03-31
SE	1971-03-31	1988-03-31	1972-06-30	1970-03-31	1988-03-31	1990-03-31
SI	1996-03-31	2007-09-30	2009-06-30	2002-06-30	2007-09-30	1995-06-30
SK	1996-03-31	2008-03-31	2007-06-30	1996-03-31	2006-03-31	1993-09-30
EA	1971-03-31	1988-03-31	1989-03-31	1980-03-31	1988-03-31	1980-03-31

Table B2: Improvement in tick loss function (5th percentile, no fixed effects)

	In sample					Out of sample				
Indicator	1	4	8	12	16	1	4	8	12	16
SRI, +lag, +int	24.4	30.1	32.1	21.1	9.0	19.0	22.0	20.6	22.9	10.4
SRI, +lag, +*CLIFS	21.1	26.5	27.7	19.0	9.7	17.4	11.3	-7.8	15.6	11.6
SRI, +lag	21.1	26.2	27.7	19.0	7.7	16.9	15.9	15.5	18.0	12.3
SRI	13.1	23.1	27.5	16.2	6.5	10.0	11.2	15.5	14.1	11.4
Bank credit gap, +lag, +int	10.3	13.8	15.2	15.2	11.0	-2.0	-7.4	-3.1	1.8	9.4
Real total credit (2y-growth), +lag	14.6	14.7	12.3	10.5	3.8	12.3	8.4	4.1	8.1	10.4
Real total credit (2y-growth)	13.6	14.0	12.5	10.1	3.1	8.3	9.0	4.1	8.6	10.9
DSR (2y-change), +lag	17.0	14.2	12.4	10.5	2.7	16.6	20.0	10.2	19.1	10.4
DSR (2y-change)	16.9	13.9	11.4	10.4	2.3	15.6	18.0	9.6	16.8	10.3
Bank credit gap, +lag	7.6	10.7	11.3	11.1	9.3	-5.0	-9.8	-12.7	-6.6	10.0
Bank credit gap	6.7	10.5	11.1	10.3	9.0	4.8	-11.5	-14.4	0.4	14.3
Financial Cycle, +lag, +*CLIFS	16.2	6.6	10.0	14.0	6.8	13.4	8.4	6.6	22.6	6.2
Financial Cycle, +lag, +int	16.6	6.4	8.8	13.8	6.6	14.7	2.2	6.6	10.9	6.1
Total credit gap, +lag, +int	8.3	8.2	8.7	7.8	3.7	14.6	-9.7	-5.5	-14.1	-2.2
Total credit gap, +lag	7.9	7.8	8.5	7.7	3.5	12.0	-9.8	1.3	1.34	6.5
Total credit gap	7.9	7.7	8.4	6.5	3.2	11.7	-8.9	3.4	0.9	8.4
Financial Cycle, +lag	16.1	6.2	7.9	12.6	6.3	13.6	6.9	-1.0	15.7	3.2
Financial Cycle	0.5	0.9	6.8	12.0	5.0	1.8	-1.1	-2.9	13.6	3.3
ESI, +lag	9.4	5.3	4.5	4.4	4.5	-4.6	-3.3	-8.0	5.2	7.9
ESI	0.1	2.3	4.5	1.6	4.5	-7.3	-7.6	0.8	3.7	6.2
CLIFS, +lag	4.9	0.9	0.9	5.2	3.2	-1.2	-0.1	-1.8	-1.6	-1.0
CLIFS	4.0	0.01	0.4	3.8	3.1	-0.6	1.4	-2.6	-0.7	-1.3
Baseline	0.39	0.41	0.39	0.36	0.36	0.43	0.44	0.47	0.58	0.53

Notes: Improvements in tick loss function are in percentage relative to the model with GDP only. The models are ordered by the performance for $h = 8$, in sample.

Table B3: Improvement in tick loss function, sequentially including variables (5th percentile)

		In sample					Out of sample				
	indicators	1	4	8	12	16	1	4	8	12	16
FE:	sri, dsr, clifs, esi	31.37	28.38	30.23	19.1	8.23	21.89	15.13	29.38	12.02	14.08
	sri, dsr, clifs	28.45	27.33	28.95	18.73	7.55	23.02	21.78	27.21	10	14.25
	sri, dsr	26.45	26.96	28.75	16.48	5.27	22.99	24.09	27.81	11.06	12.64
	sri	22.18	26.3	28.36	16.44	4.67	15.87	19.36	27.39	10.81	17.23
	baseline	0.40	0.39	0.38	0.35	0.34	0.46	0.48	0.60	0.76	0.63
no FE:	sri, dsr, clifs, esi	32.86	30.74	31.73	23.04	10.93	22.18	12.4	18.91	25.6	13.6
	sri, dsr, clifs	30.65	29.58	30.1	22.09	10.47	24.82	20.55	18.64	26.72	11.54
	sri, dsr	29.61	29.46	30.1	20.57	8.88	26.21	20.54	18.59	25.12	12.29
	sri	25.47	29.06	29.73	20.42	8.81	18.99	21.9	19.09	22.88	10.36
	baseline	0.41	0.41	0.39	0.36	0.36	0.43	0.44	0.47	0.58	0.53

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