Macrofinancial stress-testing. A practical approach to risk identification and severity calibration in the European case.

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This paper explores the application of the Growth-at-Risk (GaR) framework to assess downside risks to GDP growth and its relevance for stress testing exercises in the euro area. GaR models estimate the distribution of future output growth with an emphasis on extreme negative outcomes, offering a probabilistic approach to economic tail risks. Using quantile regressions, we first analyse the determinants of output growth and evaluate the role of macroeconomic and financial variables in shaping downside risks across the growth distribution. We show that financial stress significantly amplifies short-term risks, particularly in the lower tail of the distribution. However, at longer horizons, other variables—such as long-term interest rates, house prices, and equity markets—emerge as dominant drivers of growth dynamics. We further conduct a 'pseudo' real-time assessment of tail risks for euro area GDP growth, comparing GaR-based results with the severity of European Banking Authority (EBA) stress-test scenarios. While EBA adverse scenarios typically exceed the 10th percentile of model-implied growth distributions, their likelihood remains low yet positive, aligning with regulatory guidelines on severity and plausibility.

1. Introduction

In the past decade, a series of severe economic crises have unfolded, effectively bringing an end to the so-called Great Moderation—a period from the mid-1980s to the mid-2000s characterized by reduced volatility in key economic indicators, such as inflation and output growth. The 2008 global financial crisis exposed the risks of an increasingly interconnected global economy. Shortly after, from 2010 to 2012, the European sovereign debt crisis emerged as mounting fiscal imbalances threatened the stability of the single currency area. In early 2020, the COVID-19 pandemic led to widespread lockdowns, travel restrictions, and social distancing measures, which severely disrupted supply chains, business operations, and consumer behaviour. Most recently, since February 2022, many countries have been grappling with the fallout from Russia's invasion of Ukraine. The conflict triggered spikes in energy and commodity prices, fuelled domestic inflation, and introduced a period of uncertainty and "slowbalization".

The variety of shocks that hit economies globally, along with the resulting increase in volatility, presents significant challenges for policymakers, complicating the formulation and implementation of effective policies. For instance, with greater volatility in inflation and output growth, central banks may find it more difficult to gauge the appropriate timing and scale of interest rate adjustments.

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Higher uncertainty also calls for governments to strengthen contingency plans and respond swiftly to unexpected downturns, which is often hard to implement in practice.

In response to these challenges, advancements in modelling techniques have been developed to provide more robust tools for forecasting and risk assessment. Strasser et al. (2021) offer a concise yet comprehensive overview. One line of work has adapted traditional models—such as multivariate time series models and stochastic general equilibrium models—by mitigating the impact of large outliers that could lead to implausible estimates (Lenza and Primiceri, 2022). Researchers have also incorporated novel features, such as high-frequency data or pandemic-specific variables to help capture some of the unique patterns observed in recent years (Cardani et al., 2021). Alternatively, machine-learning techniques have emerged as a promising approach to handle complex, non-linear dynamics. However, their application to policy analysis faces some challenges, including their scalability and integration into existing frameworks, as well as concerns about the "black box" nature of such methods.

Another approach has emerged at the intersection of stress-testing and the empirical analysis of tail events. One of the leading frameworks in this context is represented by Growth-at-Risk (GaR) models, which apply techniques borrowed from financial risk management and apply them to macroeconomic conditions (Adrian et al., 2019). Essentially, GaR models assess the distribution of future output growth and aim to estimate the probability of extreme negative outcomes, conditional on a set of controls. From a philosophical perspective, this probabilistic approach views extreme events no longer as outliers but rather as part of a broader, more volatile economic landscape. Recently, these methods have been increasingly integrated into central banks' and other policy institutions' empirical toolkit (IMF, 2019).

Building on these observations, we take a practical approach and investigate how the GaR framework can be a useful complement to risks assessment and stress testing exercises. To this end, we structure our analysis around the following points. First, we investigate the determinants of output growth and underlying sources of downside risks in the euro area using quantile regression analysis. Previous research has shown that growth in the US and other advanced economies tends to be asymmetric, with tail risks rising in response to adverse financial shocks. We extend these findings by exploring the relationship between future growth and a broader set of macroeconomic variables, beyond just financial stress. Next, we assess the ability of GaR models to capture downside risks. We focus on a canonical GaR featuring GDP growth and an index of financial turbulence, and a larger model with additional control variables spanning a larger information set. We quantify the impact of alternative risk factors across the growth distribution, and the time horizon over which these materialize. Finally, we conduct a 'pseudo' real-time assessment of tail risks to euro area GDP growth, and we compare our results to the severity of the European Banking Authority (EBA) stress-tests.

Our findings confirm that financial stress is indeed a critical factor influencing short-term fluctuations in growth, particularly in the lower tail of the distribution. The negative and statistically significant coefficients at lower percentiles, across multiple regression models, confirm that financial stress can amplify downside risks in the near term. However, our analysis shows that other factors contribute to growth dynamics, and their influence varies depending on the forecast horizon and the segment of the growth distribution being examined. Variables such as short-term rates, private credit, equity markets, as well as contemporaneous GDP play a key role in driving growth up to 4-quarters ahead. At longer horizons—such as the three-year horizon relevant for stress testing exercises—the impact of financial turmoil diminishes, and the importance of variables like long-term interest rates, house prices, and equity markets becomes more pronounced.

These conclusions underscore the importance of incorporating an array of macroeconomic factors when assessing downside risks to growth. The good predictive performance of 'basic' GaR models—such as those featuring GDP and financial stress—appears to be limited to the short-term and largely driven by the high serial correlation of output changes. As the forecasting horizon extends, however, the predictive power of past growth diminishes significantly, and coincident indicators of financial stress fail to fully offset this decline in accuracy. This is consistent with other studies that highlight the limited additional predictive power of financial variables alone (Plagborg-Møller et al 2020, Brownlees and Souza 2021).

The final part of the paper quantifies the magnitude of tail risks to euro area growth at different points in time. For this analysis, we adopt a 'pseudo' real-time approach—using final data while ignoring revisions—and focus on the years when the European Banking Authority (EBA) conducted its stress-tests. Earlier contributions in this direction include Barbieri et al. (2022) and Bonucchi and Catalano (2022) who employed time-series models. In our view, the probabilistic structure of the GaR framework, with its emphasis on tail risk, aligns closely with the EBA's objective of calibrating severe, low-probability economic contractions, providing a technically rigorous benchmark for assessing the severity of adverse scenarios.

The EBA guidelines do not specify how to assess the overall severity of the scenarios. Our approach measures severity based on the likelihood of realization of the scenario. A consistent finding is that EBA adverse scenarios tend to be significantly more severe than the 10th percentile of model-implied growth distribution (GaR10). In other words, the EBA's stress scenarios consistently appear more conservative than the empirical downside distribution. The 2021 EBA stress testing round, which took place during the pandemic, is the only instance when the GaR10 (-3%) is close to the EBA adverse scenario (-3.6%). Nonetheless, all EBA adverse scenarios remain within the probability space defined by GaR models, and the likelihood of observing outcomes worse than the EBA adverse scenarios is non-zero. This aligns with regulatory guidelines indicating that adverse scenarios should be both severe and plausible.

The rest of the paper is organized as follows. Section [2] briefly reviews the literature. Section [3] introduces the key methodological concepts used in the paper. Section [4] describes the data. Section [5] and [6] present the results. Section [7] examines the sensitivity of the results to changes in modelling details. Finally, Section [8] concludes.

2. Related literature

The paper of Adrian et al. (2019) presents a foundational framework for Growth-at-Risk (GaR), making a seminal contribution to the literature. The authors aim to enhance the forecasting of future output growth by focusing on the conditional distribution of potential outcomes, emphasizing the critical role of financial conditions in identifying downturns. Their approach stands out for its relative simplicity and parsimony compared to alternative methods for modelling tail risks and heteroskedasticity. Using US data and a tailored version of quantile regressions, they demonstrate that the lower tails of output growth are highly sensitive to financial conditions, while the upper quantiles remain relatively stable over time. This empirical evidence uncovers an asymmetric and nonlinear relationship between financial conditions and economic activity, and is interpreted by the authors as suggesting that financial variables hold particular predictive value for anticipating major economic downturns.

The seminal work of Adrian et al. (2019) has been extended in a number of directions. One line of research applies the GaR methodology to countries other than the United States. For example, Figueres and Jarocinski (2020), Alessandri et al. (2019) and Alessandri and Di Cesare (2021), De Lorenzo Buratta and Maia (2022), Hartigan and Wright (2021), and Adrian et al. (2022) examine the relationship between output growth and alternative financial conditions indicators for the euro area, Italy, Portugal, Australia, and a panel of advanced and emerging market economies, respectively. Generally, these studies confirm the short-term comovement of financial stress and output growth.

Other studies have explored the out-of-sample forecasting performance of GaR models compared to alternatives, such as those by Brownlees and Souza (2021) and Plagborg-Møller et al. (2020). These analyses find that quantile regressions perform similarly to GARCH models in forecasting, and that financial variables offer little additional information beyond what is already captured by other real macroeconomic indicators. Iseringhausen (2021) models output growth using a stochastic volatility specification, replacing the assumption of Gaussian shocks with a noncentral t-distribution driven by a skewness parameter that varies over time as a function of macrofinancial conditions. He shows that this approach enhances forecast accuracy against competing models in a panel of 11 OECD countries.

Another strand of the literature expands the analysis to include a broader set of explanatory variables, incorporating factors that capture the structural characteristics of an economy, such as trade openness, financial sector size, the public spending ratio, and government effectiveness (Gachter et al., 2023). These studies show that structural differences across countries result in varying degrees of sensitivity to changes in financial risks. Additionally, factors related to the macroprudential stance—such as capital requirements, macroprudential policy indexes, and other capital- and borrower-based measures—are also examined to explore the trade-offs between mitigating risks and fostering economic growth (Skrinjaric 2024).

Recent methodological advances include the work of Chavleishvili and Manganelli (2024), who introduce a quantile vector autoregression (QVAR) model, an extension of the traditional vector autoregression (VAR) framework. Using euro area data, the authors show that the QVAR model significantly outperforms standard VAR models in forecasting, particularly at the lower quantiles.

3. Empirical framework

GaR models have been primarily designed to gauge the likelihood of adverse outcomes for economic activity. In essence, they provide a probabilistic assessment of future output growth by fitting a continuous distribution to a set of estimated quantiles, obtained by regressing output growth on one or more explanatory variables. In contrast to alternative empirical approaches that focus on point forecasts of conditional means, GaR models estimate the probability distribution of output growth. The bottom part of the probability distribution captures the severity of adverse outcomes.

GaR models are state dependent—in the sense that the assessment of risks to growth is conditional on the information set available to the econometrician and summarized by the chosen set of explanatory variables—and non-structural, and thus cannot ascertain causal links. Instead, they provide a reduced-form and tractable framework to estimate the likelihood and severity of an economic slowdown, most appropriate for comparative statics analysis.

GaR models' estimation hinges upon two main elements. First, it establishes the empirical relationship between output growth and the explanatory variables using quantile regressions. Next, the probability distribution of output growth is derived by fitting a parametric distribution using the estimated quantiles. The following two subsections describe these steps in more details.

3.1. Quantile regressions

Regression models are statistical methods used in quantitative modelling to explain or predict the value of an outcome variable of interest, based on one or more explanatory variables.

Among the most popular, the method of ordinary least squares (OLS) estimates the conditional mean of the outcome variable. Yet, the mean is a reasonable summary statistic when the relationship between the outcome variable and the explanatory variables is broadly constant across the entire distribution.

A quantile regression model offers a more complete statistical analysis of the relationship among random variables, as it estimates the relationship between a specific percentile (or quantile) of the outcome variable and the explanatory variables. This is especially useful when the underlying relationship varies across percentiles—making the mean a poor descriptor—or when the researcher is interested in investigating the relationship away from the mean.

A quantile regression of output growth on a set of explanatory variables at the 10th percentile would estimate the relationship when growth is relatively weak, while a quantile regression at the 90th percentile would be based on stronger growth. By running a battery of regressions from the lowest to the highest quantiles, the researcher can capture the heterogenous relationship between the explanatory variables and output growth, for different levels of growth.

While the specification of each quantile regression model is linear, this framework allows for nonlinearities in the sense that the explanatory variables can affect output growth differently depending on the point of the growth distribution.

The quantile regression specification used in the paper takes the following form:

$$y_{t+h}^{q} = \alpha^{q} + \sum_{i \in I} \beta_i^{q} X_{i,t} + \varepsilon_{t+h}^{q} \qquad (1)$$

where y_{t+h}^{q} represents future growth *h* quarters ahead for the *q*-th quantile, $X_{i,t}$ is the *i*-th explanatory variable and β_i^{q} the corresponding coefficients, α^{q} the constant term and ε_{t+h}^{q} the residual. Clearly, the coefficients capturing the relationship between output growth and the explanatory variable can differ across quantiles and forecast horizons. We estimate the quantile regressions at different points of the distribution, between the 10th and the 90th percentile, and across 1-, 4-, and 12-quarters ahead.

Each slope coefficient β_i^{q}, which captures the relationship between the explanatory variable $X_{i,t}$ and future growth at different points of the distribution of GDP growth, is chosen to minimize the quantile weighted absolute value of errors:

$$\hat{\beta}^{q} = argmin_{\beta} \sum_{T} (q \, I_{(y_{t+h \geq X_T \beta})} \, |y_{t+h} - X_t \beta| + (1-q) I_{(y_{t+h < X_T \beta})} \left| y_{t+h - X_T \beta} \right|) \qquad (2)$$

where q is the check loss function formally introduced by Koenker and Bassett (1978). In turn, the estimated slope coefficients feed into the calculation of a set of predicted values for each quantile of the distribution of growth, across multiple time horizons:

$$\hat{Q}^{q}_{y_{t+h|X_t}} = \hat{\alpha}^{q} + \sum_{i \in I} \hat{\beta}^{q}_{i} X_{i,t} \tag{3}$$

One potential problem with quantile regression models is that they can generate quantile estimates that cross (e.g., the model predicted value for the 5th quantile lies above the prediction for the 10th quantile), which is at odds with the monotonicity of quantile functions. To avoid this issue, we restrict the quantile space to the interval between the 10th and 90th percentiles and we pick only a few quantiles, following Adrian et al. (2019).[3]

3.2. Parametric fitting

The next step after estimating the quantile regression model, is to construct a smooth probability density function (PDF) encompassing all estimated quantiles. This can be thought of as mapping the fitted values from the quantile regressions onto a continuous distribution, serves to smooth the fitted quantile regression values, and provides a probability region which allows to quantify downside risks as the area in the left tail of the distribution.

Alternative methods are available to derive a PDF from the estimated quantiles. Following Adrian et al. (2019), a parametric method is chosen here to fit the conditional quantiles estimated in the first step to a skewed t-distribution. Non-parametric approaches are also available, which rely on fewer assumptions, but are sensitive to estimation noise and quantiles crossing. As discussed in Adrian et al. (2019), the skewed t-distribution is a good candidate for the target probability distribution, having proved useful in the finance literature to model tail events, given its thicker tails and some degree of skewness.

The skewed t-distribution is characterized by four parameters—location, scale, kurtosis, and skewness.[4] These are estimated for each time period in the sample by minimising the sum of squared errors between the set of fitted quantiles derived in the first step and the theoretical skewed t-distribution quantiles:

$$\{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = argmin_{\mu,\sigma,\alpha,\nu} \sum_{T} \left(\hat{Q}^{q}_{y_{t+h|X_t}} - F^{-1}(q; \mu, \sigma, \alpha, \nu) \right)^2 \tag{4}$$

Where the respective density function is defined as:

[3] The crossing problem is generally confined to the outlying regions of the sample space. See the quantile spacing method of Schmidt and Zhu (2016) as one option to enforce monotonicity.

[4] It is also possible to fix the location (i.e., the central estimate) of the distribution, leaving only three free parameters to be estimated (i.e., constrained optimization).

$$f(y; \mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} \cdot t(z|\nu) \cdot T(\alpha z|\nu + 1) \text{ with } z = \frac{y - \nu}{\sigma} \quad (5)$$

In turn, the estimated parameter values are instrumental to constructing a PDF for each time period, allowing to quantify downside or upside risks to future economic activity.

More formally, downside risk to economic activity can be characterized in terms of expected shortfall, or the area under the predicted PDF below the relevant quantile. For a chosen target probability π, the expected shortfall (ES) is defined as:

$$ES_{t+h} = \frac{1}{\pi} \int_0^{\pi} \hat{F}^{-1}_{y_{t+h|X_t}}(q|X_t)dq \quad (6)$$

Symmetrically, upside risks take the form of the expected longrise (LR) in the equation below:

$$EL_{t+h} = \frac{1}{\pi} \int_{1-\pi}^{1} \hat{F}^{-1}_{y_{t+h|X_t}}(q|X_t)dq$$

4. Data

Our sample consists of several macroeconomic and financial data for the euro area through the period 1986-2024. We choose to treat the euro area as a single entity for at least three reasons. First, aggregate output is the main object of macroprudential surveillance and stress testing conducted by European institutions such as the EBA. Second, GaR models are already quite complex in their basic form, and moving to a country-level disaggregation would significantly increase dimensionality and complicate the consistent estimation of a joint distribution. Third, in a monetary union with a single monetary policy, aggregate financial conditions are particularly relevant for the area-wide outlook.
That said, this approach doesn't explicitly tackle structural and cyclical heterogeneity across countries.

The data frequency is quarterly. We aim for a long sample to cover as many business cycles as possible, hopefully reducing uncertainty and bias. However, this choice limits the pool of data that we can choose from, given that most European data are available from the mid-1990s, and requires imputing some historical series backward.

Table [1] lists the series entering our sample, the database from which they were retrieved, and the year since they are available.

For data series starting only in the early- or mid-1990s, we impute the entries back using proxies that are close substitutes and show similar trend and cyclical patterns through the common part of the sample. In particular, we use EA-15 GDP for euro area GDP up to 1995; data for exports are imputed using the IMF Direction of Trade Statistics data; short-term interest rate data are derived from the

European Central Bank Area Wide Model (ECB AWM);[5] finally, data for credit to the private non-financial sector until 1999 are derived from the M1 money supply.[6]

Nominal data are deflated using the consumer price inflation (CPI) to express all macroeconomic series in real terms. Inflation is also subtracted from the short- and long-term interest rate series.

5. Growth drivers in Europe: a quantile regression approach

To investigate the sources of risk to growth in the euro area, we extend the scope of other empirical studies—focused on the relationship between output growth and financial stress indicators (Alessandri et al., 2019; Krygier and Vasi, 2021; Buratta and Maia, 2022)—by incorporating additional controls accounting for alternative transmission channels. These include the term-structure of interest rates, private sector credit, house prices, an equity index, the real effective exchange rate, oil prices, and goods exports, alongside an indicator of financial stress.

The reasons for selecting these variables are quite straightforward. The term structure of interest rates reflects the monetary policy stance. Credit flows, house prices, and equity prices all contribute to economic growth and household wealth, having played key roles in previous economic cycles. The real effective exchange rate serves as a measure of the euro area external competitiveness, while goods exports and oil prices act as proxies for external demand and the commodity cycle, respectively. Finally, we align with many related studies by adopting the Composite Indicator of Systemic Stress (CISS) as the preferred measure of financial stress.[7]

Overall, our dataset strikes a good balance between covering a sufficiently long historical sample of European data, maintaining a parsimonious set of regressors, and capturing potential sources of both upside and downside risks to growth that may not be fully reflected in financial stress indicators alone.

In the following subsections, we explore the data using univariate and multivariate quantile regressions to examine the empirical relationship with future GDP growth. The analysis covers the sample period from 1986 to 2024. Results excluding the pandemic period (using data up to end-2019) are discussed in Section [7].

5.1 Univariate regressions

We use univariate quantile regressions where output growth 1-, 4-, and 12-quarters ahead is regressed on each explanatory variable at a time. The scatterplots in Figure [1] illustrate these relationships in Cartesian coordinates, with the dependent variable (future output growth) plotted on the vertical axis. Each scatterplot displays regression lines corresponding to the 10th, 50th, and 90th percentiles of the growth distribution. The goal is to illustrate the non-linearity in the data visually:

[5] The ECB AWM is an estimated structural macroeconomic model for the euro area developed for the assessment of economic conditions in the area, forecasting and policy analysis. The model stopped being updated in 2017, but researchers can still refer to the historical databases to complement official statistics compiled by Eurostat and the European Central Bank.

[6] There is no material difference between this and broader measures of money. The correlation coefficient with credit to the private sector in the common part of the sample is 0.98 for M3 compared to 0.93 for M1.

[7] The CISS is a daily indicator capturing volatility across several market segments, including bank and non-bank financial intermediaries, money markets, securities (equities and bonds) markets as well as foreign exchange markets. The CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time, with the intent to better capture systemic stress. Compared to earlier works, we can use a version of the CISS that has been recently made available ad goes back to 1980.

diverging or converging quantile lines highlight asymmetric effects. For example, if the 10th percentile becomes sharply negative as the regressor increases, while the 90th remains flat, this suggests that the impact is concentrated to the lower tail of the distribution.

The plots show that future GDP growth is generally positively correlated with private credit growth, the Euro Stoxx 50 (a proxy for equity prices), house prices, and current GDP growth. In contrast, higher levels of financial stress are strongly associated with lower future growth. The negative relationship with interest rates in the medium- and long-term stands out from these preliminary regressions.

In most regressions, the slopes and levels of the regression lines differ across percentiles, suggesting some heterogeneity in the effects of each explanatory variable across the growth distribution. For instance, financial stress (CISS) exerts a stronger negative effect at the lower tail of the distribution. Similarly, the adverse effects of higher short- and long-term interest rates and oil prices is larger at the left tail.

The results also vary with the forecast horizon. Private sector credit, equity prices and house prices comove positively with GDP growth at 1- and 4-quarter horizons, but the correlation tends to weaken at longer horizons. For example, at the 12-quarter horizon, the regression line for the 10th percentile becomes negative for credit growth and house prices, indicating rising downside risks associated with asset price growth over the medium term. The effect of financial stress fades beyond the 4-quarter horizon. A similar pattern is evident for exports, where the short-term comovement diminishes over time, as well as for current GDP growth, which naturally exhibits weaker comovement at the 12-quarter horizon compared to shorter horizons. In contrast, the impact of higher interest rates becomes more visible over time, reflecting the delayed impact of monetary tightening on economic activity.

In some other cases the results are less straightforward. For example, the real effective exchange rate (REER) regression lines are broadly flat at the median, upward-sloping at the top percentile, and downward-sloping at the bottom percentile.

Overall, these preliminary findings underscore the need to account for both temporal dynamics and forecast horizon variations when evaluating the factors driving future growth.

5.2 Multivariate regressions

We complement the univariate quantile regressions with multivariate regressions, gradually adding explanatory variables in each iteration. This helps to validate the stylized findings discussed above and to assess the stability of the estimated coefficients across different model specifications with varying combinations of regressors. For each model specification, we estimate the distribution of coefficients via bootstrapping to capture sampling uncertainty. We then combine model uncertainty—across alternative regression models—and parameter uncertainty—via bootstrapping—to explore a probability space across quantiles that is broader than the canonical point estimates and associated confidence intervals. This broader distribution of estimates gives a more comprehensive view of where the bulk of the coefficients lie, while also highlighting the behaviour of outliers.

Table [2] presents the estimated slope coefficients from the multivariate regressions for the 10th and 90th percentiles, as well as the OLS coefficients, at the 1-, 4-, and 12-quarter horizons.[8] Figure [2] visualizes the distributions of each coefficient, reflecting both model and parameter uncertainty across the 10th, 25th, 50th, 75th, and 90th percentiles.

The CISS financial stress index consistently exhibits a negative and statistically significant effect on output growth across model specifications (Table [2]). OLS regressions indicate that higher financial stress consistently reduces growth. The coefficient of the 10th percentile is always larger than that at the 90th percentile, underscoring the asymmetric impact of financial crises. At the 10th percentile, a one-unit increase in CISS reduces future GDP growth by approximately 4 to 9 percent, with the magnitude varying somewhat depending on the model specification but primarily determined by the forecast horizon—being most pronounced at the 1- and 4-quarter horizon.[9] Notably, including CISS after other financial variables does not substantially alter the significance of these controls, suggesting no clear issues with multicollinearity, omitted variable bias, or diminished statistical power. The boxplots in Figure [2] reinforce these findings. The interquartile range of CISS coefficients remains consistently negative across quantiles and time horizons, except for a minor deviation at the 12-quarter horizon, as it appears also from Table [2]. The coefficients at the 10th and 25th percentiles are largest, while those at the 75th and 90th percentiles are less negative, highlighting the disproportionately negative effects of financial crises on the lower tail of GDP growth.

In addition to CISS, the results point to house prices, credit growth, and the term structure of interest rates as important determinants of future GDP growth.

Higher house prices have a positive short-term impact on GDP growth. OLS estimates indicate a positive coefficient of approximately 0.2 percent, statistically significant at conventional levels. Quantile regressions indicate that this effect is more pronounced at higher quantiles (Q75 and Q90), where strong housing markets tend to amplify wealth effects, boost consumption and support construction activity (Table [2] and Figure [2]). In the long term, the relationship between house prices and GDP growth is not statistically significant. The interquartile range of bootstrapped coefficients predominantly lies below zero. This suggests that excessive growth in real estate valuations or prolonged reliance on housing market activity may pose risks to sustained GDP growth in the future.

Higher credit to the non-financial private sector—primarily households and firms—has a positive but diminishing effect on growth. At the 1- and 4-quarter horizons, the coefficients are generally positive, averaging around 0.1 percent, particularly at lower levels of GDP growth. This suggests that credit growth provides essential liquidity and stimulus in weak-growth environments, helping to alleviate credit constraints and boost consumption or investment. However, these coefficients tend to decrease and turn negative as GDP growth rises, indicating diminishing returns from credit expansion in stronger growth environments. At the 12-quarter horizon, the relationship becomes negative across various regression models in both high- and low-growth states. This can reflect the build-up of vulnerabilities, such as financial instability or inefficient credit allocation.

Short-term interest rates exhibit a clear negative relationship with GDP growth at the 4-quarter horizon. The OLS coefficients are consistently negative, averaging around -0.3 percent, reflecting the

[8] Quantile regression coefficients do not lend themselves to causal interpretation or cross-model comparisons, particularly when multiple regressors interact. However, we use them as a reduced-form, flexible description of the conditional relationship between explanatory variables and output growth across different quantiles.

[9] Note that the CISS ranges between 0 and 1, and it peaked at 0.94 during the Great Financial Crisis on December 8th, 2008. Therefore, a unit increase corresponds to an extremely severe outcome.

lagged dampening effect of higher rates on aggregate demand, typically over the course of one year. Notably, coefficients at the 10th percentile are significantly larger than those at the 90th percentile. This is supported by boxplots, which consistently display a negative interquartile range, with outliers concentrated in the lower tails of the GDP growth distribution. At the 12-quarter horizon, the distribution of coefficients at lower quantiles shifts closer to zero, indicating a weakening relationship between short-term rates over longer horizons. At the 1-quarter horizon, the median coefficients can be small but positive at lower quantiles, hinting that modest rate increases may signal normalization and a slight improvement in confidence, particularly under weaker growth conditions.

The negative impact of higher long-term interest rates is particularly pronounced at the 12-quarter horizon. Across different models, nearly all coefficients are negative, with a significantly larger effect on the left tail of the growth distribution (median coefficient around -2 percent) compared to the right tail (around -0.6 percent). This pattern is clearly illustrated in the boxplots in Figure [2]. These findings emphasize the heightened vulnerability of low-growth states to adverse long-term financing conditions, such as tighter monetary policy or worsening credit conditions, which can disproportionately affect the economy over the long-term during periods of economic slack. The observed negative effect may also reflect the lagged response of investment and output to changes in long-term borrowing costs, with low-growth states amplifying the adverse impact of higher rates.

The Euro Stoxx 50 index shows a positive short-term comovement with GDP, likely driven by increased access to capital, improved investor confidence, and spillovers to broader economic activity. A 10 percent increase in the Euro Stoxx 50—plausible in a strong stock market year—can boost GDP growth by up to 0.5 percent, with the effect being stronger at lower GDP growth quantiles. In the sample excluding the pandemic period, a series of large negative outliers appear at the 90th percentile, signalling potential risk buildup in high-growth environments. At longer forecast horizons, the distribution of coefficients from bootstrapped draws skews toward the negative quadrant at lower quantiles, and the quantile distribution takes on a u-shaped pattern. These findings reinforce the notion of risk accumulation at both extremes of the growth spectrum.

Current GDP growth shows a strong positive relationship with future GDP growth. At the one-quarter horizon, the OLS coefficient is 0.6. Across quantiles, the coefficients increase as we move to higher GDP growth levels, suggesting that recessions tend to be shorter-lived compared to expansionary business cycles. At the 12-quarter horizon, a distinct u-shaped pattern emerges across quantiles, indicating that both low-growth and high-growth states tend to have longer-lasting consequences compared to average growth cycles.

The coefficients for exports are generally small and statistically insignificant across the models presented in Table [2]. This is further corroborated by the boxplots, which show that the bulk of the coefficient distribution clusters around zero. While some heterogeneity is observed across quantiles, it does not alter the overall conclusion of limited statistical and economic significance. The REER yields mixed and generally insignificant coefficient estimates. Similarly, the WTI oil price, which serves as both a cost factor and an indicator of global economic conditions, has a limited direct impact on GDP growth in most specifications.

5.3 Standardized coefficients

Since not all data are expressed as percentage changes, directly comparing the estimated coefficients in terms of their contributions GDP growth can be misleading. To address this, Figure [3] presents the standardized coefficients from our most comprehensive regression model (Model #10 in Table [2]), evaluated at the 10th, 25th, 50th, 75th, and 90th percentiles for horizons 1-, 4-, and 12-quarter.[10]

At the 1-quarter horizon, current GDP growth is the strongest predictor of future growth, with a standardized coefficient consistently around 0.8 across all quantiles. In contrast, a one-standard-deviation increase in the CISS is associated with a reduction in GDP growth by less than 0.4 standard deviations. Other controls, such as credit growth and house prices, exhibit normalized coefficients below 0.2 standard deviations, with limited variation across quantiles. The contractionary impact of a one-standard-deviation increase in short-term interest rates is modest and relatively uniform at approximately -0.1, comparable to the effect of an exchange rate appreciation. Oil prices show virtually no impact on GDP growth at this horizon.

At the 4-quarter horizon, the contributions of regressors to GDP growth are more evenly distributed. The relative importance of predictors varies across quantiles and depending on whether the pandemic period is included in the sample. Nonetheless, the standardized coefficients for credit growth, the equity index, house prices, the CISS, exports, and short-term interest rates are broadly comparable. At lower quantiles, these coefficients are approximately 0.45, whereas at higher quantiles, they tend to decline to 0.2 or below. Notably, the standardized coefficients for current GDP growth are significantly smaller compared to the 1-quarter horizon.

At the 12-quarter horizon, long-term interest rates exhibit the largest standardized impact on GDP growth, with a coefficient of -0.8 at the 10th percentile. This finding underscores the persistent adverse effects of tighter financing conditions, particularly in low-growth states. Depending on the quantile, equity prices, house prices, and current GDP emerge as the most influential predictors, alongside financial stress. Together, these factors substantially drive long-term GDP growth, particularly in scenarios marked by financial and economic vulnerabilities.

6. Assessing Downside Risks

So far, our findings confirm the negative impact of financial stress on future GDP growth, particularly in the short-term. Additionally, we show that other variables—such as current GDP growth, house and equity prices, private credit, and interest rates—play a non-negligible role in shaping growth dynamics across both short- and long-term horizons. This is relevant in the context of stress-testing, where the focus on longer horizons and multiple sources of risks calls for a broader assessment of the drivers of economic growth.

In this section we evaluate the ability of GaR models to capture downside risks to growth. Specifically, we compare the performance of a canonical GaR—featuring GDP growth and an index of financial turbulence, as commonly found in the literature— with that of an expanded model incorporating a richer set of control variables to provide a more comprehensive information set. Building on the findings from our univariate and multivariate regressions, we extend the GaR model to include the controls considered there. For simplicity, we refer to the canonical model as the "small model", and

[10] All data enter the model in percentage changes except for interest rates, that are expressed in percentage points, and the CISS, which is an index between 0 and 1. To standardize the data, each estimated coefficient is multiplied by the ratio of the standard deviation of the corresponding regressor to the standard deviation of the dependent variable. The original units of measurement are lost, and the interpretation shifts to the impact of a one-standard-deviation increase in each regressor on the dependent variable (GDP growth), measured in standard deviations, while holding all other variables constant.

our enhanced version as the "large model". The models are estimated over the entire sample, with results capturing average outcomes across cycles.

Following others in the literature, we define GaR as the prediction of the 10th percentile of the conditional GDP growth distribution and identify this metric as an indicator of the likelihood of extreme negative outcomes for future GDP growth. Figure [4] shows actual GDP growth alongside the in-sample 10th and 90th percentiles for both the small and large model. Figure [5] illustrates the probability of negative GDP growth, which we describe as a recession probability, albeit loosely, as it does not strictly align with the technical definition of a recession.

At the 1-quarter horizon, both models yield similar results: they closely track actual GDP growth, indicate comparable downside risks, and provide timely signals for CEPR-designated recessions, including at the onset of the pandemic.

At the 4-quarter horizon, the differences between the models become more pronounced. The small model's GaR is less volatile, failing to capture key downturns such as the 1992 recession and significantly overestimating the GDP contraction during the 2008 financial crisis. The large model better anticipates the 1992 recession by signalling heightened risks and accurately assessing the scale of the GDP slowdown in 2008. During the mid-1990s and early 2000s, the large model aligns more closely with actual GDP growth trends. Additionally, the large model assigns higher recession probabilities during the 2009 crisis (95 percent compared to 65 percent) and provides a more precise timeline of the peak-to-trough periods compared to the small model, including through the euro area debt crisis of 2012-2013. While neither model successfully tracks the extreme GDP volatility during the pandemic period, the large model correctly signals lower recession risks around 2021.

At the 12-quarter horizon, the difference between the two models is even more pronounced. The small model consistently fails to capture the depth of recessions and produces a GaR (as well as the upper tail) that is essentially stable over time, with no foresight into possible downturns. In contrast, the large model’s GaR shows greater variability and better anticipates periods of economic slack, such as the early 1990s and through the 2007-2013 period. However, it also flags downside risks where they did not materialize, such as the early 2000s and in 2017. Unsurprisingly, both models struggle with precise long-term recession predictions.

Figure [6] provides some insights into these findings by decomposing the contributions of the explanatory variables to GaR fluctuations. At the 1-quarter horizon, GDP growth is the main driver of GaR changes in either case. This explains the models’ similar short-term performance and aligns with other literature that highlights the limited incremental predictive power of financial variables alone (Plagborg-Møller et al 2020; Brownlees and Souza 2021). The contribution of the CISS in the small model is essentially limited to the 2009-2012 period, during peaks of financial stress. The large model also incorporates some contributions from the credit channel (which combines the coefficients associated with short- and long-term interest rates and private sector credit), external demand (represented by the REER and goods exports) and the CISS again. However, these contributions are generally smaller relative to the persistent effects of current GDP growth.

As we move to longer forecast horizons, the small model's explanatory power is dominated by the intercept. This is an indication that crucial long-term growth drivers are absent from its structure (Diebold 2007; Burnside 1998; Romer and Romer 2000). The large coefficient for the intercept highlights the model's inability to explain longer-term risks, as it compensates for omitted variables by attributing much of the variation in GaR to baseline factors absorbed by the intercept’s coefficient.

Instead, the large model distributes the explanatory power more evenly among various factors. While the constant term still accounts for a significant portion of growth, other variables, such as assets, credit, and external factors, exhibit greater variability and sensitivity to macro-financial conditions. For example, at the 4-quarter horizon, in the 1990s and early-2000s the large GaR model reveals occasional spikes in external and credit-driven dynamics, likely associated with emerging-market crises (e.g., the Asian Financial Crisis in 1997 and the Russian debt default in 1998). During the Global Financial Crisis, the asset and credit components sharply detract from GDP growth, reflecting the collapse of financial markets and credit flows. The credit factor mitigated downside risks during both the 2001 and 2008 crises, aligning with periods of monetary easing and declining interest rates. Both models indicate a slow recovery in the post-2010 years, with the large model emphasizing the importance of credit and external factors. During the COVID-19 pandemic, the combined contributions of credit and external factors amplify the negative impact on GDP, capturing the simultaneous contraction in global trade and financial markets. The small model, while highlighting financial stress, underestimates the broader economic disruptions. At the 12-quarter horizon, the GaR is almost entirely driven by changes in the credit cycle and assets valuations. This is in line with the literature on financial cycles and the importance of feedback effects from mortgage lending, credit to households and more generally fluctuations in assets prices to economic activity (Jordà et al. 2015; Borio 2014; Reinhart and Rogoff 2009).

Comparing the two models, the large model not only captures more detailed dynamics but also provides a clearer picture of the mechanisms driving growth over longer horizons. The additional macrofinancial controls allow it to attribute changes in growth forecasts more accurately to shifts in key variables, particularly during crises. This underscores the added value of incorporating a richer set of variables when modelling growth risks, as it enhances the model's ability to identify periods of vulnerability and resilience in the economy. Overall, the large model's decomposition aligns more closely with observed macro-financial episodes, making it a more robust tool for long-term risk assessment and policy analysis.

Figure [7] plots the one-, four- and twelve-quarter ahead forecasts of the fitted conditional probability density function of GDP growth in each year from 1986 to 2024, using both the small and large models. At shorter horizons, the distribution exhibits dynamic shifts in its central tendency, skewness, and kurtosis, reflecting evolving macro-financial conditions. Periods of financial or economic crises, such as the early 1990s and the Global Financial Crisis, are marked by pronounced leftward skewness and heightened kurtosis, indicating elevated tail risks and an increased probability of severe negative growth outcomes. These episodes are characterized by a contraction in the range of possible outcomes (distribution narrowing), with a concentration of density in the lower-growth region. This pattern is especially evident during the COVID-19 pandemic, where the distributions for both models exhibit a sharp leftward shift and compression, reflecting the simultaneous impact of economic contraction and heightened financial stress. Conversely, periods of economic recovery, such as the mid-1990s and the post-sovereign debt crisis rebound in the early 2010s, are marked by a rightward shift in the distribution, indicating improved growth expectations. During these recovery phases, the distributions widen and become more symmetric, signalling reduced downside risks and greater stability, though the broader range of potential outcomes highlights the uneven and gradual nature of such recoveries.

At longer horizons, notable differences emerge between the PDFs generated by the small and large models. The small model yields relatively smoother and more constrained distributions, reflecting its limited ability to capture complex interactions between macro-financial variables and GDP growth over extended periods. While it registers some increased left-tail risks during periods of systemic stress, such as the Global Financial Crisis and COVID-19, the lack of additional explanatory variables leads to less pronounced dynamics and a muted representation of risk. In contrast, the large model exhibits richer dynamics, capturing sharper spikes, heightened kurtosis, and significant shifts in skewness during key macroeconomic episodes. For example, the large model's distributions during the Global Financial Crisis reveal severe leftward skewness and more extreme downside risks compared to the small model. Around the COVID-19 pandemic, the large model provides a more detailed representation of the substantial compression and leftward shift in the distribution, capturing the pronounced uncertainty and elevated risks stemming from financial market volatility and the economic contraction.

Across all horizons, the inclusion of a broader set of macrofinancial variables in the model enhances its responsiveness to macroeconomic shocks, making it more effective at capturing shifts in risk profiles and reflecting broader ranges of economic outcomes. These features underscore the model's superior relevance for long-term risk assessment and policy analysis, particularly during periods of systemic stress and heightened uncertainty.

6.1 GaR Forecasts and EBA Scenarios

To conclude our analysis, we apply the GaR model in an out-of-sample forecasting exercise to assess the distribution of risks to euro area growth in 'pseudo' real time. Unlike a true real-time analysis, we rely on final data. This is unlikely to materially affect our results, as the macroeconomic series we use are not subject to large revisions.

To establish a realistic policy benchmark, we select the years in which the European Banking Authority (EBA) conducted its stress-tests and align our forecast horizon with the EBA's three-year timeframe. The cutoff date for the out-of-sample forecasts is set at the last quarter (Q4) of the year preceding the EBA stress test exercise. Since the EBA does not clearly indicate the information that feeds into the exercise, in the next section we also check the results using the average growth across the first three quarters (Q1, Q2, Q3) of the year preceding the EBA stress test exercise.

Since 2011, the European Banking Authority (EBA) has conducted multiple rounds of stress testing that have progressively evolved in complexity, scope, and severity (Table [3]). A key component of these exercises is the design of adverse macro-financial scenarios, which aim to capture a range of potential shocks, including recessions, asset price collapses, and market disruptions. These scenarios are intentionally severe, reflecting potential tail events that, while unlikely, could have profound impacts on the financial system. This approach aligns closely with the probabilistic structure of the GaR framework, that provides a technically robust benchmark for assessing the severity of EBA's downside scenarios.

Table [4] compares projected and realized GDP growth across different EBA stress-testing rounds, together with some GaR model results. The upper section of the table shows three-year cumulative real GDP growth under the European Commission (EC) baseline scenario, the EBA's adverse scenario (AS), and actual outcomes where available. The lower section reports the out-of-sample GaR projections, including downside risks, total uncertainty, the probability of materialization of a recession, and the probability to observe an outcome more severe than EBA's AS. These statics correspond to the median computed from four alternative GaR models. Two models are identical to those described in earlier sections: the small GaR model including GDP and CISS, and the large GaR model incorporating all available regressors. Two additional intermediate models are also presented to see even better the sensitivity of the results to alternative combinations of the regressors. One model includes GDP, CISS, long-term interest rates, private sector credit, and house prices, while the other extends this set by adding the stock market index and the REER.

Figure [8] illustrates the corresponding probability densities. In most years these are unimodal and with a clear peak, indicating the most likely outcomes for three-year cumulative real GDP growth. Over time, the shape of these distributions changes reflecting shifts in midpoints, dispersion, and skewness.

A few key insights emerge. First, GaR10—the 10th percentile of the projected three-year cumulative GDP growth distribution—shows substantial variation across different stress-testing rounds, reflecting shifts in macroeconomic uncertainty and the business cycle. For instance, in 2014, the distribution is symmetric, indicating balanced risks, and peaks around 6%, reflecting a relatively optimistic central growth projection. GaR10 was 3.4%, implying limited downside risks in the euro area. However, by the 2021 stress testing round, amid the COVID-19 pandemic, the distribution shifts markedly to the left with a peak around zero and a relatively tight bell. Gar10 had plunged to -3%, signalling a heightened probability of significant contractions. Downside risks remained large also in the 2023 round, with fat left tails in most models and a median GaR10 of -2.6%. In the 2025 EBA stress test round, GaR10 rebounded to 1.6%, indicating an expected stabilization of risks in the post-pandemic environment.

An interesting comparison is between GaR10 and EBA's AS. Since the latter represents a counterfactual worst-case scenario, it is naturally lower than both the EC baseline and actual growth. The key question, however, is whether GaR10—which represents a lower bound to the empirical growth distribution—aligns with or significantly deviates from the EBA's stress level assumption. In earlier stress-testing rounds, from 2014 to 2018, EBA's AS appear more severe than GaR10. For example, in the 2014 stress test, GaR10 was 3.4%, meaning that only 10% of 3-year cumulative growth outcomes are expected to be below this threshold, compared to the EBA AS of -2.1%. This suggests that the stress scenario was significantly more pessimistic than the empirical downside risk distribution implied by GaR models. Similarly, in 2016, GaR10 was 2.3%, while the EBA AS stood at -1.7%. By 2018, GaR10 rises to 3%, while the EBA adverse scenario further deepens to -2.4%.

However, it is also the case that all these EBA adverse scenarios fall under the models' probability space, and the likelihood of observing outcomes worse than EBA's AS is low yet positive and fairly stable across stress testing rounds: 2.1% in 2014, 2.5% in 2016, and 3.5% in 2018. Indeed, these probabilities align with regulatory guidelines indicating that adverse scenarios should be severe and plausible.

The 2021 EBA stress testing round, which took place during the COVID-19 crisis, is quite unique. GaR10 dropped sharply to -3%, closely aligning with the EBA's AS of -3.6%. In this occasion, the empirical tail distribution validated the EBA's stress level assumptions, reflecting the extreme nature of the economic shock. In the latest stress-testing rounds of 2023 and 2025, GaR10 recovered to -2.6% and 1.6%, while the EBA AS became significantly more severe (-5.9% and -6.3%, respectively). The widening gap suggests that, under normalizing macroeconomic conditions, the EBA's stress scenarios have become increasingly conservative relative to the empirical downside distribution.

The probability of growth falling below EBA's AS provides a direct gauge of whether the empirical downside tail is as severe as the regulatory stress scenario. Prior to the pandemic, this probability was uniformly low (ranging between 2.1% and 3.5%), suggesting that GaR-based forecasts rarely implied a contraction of the magnitude assumed under EBA stress tests. In 2021, this probability surged to 8.5%, underscoring that the pandemic shock was an outlier event with a downside severity broadly in line with the EBA AS. Notably, in the latest rounds this probability fell again to 2.4% in 2023 and 1.7% in

2025, reinforcing the view that the EBA's assumptions are currently far more pessimistic than what empirical downside risk estimates suggest.

Total uncertainty, measured as the difference between the 90th and 10th percentiles, peaked in 2018 (8.6%), likely reflecting concerns over financial market turbulence and macroeconomic instability at that time. Conversely, during the acute phase of the COVID-19 crisis, total uncertainty was lower (5.3%), which may be counterintuitive but aligns with the rapid and extreme policy responses that reduced immediate tail risks. More recently, uncertainty remained elevated (6.6% in 2023 and 6.2% in 2025), possibly reflecting lingering concerns about long-term economic scarring and persistent risks. Downside risks, defined as the difference between the 50th and 10th percentiles, exhibits a similar pattern, peaking at 6.2% in 2018.

The likelihood of recession, defined as the probability that three-year cumulative growth falls below zero, surged to 54.8% in 2021 and stayed elevated at 30.5% in 2023, consistent with the severe contraction in activity. This probability declined over subsequent rounds, in light with a perceived return to macroeconomic stability.

7. Sensitivity

The tables and figures in the Appendix present results based on a data sample ending in 2019, deliberately excluding the pandemic period. The rationale for this exclusion is that the unprecedented nature of the COVID-19 shock, along with the extraordinary policy responses it triggered, may have distorted historical correlations between key variables. For instance, economic activity collapsed due to mandated shutdowns, only to rebound sharply once restrictions were lifted—an atypical pattern not observed in conventional recessions. Moreover, in a typical downturn, a sharp contraction in activity would be accompanied by pronounced fluctuations in other macroeconomic variables, such as consumption, financial markets, asset prices, labour market indicators, and inflation. However, during the pandemic, many of these variables exhibited unusual dynamics due to decisive policy interventions, potentially skewing historical relationships and affecting the robustness of the results.[11]

Overall, we do not observe significant deviations from the results of the univariate and multivariate regressions discussed earlier in the paper, likely because the long sample smooths out the impact of a few anomalous data points. That said, some differences emerge at the margin. For instance, the adverse effects of higher short- and long-term interest rates and oil prices in the left tail of the distribution are more pronounced. The negative relationship between GDP growth and short-term interest rates is slightly stronger, with an OLS coefficient of -0.4 percent compared to -0.3 in the baseline. Similarly, the correlation between current GDP growth and one-quarter-ahead GDP growth is marginally higher (0.9 percent compared to 0.6 percent). Lastly, the results for the REER are more clearly defined, suggesting a stronger negative short-term relationship with growth.

Our findings suggest that the probabilistic assessment of future growth distribution is sensitive to the choice of the cut-off date for out-of-sample forecasts. In the previous section, we used data from the fourth quarter (Q4) of the year preceding the EBA stress test exercise. As an alternative, we also

[11] Consumption initially fell due to restrictions, only to surge as pent-up demand was released. Financial markets, which typically decline in recessions, rebounded swiftly due to massive policy intervention. Housing prices, rather than falling as they usually would in a downturn, rose in many countries due to low interest rates and shifting preferences. Labor markets also behaved atypically, with employment plummeting rapidly due to policy-driven shutdowns but recovering swiftly thanks to wage support programs. Finally, inflation, which normally weakens in recessions, saw a delayed but sharp resurgence due to supply constraints and stimulus-fueled demand.

consider the average of the first three quarters (Q1-Q3).[12] This approach is reasonable, as it aligns with the EBA's need to incorporate economic developments throughout the year before finalizing its assessment by year-end. As noted earlier, the EBA does not explicitly specify the information set used to construct the scenarios. Therefore, it is useful to check whether our conclusions hold when using a different reference period. The relevant results are presented in the bottom half of Table [4] and in Figure [8] in the Appendix.

For stress test exercises conducted before the pandemic, the results remain broadly comparable across different cut-off periods. Comparing probabilistic measures from 2014, 2016, and 2018, we observe only minor differences. For instance, the probability of growth falling below the EBA adverse scenario in 2014 is 2.1% when using Q4 data and 2.8% when averaging Q1-Q3. Similarly, GaR10 thresholds, as well as measures of uncertainty and downside risks, remain consistent.

The results diverge significantly in 2021, where shifting the cut-off from Q1-Q3 2020 to Q4 2020 changes risk assessment. GaR10 improves from -6.5% to -3.0%, indicating a perceived reduction in extreme downside risks. Meanwhile, total uncertainty rises from 3.3% to 5.3%, suggesting a wider range of possible outcomes despite an improved worst-case scenario. Downside risks also increase from 1.7% to 3.9%, reinforcing this trend. The most striking shift occurs in the likelihood of recession, which drops sharply from 96.9% to 54.8%, signalling a significant reassessment of immediate contraction risks. Likewise, the probability of cumulative GDP growth falling below the EBA adverse scenario declines from 83.1% to 8.5%, indicating that by Q4 2020, the model had adjusted to a less severe downturn than previously anticipated. Therefore, as the cutoff dates change, the model dynamically adjusts to new data, refining risk assessments as conditions evolve.

8. Conclusions

GaR models have been increasingly used in policy circles to assess downside risks to growth. In this paper, we take a practical approach and evaluate how this empirical framework can be a useful complement to risk assessment and stress testing exercises in the euro area. To this end, we first investigate the relationship between future GDP growth and several macroeconomic variables, extending our analysis beyond financial stress episodes, which already feature prominently in the existing literature. Next, we assess the ability of GaR models to capture downside risks, focusing on two alternative specifications: a canonical GaR featuring GDP and a measure of financial stress as regressors, and a larger model with additional control variables covering a broader information set. Finally, we estimate the out-of-sample cumulative distribution function of GDP growth at different points in time and compare it to the severity of downside scenarios prepared by the European Banking Authority (EBA).

Our results confirm the strong link between financial crises and economic downturns in the euro area, as rising in financial stress is associated with sharp declines in economic activity. However, our analysis also suggests that financial turmoil is not the sole driver of GDP fluctuations. In fact, we show that including additional macroeconomic controls in the GaR model enhances its ability to track actual GDP growth, particularly over longer forecast horizons.

More specifically, preliminary quantile regressions reveal that GDP, equity prices, private credit, house prices, and external demand are all positively correlated with GDP growth in the short term (1- and 4-

[12] Except for the 2025 EBA stress test round which has a cut-off date in mid-2024. In this case we use either Q2 2024, or the average of Q1 and Q2 2024.

quarters ahead). Most of these drivers exhibit heterogeneous effects across the GDP growth distribution, with larger impacts observed on the lower tails. Financial stress, as captured by the Composite Indicator of Systemic Stress (CISS), consistently detracts from growth, corroborating findings from previous research. Standardized coefficients indicate that a one-standard-deviation increase in current GDP is associated with a 0.6 standard deviation increase in future GDP growth, while a similar rise in the CISS reduces future growth by 0.3 standard deviations at lower quantiles. House prices, equity prices, credit growth, and exports also have notable impacts, typically ranging from 0.2 to 0.3 standard deviations.

Our findings at longer forecast horizons (12-quarter ahead) present a different picture. The predictive power of past GDP growth diminishes substantially, and coincident indicators of financial stress become less accurate. Instead, long-term interest rates, house prices, and equity indices emerge as the most significant predictors of growth at these horizons. Models relying solely on GDP and financial stress—such as the approach proposed by Adrian et al. (2019)—are less capable of identifying future downside risks, which is particularly relevant in the context of stress testing exercises that span multiple years.

In the final part of the paper, we quantify the magnitude of tail risks to euro area growth and compare these estimates with the severity of EBA's adverse scenarios. A consistent finding is that EBA adverse scenarios tend to be significantly more severe than the 10th percentile of the model-implied growth distribution (GaR10). The 2021 EBA stress testing round stands out as the only case where GaR10 (-3%) closely aligns with the EBA adverse scenario (-3.6%). By contrast, in the 2023 and 2025 stress-testing rounds, GaR10 recovers to -2.6% and 1.6%, respectively, while the EBA adverse scenarios become markedly more severe, at -5.9% and -6.3%. This widening gap suggests that, as macroeconomic conditions normalize, the EBA's stress scenarios have become increasingly conservative relative to the empirical downside distribution.

Nonetheless, all EBA adverse scenarios remain within the probability space defined by GaR models, and the likelihood of observing outcomes worse than these scenarios remains non-zero: 2.1% in 2014, 2.5% in 2016, 3.5% in 2018, 8.5% in 2021, 2.4% in 2023 and 1.7% in 2025. These probabilities align with regulatory principles requiring that adverse scenarios should be both severe and plausible.

Ultimately, assessing the severity of stress-test scenarios requires a broader perspective than comparing GDP growth rates alone. While GaR10 offers a useful benchmark for gauging plausibility, a comprehensive evaluation must also consider potential shocks to other macroeconomic and financial variables, as well as heterogeneity across countries and differences in banks' risk exposures. Having said that, we believe that closer alignment between adverse scenarios and probabilistic metrics like GaR could enhance the relevance and credibility of stress tests, while mitigating the risk of excessive pessimism.

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Tables

Table [1]. Data used in the analysis		
Series	**Source**	**Available since**
Gross domestic product	S&P GLM	Q1:1995
Exports of goods	FRED, IMF DTS	Q1:1990
Real effective exchange rate	FRED	Q1:1970
Interest rate, short-term	S&P GLM, ECB AWM	Q1:1984
Interest rate, long-term	S&P GLM	Q1:1974
Credit to private non-financial sector	FRED	Q1:1999
Dow Jones Euro Stoxx 50	S&P GLM	Q1:1970
New Composite Indicator of Systemic Stress (CISS)	ECB	Q1:1980
House price index	FRED	Q1:1975
BRENT oil price	S&P GLM	Q1:1970

Table [2]. Explanatory variables' coefficients and p-value across term structure of forecast horizon and growth distribution quantiles

1-quarter ahead

	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	-0.03	0.05	-0.07	-0.03	-0.10	-0.07	-0.03	-0.05	-0.04	-0.04	-0.10	-0.03	-0.01	0.05	-0.05	-0.02	0.06	-0.06	-0.05	-0.03	-0.05	0.01	0.01	-0.04	0.01	0.00	-0.02	-0.03	-0.07	-0.06
	0.44	0.30	0.12	0.35	0.06	0.14	0.38	0.29	0.45	0.22	0.03	0.49	0.68	0.33	0.28	0.58	0.17	0.21	0.07	0.37	0.20	0.70	0.88	0.40	0.85	0.98	0.66	0.27	0.05	0.12
Short-term rate				0.32	0.59	0.21	0.26	0.35	-0.46	0.27	0.76	-0.46	0.09	-0.21	-0.65	0.13	-0.04	-0.32	0.03	-0.01	-0.31	-0.05	0.17	-0.22	-0.04	0.16	-0.26	-0.19	-0.18	-0.26
				0.05	0.01	0.32	0.14	0.16	0.07	0.12	0.00	0.07	0.58	0.41	0.01	0.43	0.87	0.17	0.85	0.95	0.15	0.76	0.37	0.30	0.80	0.38	0.22	0.14	0.24	0.12
Long-term rate							0.18	0.20	0.82	0.33	0.22	0.83	0.56	1.01	0.97	0.31	0.79	0.08	0.62	0.79	0.20	0.42	0.53	0.17	0.37	0.55	0.32	0.41	0.39	0.20
							0.40	0.51	0.01	0.12	0.48	0.01	0.01	0.00	0.00	0.14	0.01	0.80	0.00	0.00	0.50	0.04	0.04	0.55	0.09	0.04	0.31	0.03	0.09	0.40
Private sector credit										0.14	0.24	-0.01	0.11	0.08	-0.05	0.02	0.11	-0.13	0.09	0.14	-0.10	0.05	0.15	-0.07	0.05	0.16	-0.10	0.06	0.12	-0.05
										0.00	0.00	0.87	0.02	0.24	0.44	0.75	0.11	0.05	0.07	0.01	0.14	0.28	0.01	0.31	0.31	0.01	0.16	0.11	0.02	0.29
Euro Stoxx 50													0.04	0.10	0.02	0.04	0.08	0.00	0.01	0.03	0.00	0.01	0.02	0.00	0.01	0.02	0.00	0.01	0.00	0.01
													0.00	0.00	0.27	0.00	0.00	0.84	0.24	0.02	0.90	0.52	0.10	0.83	0.58	0.10	1.00	0.52	0.86	0.62
House prices																0.23	0.12	0.35	0.13	0.10	0.33	0.15	-0.02	0.33	0.15	-0.03	0.35	0.02	-0.07	0.16
																0.00	0.11	0.00	0.02	0.16	0.00	0.01	0.79	0.00	0.01	0.69	0.00	0.65	0.22	0.01
CISS																			-6.77	-6.31	-2.90	-5.32	-5.94	-4.66	-5.42	-6.08	-3.84	-4.18	-5.40	-1.48
																			0.00	0.00	0.17	0.00	0.00	0.03	0.00	0.00	0.08	0.00	0.00	0.37
Exports																						0.10	0.11	0.02	0.09	0.10	0.03	-0.02	-0.02	-0.04
																						0.00	0.00	0.66	0.00	0.00	0.43	0.44	0.57	0.33
BRENT																									0.00	0.00	0.00	0.00	0.00	0.00
																									0.48	0.88	0.73	0.74	0.75	0.88
GDP																												0.60	0.83	0.49
																												0.00	0.00	0.00

4-quarters ahead

	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	0.02	-0.07	0.10	0.02	0.04	0.10	0.02	0.04	0.08	0.01	-0.06	0.10	0.04	-0.01	0.13	0.03	0.01	0.04	0.02	-0.03	0.07	-0.03	-0.06	-0.02	-0.02	-0.08	-0.02	-0.01	-0.08	-0.02
	0.61	0.15	0.05	0.52	0.35	0.04	0.53	0.44	0.12	0.74	0.24	0.03	0.28	0.80	0.01	0.31	0.84	0.38	0.56	0.50	0.14	0.51	0.33	0.72	0.68	0.21	0.77	0.86	0.21	0.77
Short-term rate				-0.26	-0.73	-0.09	-0.26	-0.72	-0.42	-0.25	-0.77	-0.10	-0.41	-0.72	-0.04	-0.39	-0.77	-0.25	-0.42	-0.86	-0.49	-0.37	-0.85	-0.49	-0.38	-0.82	-0.46	-0.34	-0.89	-0.55
				0.10	0.00	0.70	0.15	0.00	0.11	0.15	0.00	0.69	0.02	0.00	0.86	0.02	0.00	0.30	0.01	0.00	0.04	0.03	0.00	0.05	0.03	0.00	0.06	0.05	0.00	0.03
Long-term rate							-0.02	-0.08	0.80	0.12	0.33	0.34	0.33	0.54	0.37	0.15	0.67	-0.27	0.26	0.92	0.14	0.39	0.96	0.20	0.46	1.07	0.24	0.45	1.01	0.30
							0.91	0.78	0.01	0.58	0.30	0.26	0.13	0.06	0.23	0.49	0.04	0.38	0.26	0.01	0.66	0.10	0.01	0.57	0.07	0.00	0.51	0.07	0.01	0.41
Private sector credit										0.13	0.17	0.17	0.10	0.12	0.13	0.04	0.10	-0.07	0.06	0.15	-0.02	0.09	0.14	-0.14	0.09	0.17	-0.12	0.09	0.16	-0.14
										0.01	0.01	0.01	0.03	0.04	0.05	0.43	0.16	0.33	0.22	0.04	0.77	0.10	0.08	0.07	0.09	0.03	0.12	0.10	0.05	0.07
Euro Stoxx 50													0.04	0.06	0.02	0.04	0.07	0.01	0.03	0.04	0.00	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.04	0.01
													0.00	0.00	0.29	0.00	0.00	0.71	0.03	0.01	0.95	0.01	0.02	0.46	0.01	0.03	0.42	0.01	0.03	0.43
House prices																0.16	-0.07	0.33	0.13	-0.05	0.22	0.11	-0.04	0.30	0.12	-0.06	0.29	0.14	-0.08	0.29
																0.01	0.41	0.00	0.05	0.58	0.01	0.09	0.65	0.00	0.07	0.50	0.00	0.03	0.45	0.00
CISS																			-2.39	-7.08	-3.62	-3.42	-9.78	-3.47	-3.28	-9.34	-3.72	-3.55	-9.28	-4.11
																			0.16	0.00	0.12	0.05	0.00	0.16	0.06	0.00	0.13	0.04	0.00	0.10
Exports																						-0.07	-0.02	-0.07	-0.05	-0.03	-0.05	-0.03	-0.04	-0.05
																						0.03	0.60	0.13	0.11	0.61	0.29	0.47	0.49	0.35
BRENT																									-0.01	0.00	0.00	-0.01	0.00	0.00
																									0.41	0.65	0.76	0.45	0.74	0.89
GDP																												-0.14	0.09	-0.02
																												0.18	0.58	0.90

12-quarters ahead

	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	0.02	-0.19	0.04	0.02	-0.21	-0.01	0.02	-0.03	0.03	0.03	0.00	0.01	0.02	-0.03	0.00	0.02	-0.01	0.00	0.00	-0.01	0.01	0.02	-0.01	0.03	0.02	0.00	0.02	0.00	0.04	-0.07
	0.60	0.00	0.43	0.53	0.00	0.87	0.59	0.48	0.48	0.43	0.93	0.91	0.57	0.58	0.93	0.55	0.82	0.95	0.89	0.82	0.79	0.71	0.86	0.64	0.67	0.94	0.73	0.96	0.52	0.27
Short-term rate				-0.34	-0.26	-0.64	-0.15	0.23	0.04	-0.14	0.19	-0.18	-0.09	0.44	-0.25	-0.08	0.47	-0.27	-0.11	0.47	-0.35	-0.14	0.41	-0.38	-0.15	0.37	-0.48	-0.17	0.16	-0.14
				0.06	0.38	0.01	0.41	0.40	0.88	0.46	0.47	0.48	0.62	0.12	0.35	0.68	0.12	0.32	0.55	0.12	0.20	0.47	0.18	0.18	0.47	0.24	0.09	0.40	0.60	0.60
Long-term rate							-0.69	-1.67	-0.36	-0.79	-1.67	-0.57	-0.84	-2.13	-0.54	-0.78	-2.49	-0.52	-0.65	-2.45	-0.60	-0.69	-2.36	-0.68	-0.67	-2.18	-0.66	-0.62	-2.19	0.11
							0.00	0.00	0.23	0.00	0.00	0.07	0.00	0.00	0.09	0.00	0.00	0.14	0.01	0.00	0.09	0.01	0.00	0.07	0.02	0.00	0.10	0.03	0.00	0.79
Private sector credit										-0.11	-0.11	-0.20	-0.10	-0.09	-0.20	-0.08	-0.11	-0.21	-0.05	-0.10	-0.06	-0.06	-0.12	-0.08	-0.06	-0.12	-0.08	-0.05	-0.07	0.05
										0.02	0.11	0.00	0.04	0.23	0.00	0.12	0.19	0.01	0.37	0.24	0.45	0.32	0.17	0.35	0.34	0.17	0.35	0.42	0.46	0.52
Euro Stoxx 50													-0.01	-0.04	0.00	-0.01	-0.05	0.00	-0.02	-0.06	-0.02	-0.02	-0.06	-0.03	-0.02	-0.07	-0.03	-0.02	-0.06	-0.01
													0.31	0.01	0.87	0.36	0.00	0.85	0.10	0.01	0.18	0.09	0.01	0.13	0.09	0.00	0.13	0.10	0.00	0.48
House prices																-0.05	0.08	-0.01	-0.09	0.06	-0.02	-0.08	0.06	0.05	-0.08	0.03	0.03	-0.14	-0.07	-0.28
																0.50	0.47	0.92	0.21	0.58	0.86	0.29	0.59	0.64	0.30	0.79	0.80	0.10	0.59	0.02
CISS																			-3.08	-0.40	-5.99	-2.77	-0.34	-5.46	-2.73	-1.36	-5.58	-2.39	-0.56	-6.67
																			0.08	0.89	0.02	0.14	0.91	0.04	0.15	0.65	0.04	0.21	0.85	0.01
Exports																						0.02	0.02	0.03	0.02	0.04	0.02	-0.02	0.02	-0.15
																						0.62	0.79	0.57	0.58	0.50	0.67	0.63	0.73	0.02
BRENT																									0.00	-0.01	0.00	0.00	-0.01	-0.01
																									0.81	0.52	0.88	0.73	0.50	0.38
GDP																												0.20	0.26	0.37
																												0.07	0.13	0.01

Notes: Coefficients and p-values are based on OLS regressions and quantile regressions of growth distributions at the 10th and 90the percentiles. The estimation period is Q1:1986-Q4:2024.

Table [3]. EBA stress-testing rounds

Year	Severity	Shocks	Transmission channels
2014	-2.1%	Higher global bond yields	Interest rates and credit spreads
2016	-1.7%	Reversal of risk premia	Equity and commodity prices
2018	-2.4%	Repricing of risk premia	Confidence and uncertainty
2021	-3.6%	Re-emerging waves of infections	Real estate sector
2023	-5.9%	Geopolitical polarization	Consumption and investment
2025	-6.3%	Geopolitical tensions	Trade routes

Notes: Severity refers to the cumulative drop in GDP over a three-year period. We exclude from the scope of this exercise the very first stress test conducted in 2011.

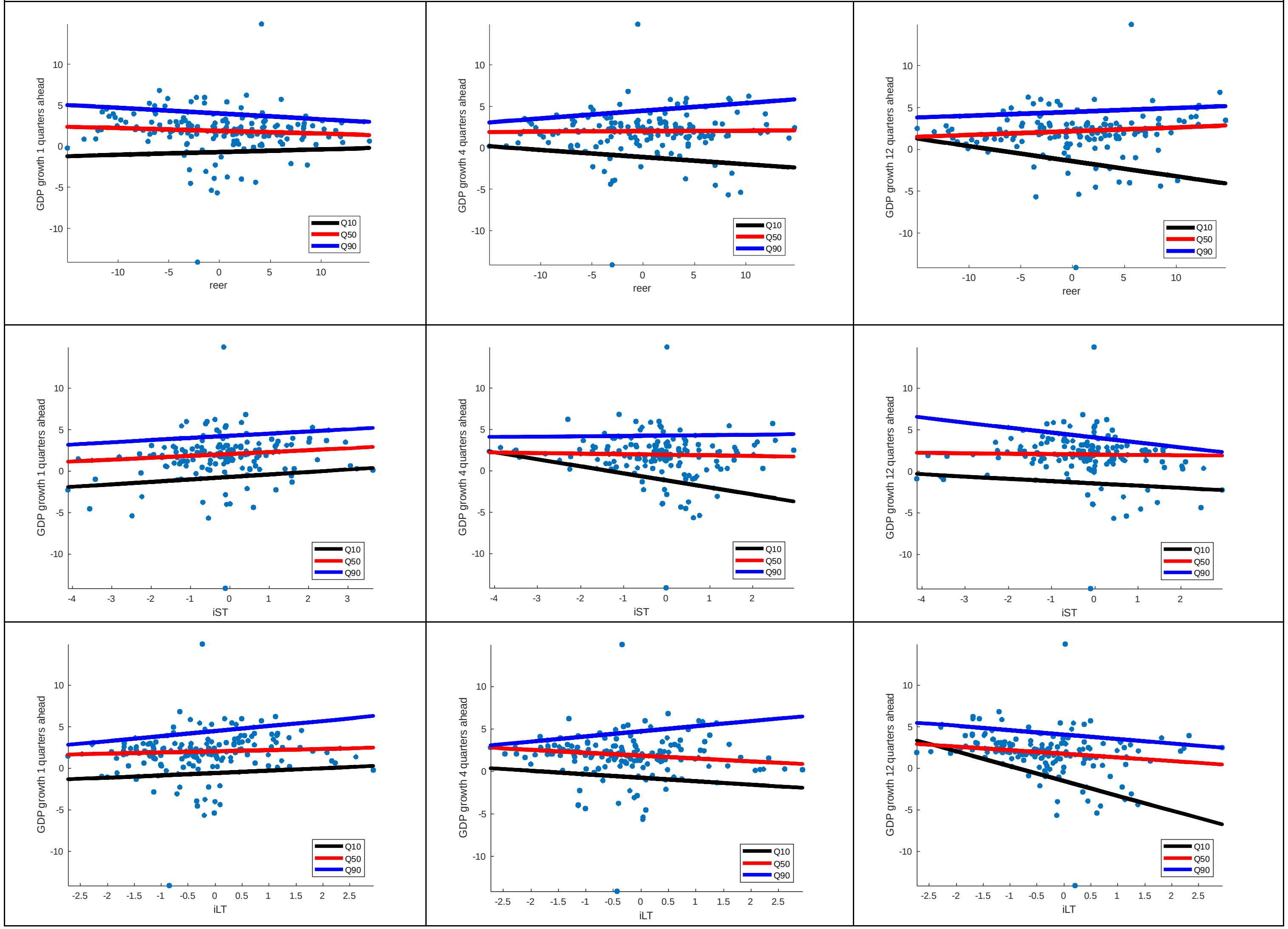
Table [4]. Macroeconomic Projections and Risk Measures Across Stress Test Rounds

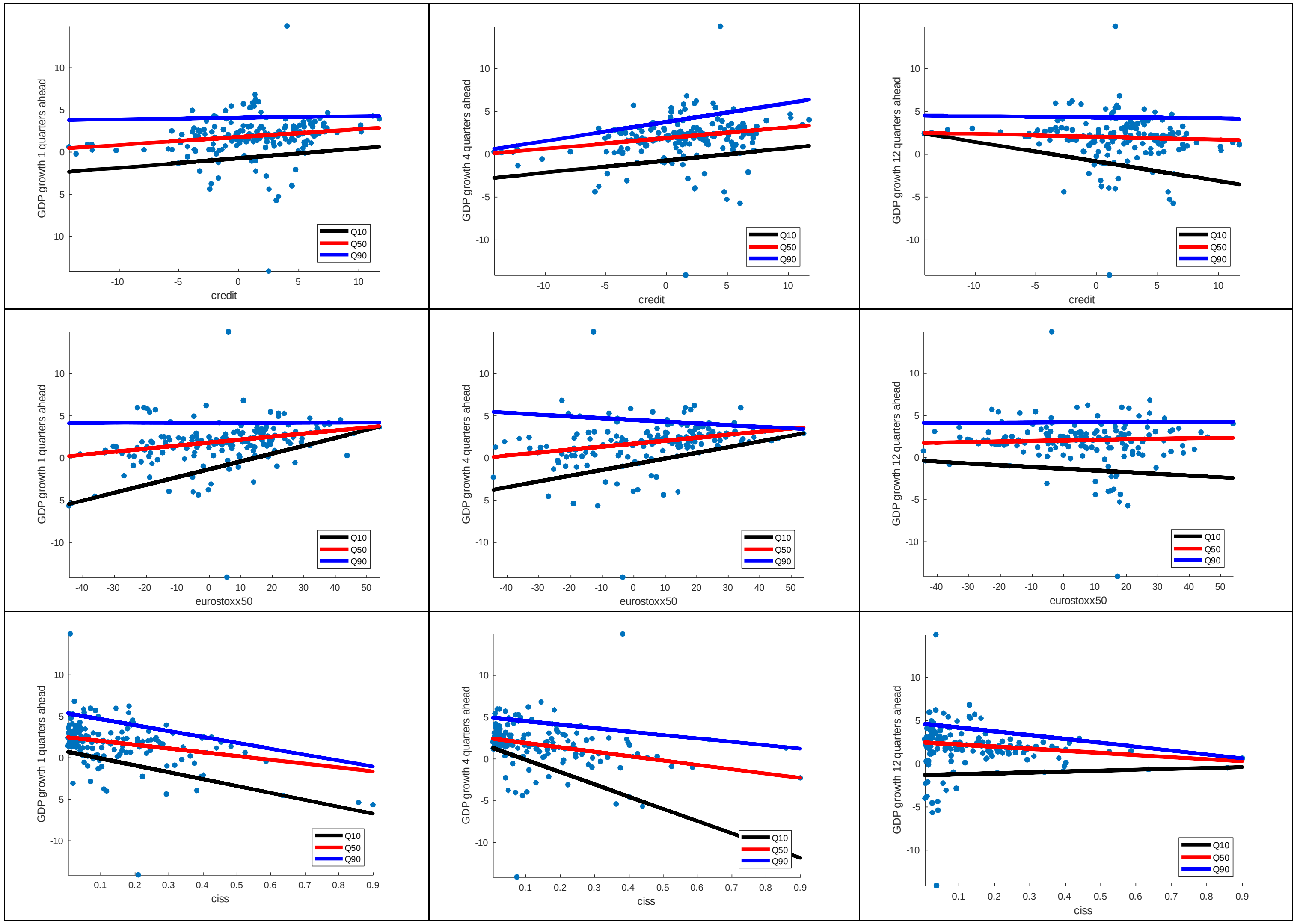
	EBA Stress Testing rounds					
	2014	2016	2018	2021	2023	2025
EBA adverse scenario (AS)	-2.1	-1.7	-2.4	-3.6	-5.9	-6.3
	Model Results					
Cutoff date	**Q4 2013**	**Q4 2015**	**Q4 2017**	**Q4 2020**	**Q4 2022**	**Q2 2024**
GaR 10%	3.4	2.3	3.0	-3.0	-2.6	1.6
Total uncertainty	3.3	7.7	8.6	5.3	6.6	6.2
Downside risks	2.0	5.4	6.2	3.9	4.4	3.4
Likelihood of recession	3.2	4.5	5.6	54.8	30.5	5.7
Likelihood of growth below EBA AS	2.1	2.5	3.5	8.5	2.4	1.7
Cutoff date	**Q1-Q3 2013**	**Q1-Q3 2015**	**Q1-Q3 2017**	**Q1-Q3 2020**	**Q1-Q3 2022**	**Q1-Q2 2024**
GaR 10%	2.0	2.9	2.8	-6.5	-0.8	1.4
Total uncertainty	3.4	6.5	7.8	3.3	11.3	6.4
Downside risks	2.1	4.2	5.3	1.7	6.3	3.4
Likelihood of recession	4.6	4.3	5.2	96.9	13.7	5.6
Likelihood of growth below EBA AS	2.8	2.8	3.2	83.1	2.3	1.6

Notes: EBA AS are those reported in the European Systemic Risk Board reports. The numbers in "Model Results" are medians of four different models (from smallest to largest). GaR10 is a metric that quantifies the worst potential cumulative GDP growth over a specific period (e.g., 3 years in this case) that is expected to occur with a 10% probability, based on a given probability distribution of growth outcomes. Total uncertainty is the difference between the 90th and the 10th percentile of the growth distribution. Downside risks is the difference between the 50th and the 10th percentile of the growth distribution. Likelihood of recession indicates the probability that 3-year cumulative real GDP growth is negative. Finally, the bottom row shows the probability to observe growth below the EBA AS. The cutoff date is set at the last quarter (Q4) or the average values during Q1-Q3 of the year preceding the EBA stress test exercise.

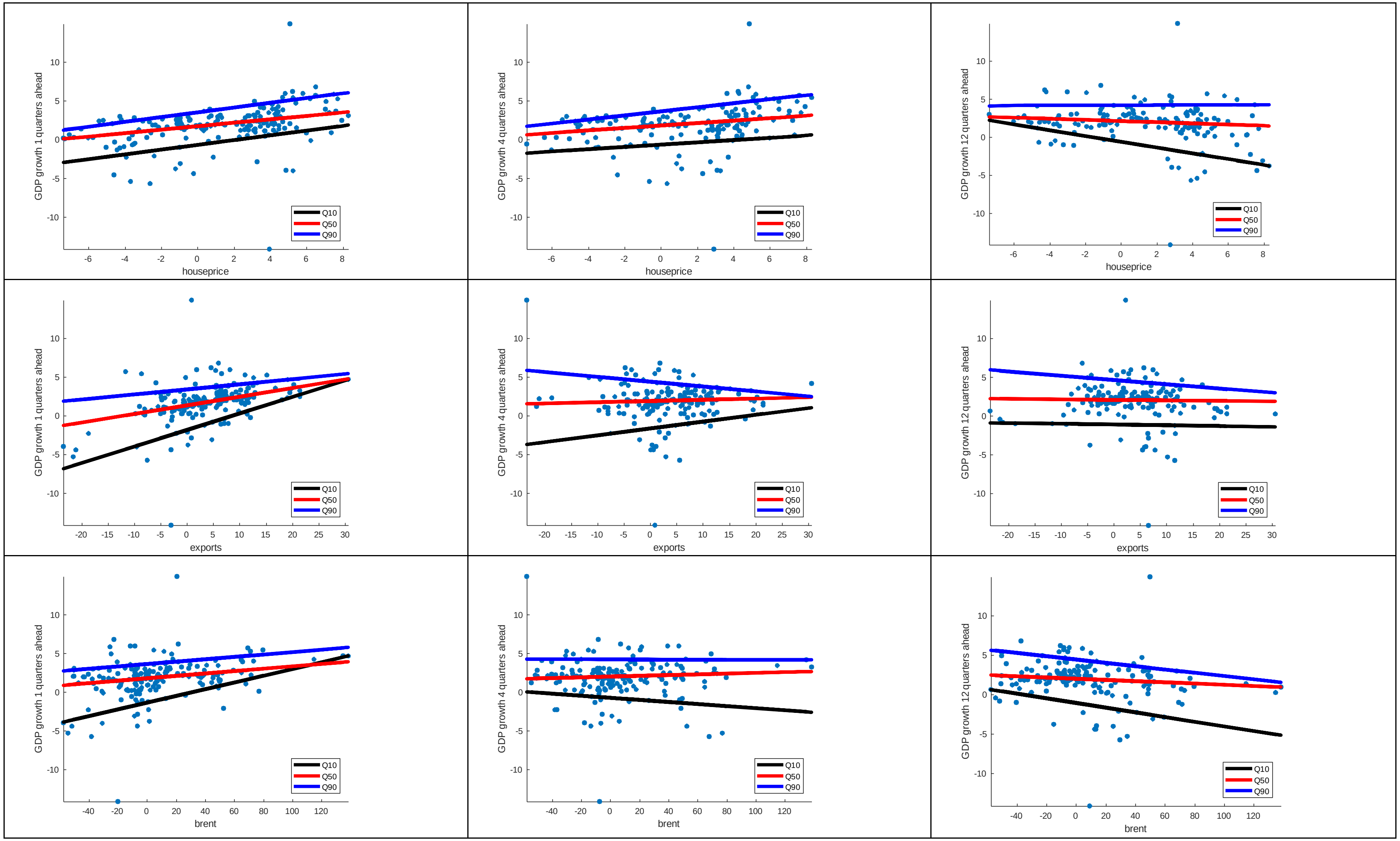
Figures

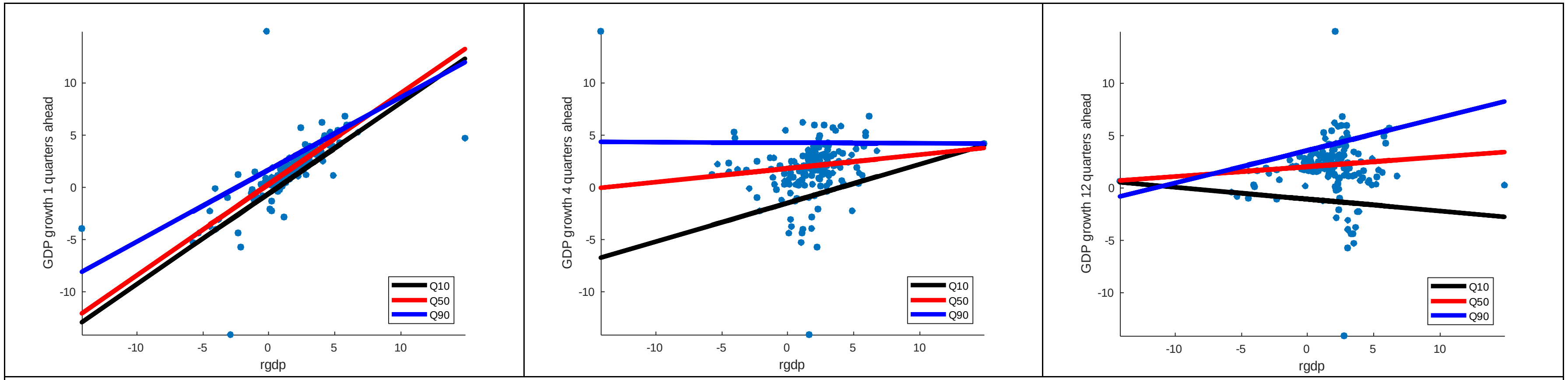
Figure [1]. Univariate quantile regressions between future GDP growth and the contemporaneous dependent variable





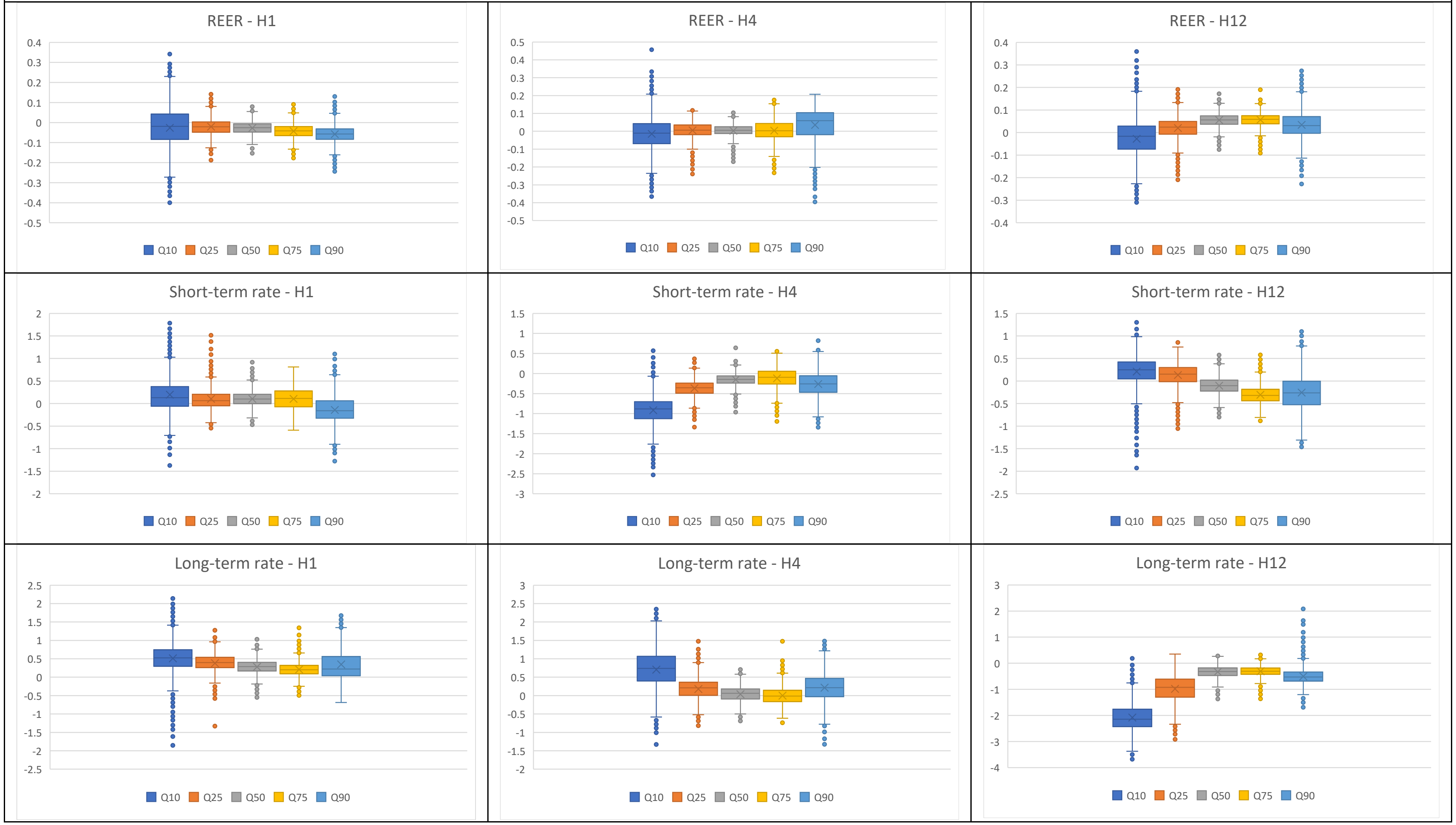
GDP growth 1 quarters ahead
GDP growth 4 quarters ahead
GDP growth 12 quarters ahead
credit
eurostoxx50
ciss
Q10
Q50
Q90

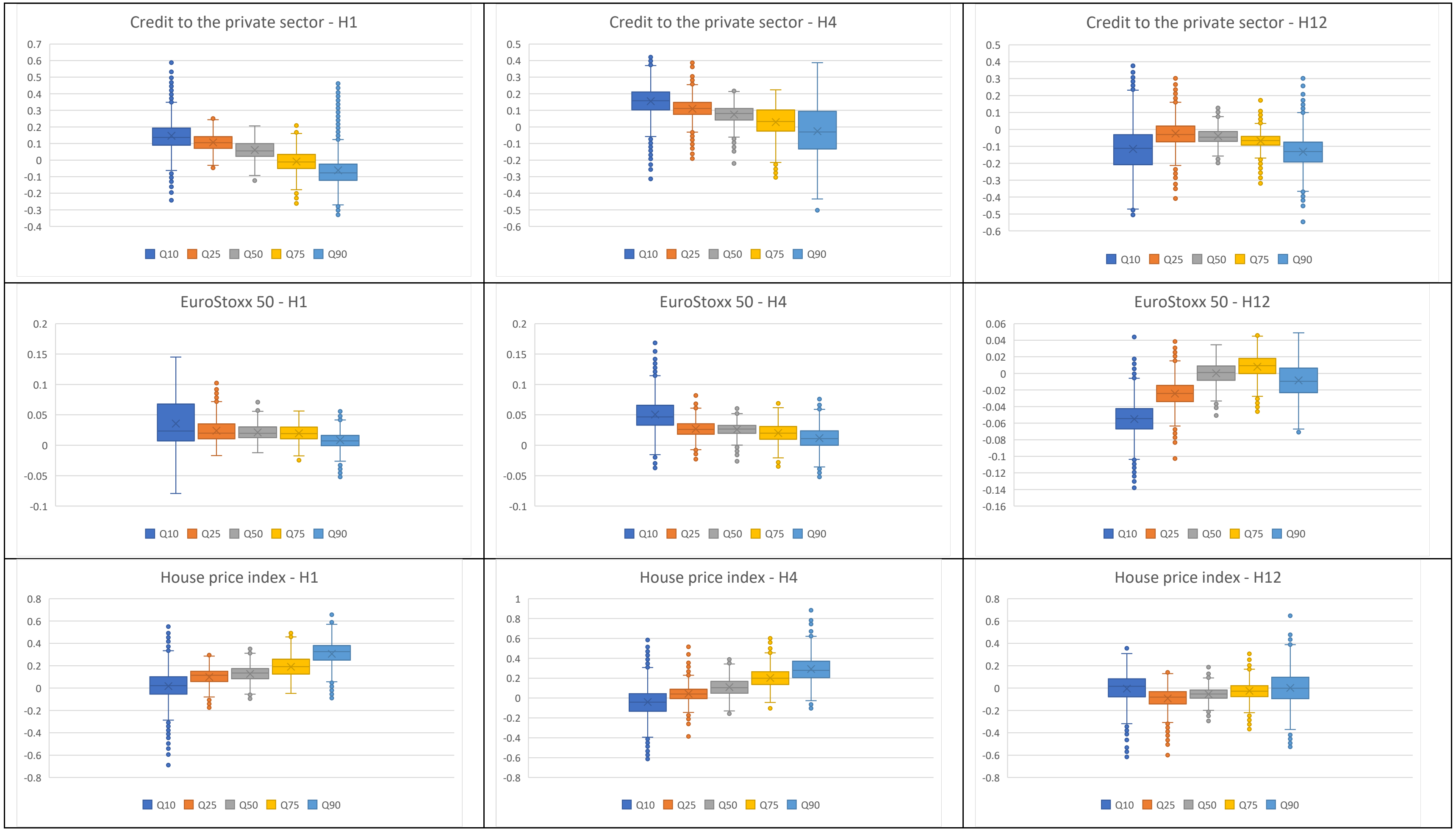

GDP growth 1 quarters ahead
GDP growth 4 quarters ahead
GDP growth 12 quarters ahead
houseprice
exports
brent
Q10
Q50
Q90

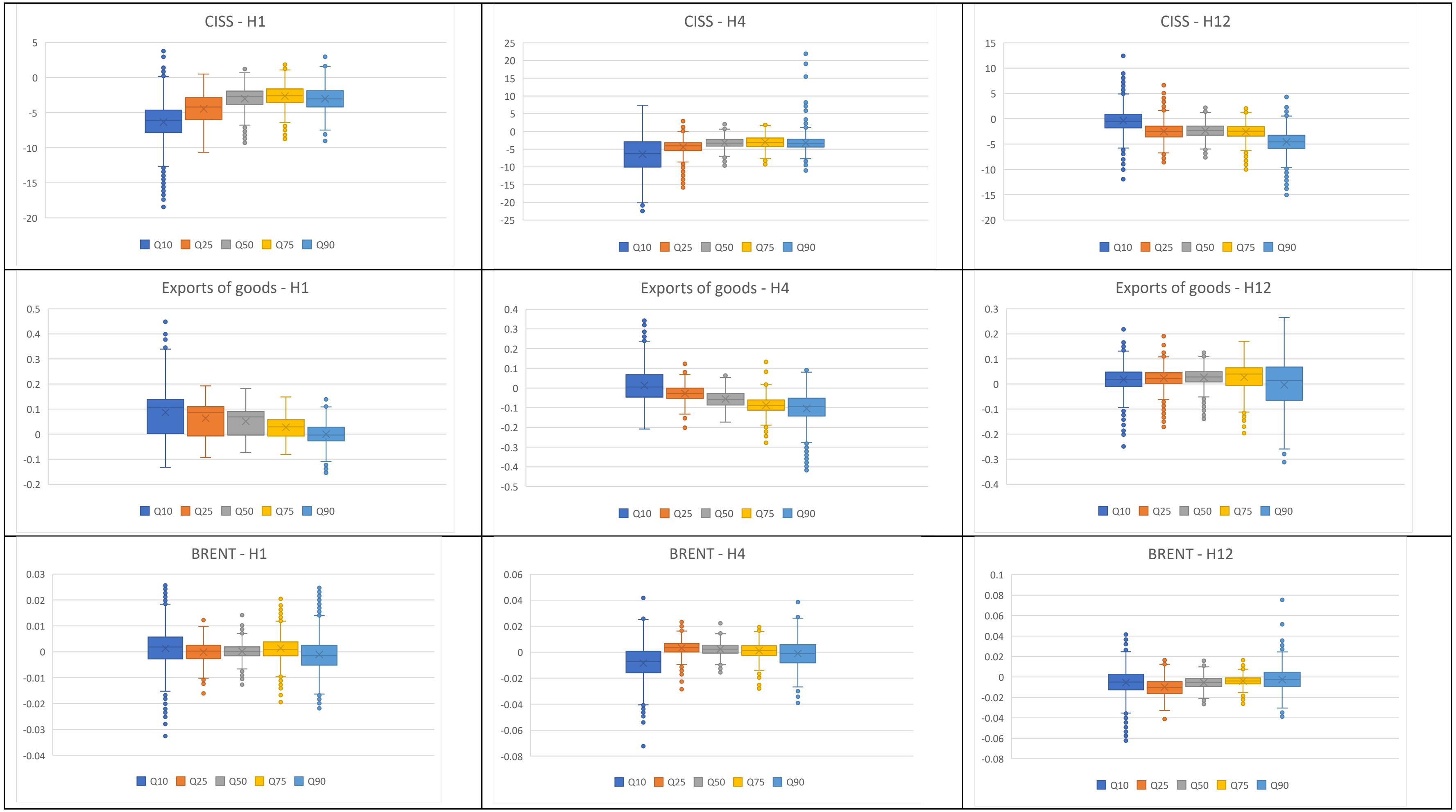


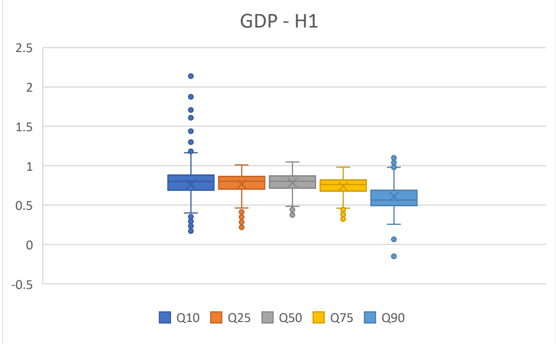
Notes: GDP growth 1-, 4-, and 12-quarters ahead (vertical axis) versus contemporaneous control variable (horizontal axis). Black, red, and blue lines represent three univariate quantile regressions fitted around the 10th, 50th and 90the percentiles of the GDP growth distribution, respectively. The estimation period is Q1:1986-Q4:2024.

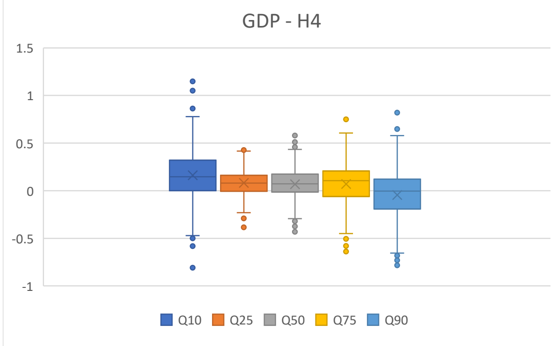
Figure [2]. Distribution of estimated coefficients from quantile regressions – Model and parameter uncertainty

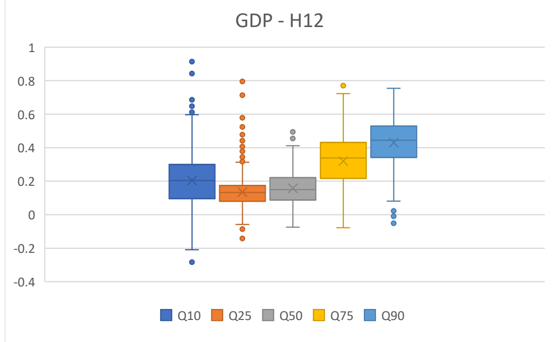



Credit to the private sector - H1
0.7 0.6 0.5 0.4 0.3 0.2 0.1 0 -0.1 -0.2 -0.3 -0.4
Q10 Q25 Q50 Q75 Q90
Credit to the private sector - H4
0.5 0.4 0.3 0.2 0.1 0 -0.1 -0.2 -0.3 -0.4 -0.5 -0.6
Q10 Q25 Q50 Q75 Q90
Credit to the private sector - H12
0.5 0.4 0.3 0.2 0.1 0 -0.1 -0.2 -0.3 -0.4 -0.5 -0.6
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H1
0.2 0.15 0.1 0.05 0 -0.05 -0.1
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H4
0.2 0.15 0.1 0.05 0 -0.05 -0.1
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H12
0.06 0.04 0.02 0 -0.02 -0.04 -0.06 -0.08 -0.1 -0.12 -0.14 -0.16
Q10 Q25 Q50 Q75 Q90
House price index - H1
0.8 0.6 0.4 0.2 0 -0.2 -0.4 -0.6 -0.8
Q10 Q25 Q50 Q75 Q90
House price index - H4
1 0.8 0.6 0.4 0.2 0 -0.2 -0.4 -0.6 -0.8
Q10 Q25 Q50 Q75 Q90
House price index - H12
0.8 0.6 0.4 0.2 0 -0.2 -0.4 -0.6 -0.8
Q10 Q25 Q50 Q75 Q90


CISS - H1
CISS - H4
CISS - H12
Exports of goods - H1
Exports of goods - H4
Exports of goods - H12
BRENT - H1
BRENT - H4
BRENT - H12
Q10 Q25 Q50 Q75 Q90

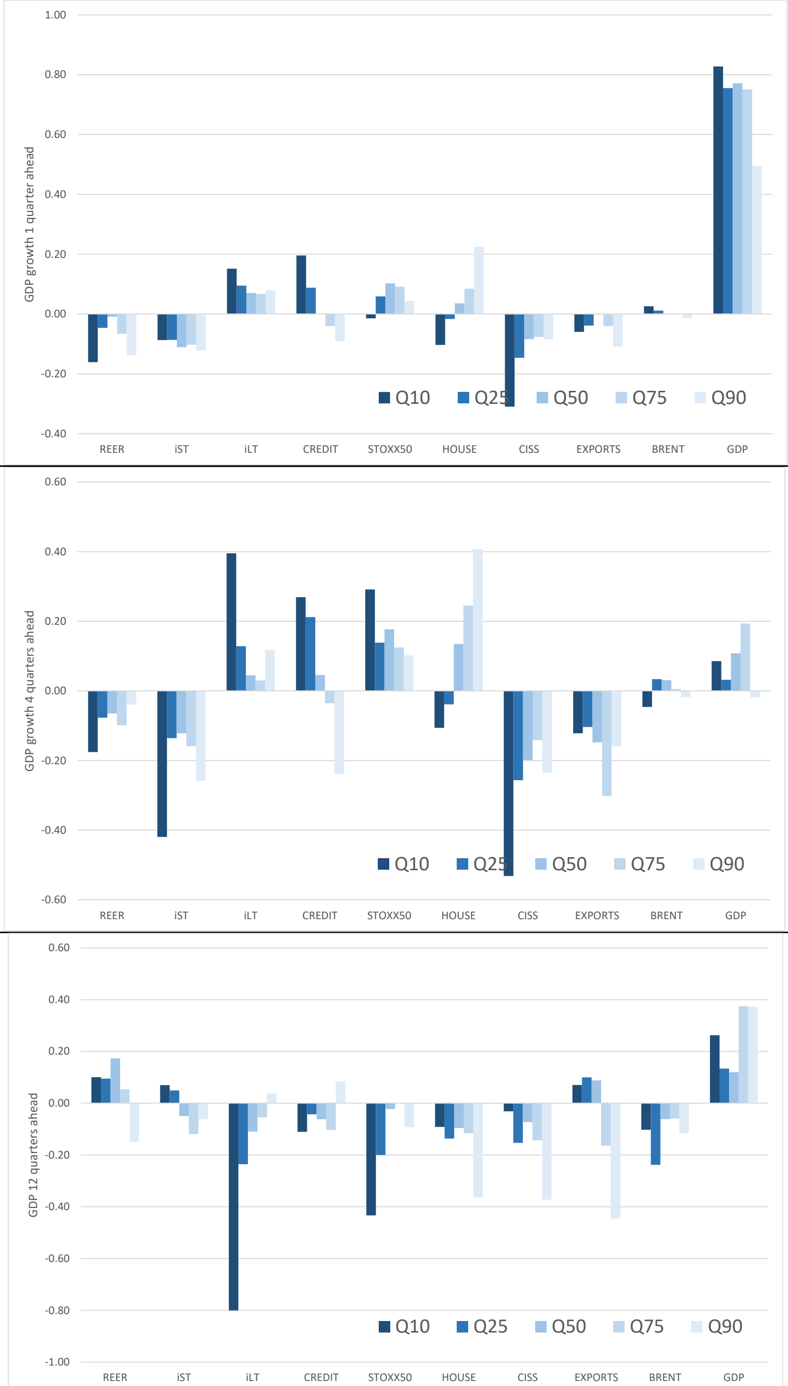






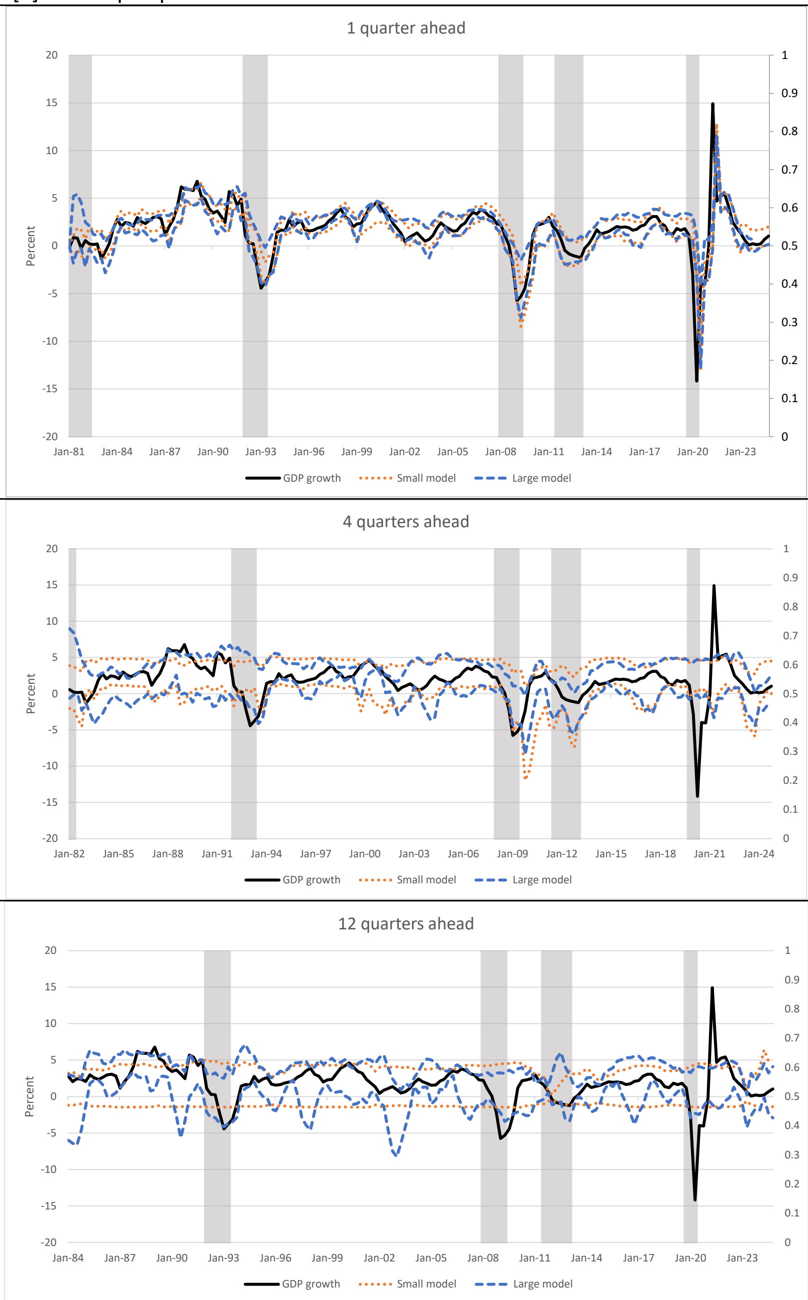
Notes: Estimated coefficients (rows) at 1-, 4-, and 12-quarters horizons (columns) for different percentiles. The boxplots reflect model uncertainty from the alternative regression models listed in Appendix Table [1], as well as parameter uncertainty from 1000 bootstrapped replication of the estimated regression coefficient. The estimation period is Q1:1986-Q4:2024.

Figure [3]. Standardized quantile regression coeffiecients



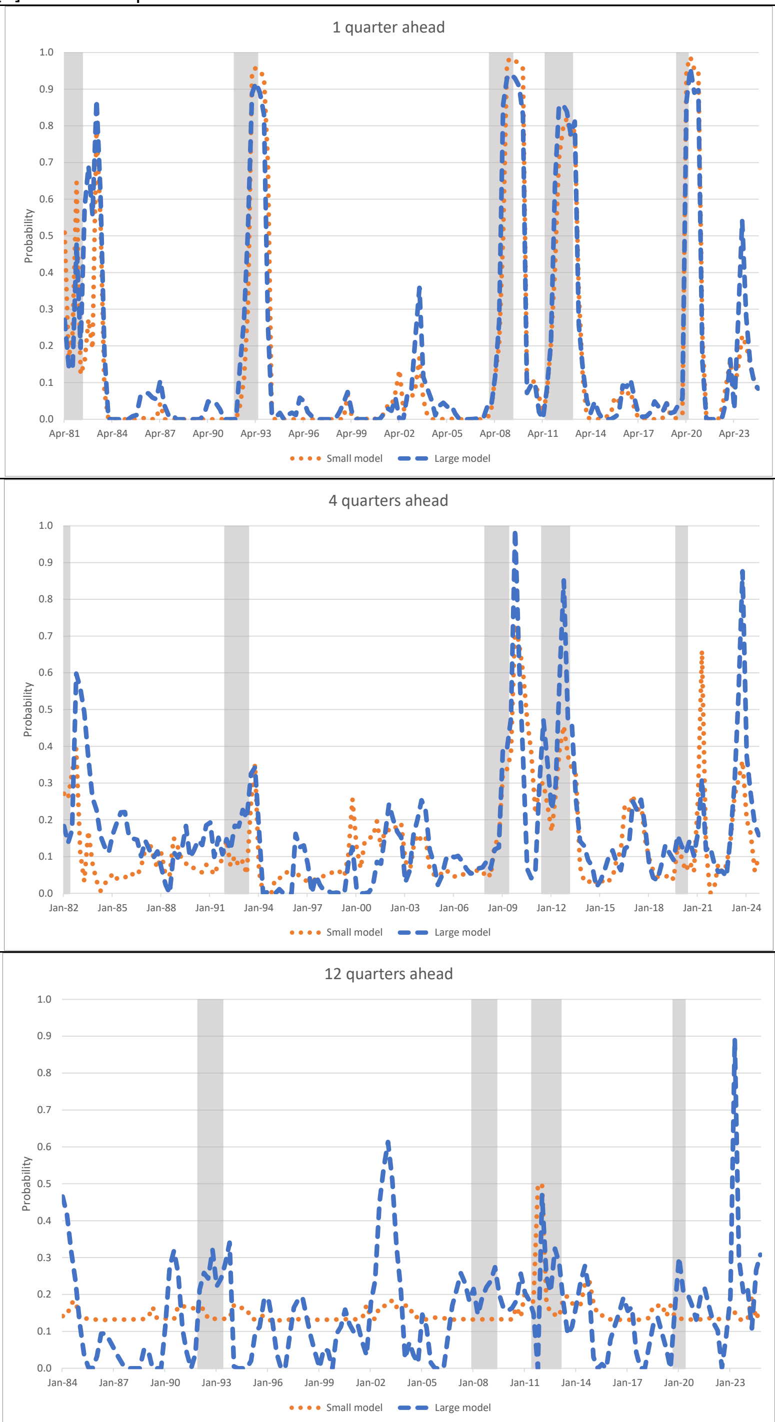
Notes: Standardized coefficients across percentiles from the benchmark regression model (i.e., model #10 in Table [2]). The estimation period is Q1:1986-Q4:2024.

Figure [4]. In-sample quantile forecasts



Notes: In-sample quantile forecasts obtained from the model with GDP and CISS (small model) as well as the model with the full set of regressors (large model). In each panel, the black line represents realized GDP growth; the orange dotted lines the forecasts for the upper (90th percentile) and lower (10th percentile) tails of the small model; and the blue dashed line those for the large model. CEPR recession bands are in light grey. The estimation period is Q1:1986-Q4:2024.

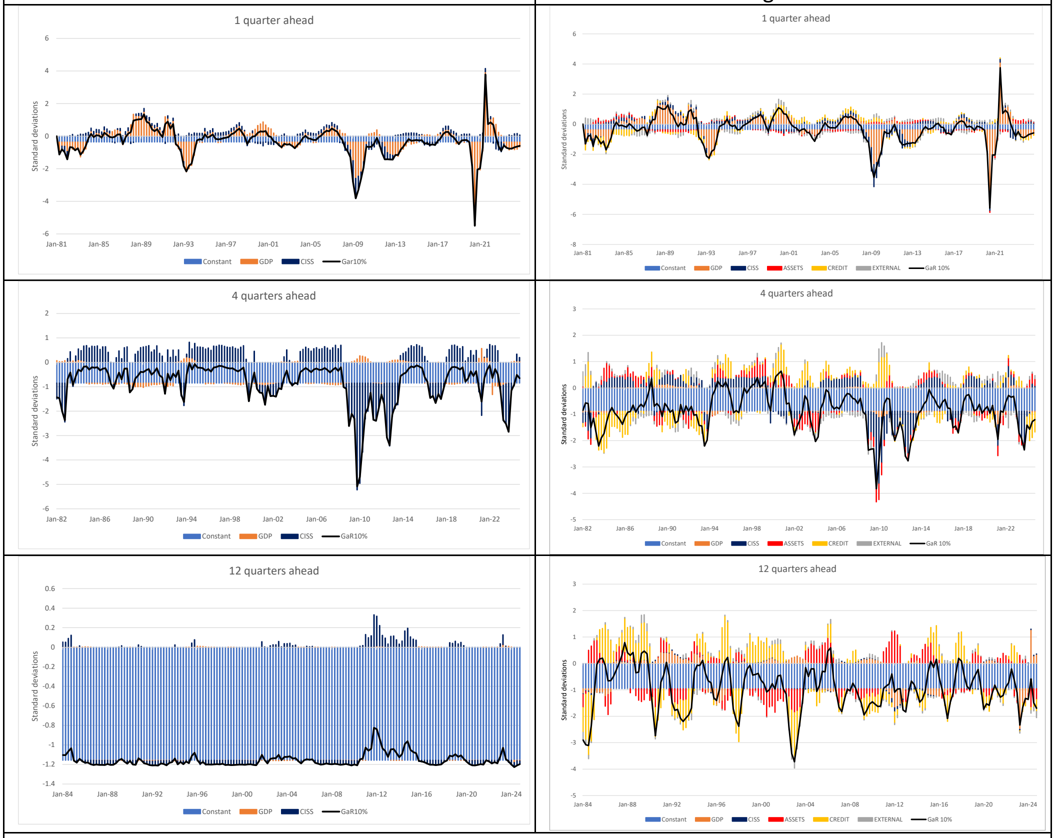
Figure [5]. Recession probabilities



Notes: Probability that annual GDP growth is below zero, as estimated using the small (orange dotted line) and large (blue dashed line) models. CEPR recession bands are in light grey.

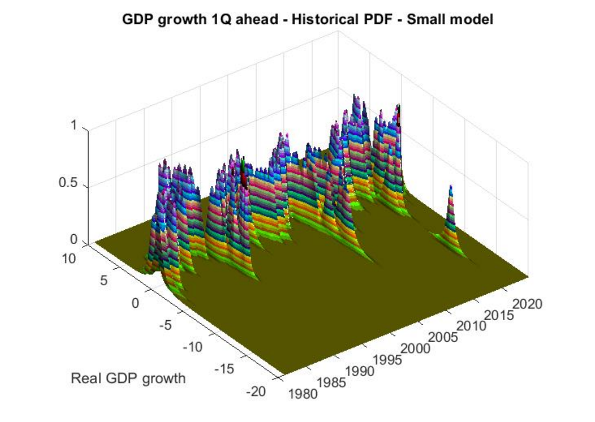
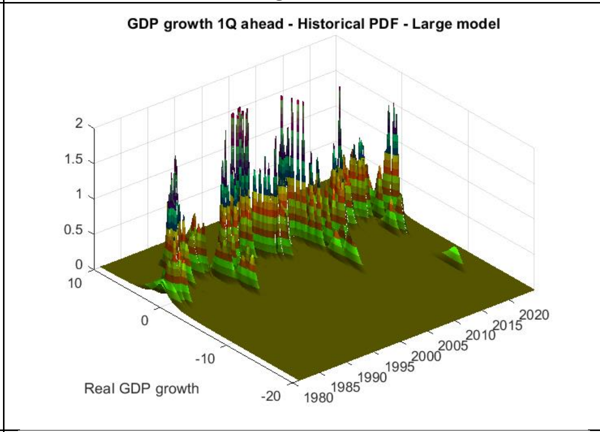
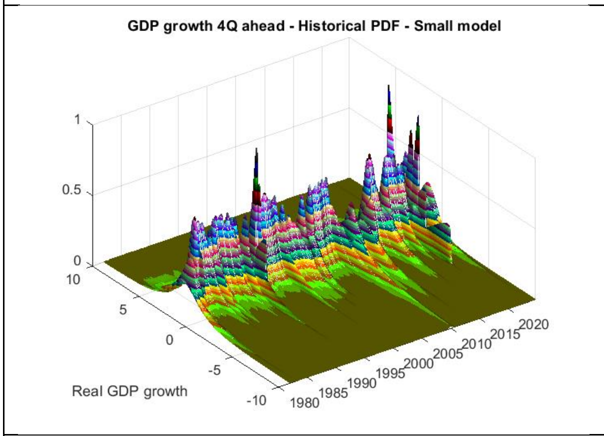
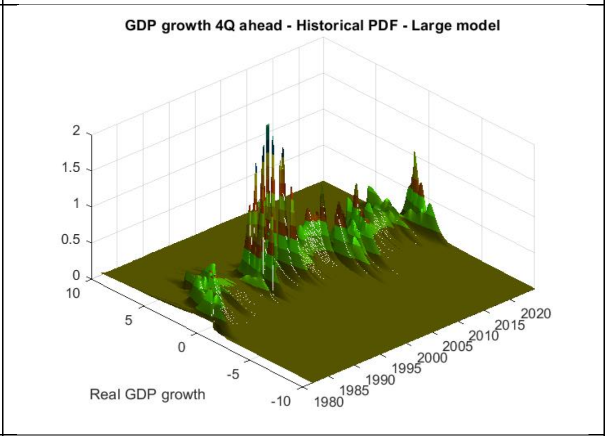
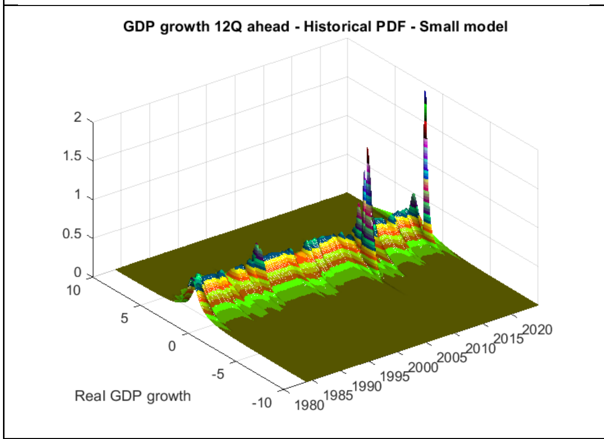
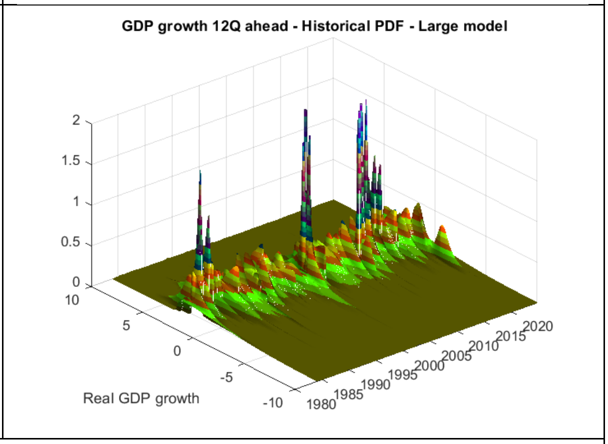
Figure [6]. Growth-at-Risk decomposition

Small model	Large model



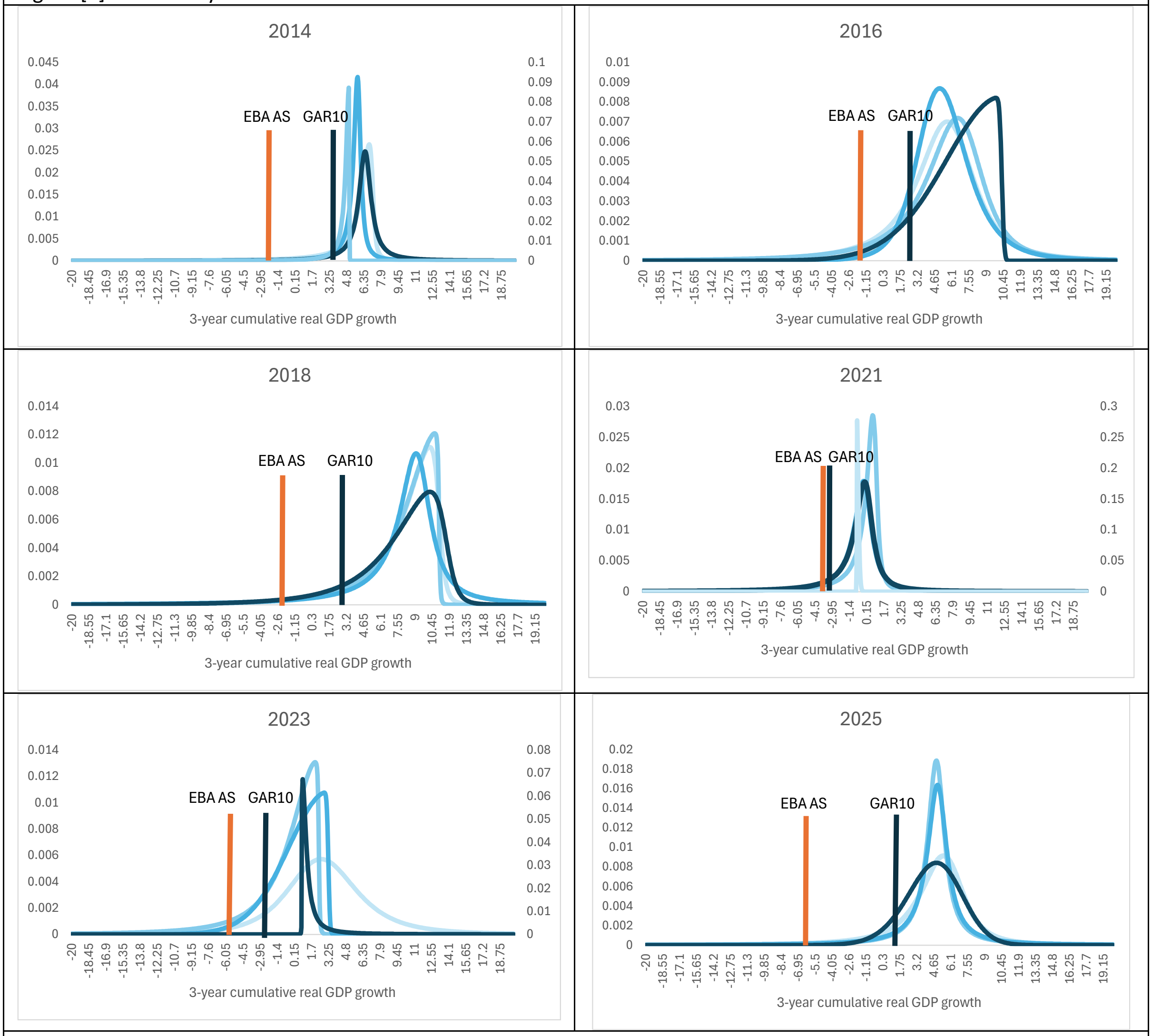
Notes: Contributions of the explanatory variables to Growth-at-Risk (GaR) in both the small and large models. In the large model, some regressors have been grouped for clarity. Specifically, the "assets factor" includes the coefficients associated with the Euro Stoxx 50 and house prices; the "credit factor" combines the coefficients of short- and long-term interest rates, as well as private sector credit; finally, the "external factor" combines the real effective exchange rate, goods exports and oil prices.

Figure [7]. Historical conditional probabilities of GDP growth

Small model	Large model
	
	
	

Notes: Fitted conditional probability density function of future GDP growth one-, four- and twelve-quarter ahead in each year through the estimation sample, using both the small (left) and large (right) GaR models.

Figure [8]. Probability Distribution of 3-Year Cumulative real GDP Growth



Notes: The forecast distributions are based on an out-of-sample projection, with the cutoff date set at the last quarter (Q4) of the year preceding the EBA stress test exercise. The figure illustrates the probability distribution of three-year cumulative GDP growth across four different models. The small GaR model (light blue) includes GDP and CISS. The large GaR model (dark blue) incorporates all available regressors. Two intermediate models are also presented: one (medium blue) includes GDP, CISS, long-term interest rates, private sector credit, and house prices, while the other (darker medium blue) extends this set by adding the stock market index and the REER. The EBA Adverse Scenario (AS) represents the severity of the adverse scenario used in the European Systemic Risk Board reports. The GaR10 metric captures the worst potential cumulative GDP growth over a given horizon (three years in this case) that is expected to occur with a 10% probability, based on the estimated probability distribution of growth outcomes. The figure reports the median GaR10 across the four models.

Appendix

Appendix Table [1]. Explanatory variables' coefficients and p-value across term structure of forecast horizon and growth distribution quantiles

1-quarter ahead

	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	-0.03	0.06	-0.06	-0.04	-0.02	-0.05	-0.04	-0.02	-0.03	-0.05	-0.05	-0.02	-0.03	0.03	-0.03	-0.03	0.01	-0.06	-0.06	-0.08	-0.06	-0.02	-0.06	-0.04	-0.02	-0.04	-0.05	-0.03	-0.05	-0.03
	0.19	0.11	0.09	0.11	0.67	0.14	0.12	0.63	0.37	0.05	0.17	0.48	0.27	0.38	0.42	0.10	0.87	0.10	0.00	0.00	0.08	0.31	0.08	0.39	0.35	0.26	0.30	0.04	0.02	0.09
Short-term rate				0.51	0.52	0.27	0.48	0.67	0.23	0.46	0.77	0.36	0.31	0.11	0.33	0.23	0.20	-0.19	0.15	0.18	-0.23	0.04	0.10	-0.26	0.04	0.13	-0.23	-0.32	-0.22	-0.35
				0.00	0.01	0.16	0.00	0.00	0.24	0.00	0.00	0.05	0.02	0.59	0.13	0.05	0.30	0.35	0.15	0.21	0.23	0.72	0.52	0.19	0.72	0.40	0.25	0.00	0.05	0.00
Long-term rate							0.12	0.39	0.32	0.25	0.38	0.34	0.42	0.63	0.34	0.07	0.10	-0.09	0.33	0.55	-0.01	0.20	0.59	-0.01	0.21	0.52	-0.13	0.20	0.27	0.09
							0.48	0.13	0.17	0.13	0.11	0.13	0.01	0.01	0.21	0.64	0.68	0.73	0.02	0.01	0.96	0.19	0.00	0.97	0.18	0.02	0.66	0.02	0.07	0.51
Private sector credit										0.13	0.19	0.08	0.11	0.15	0.14	0.02	0.13	-0.13	0.09	0.13	-0.09	0.06	0.13	-0.06	0.06	0.11	-0.09	0.02	0.10	-0.07
										0.00	0.00	0.10	0.00	0.00	0.02	0.55	0.01	0.03	0.01	0.00	0.14	0.07	0.01	0.28	0.07	0.01	0.15	0.26	0.00	0.01
Euro Stoxx 50													0.04	0.07	-0.02	0.03	0.06	0.00	0.01	0.02	0.00	0.01	0.02	0.00	0.01	0.02	0.00	0.01	-0.01	0.02
													0.00	0.00	0.24	0.00	0.00	0.86	0.25	0.07	0.85	0.39	0.07	0.78	0.38	0.04	0.72	0.01	0.41	0.01
House prices																0.27	0.29	0.38	0.18	0.13	0.38	0.21	0.12	0.36	0.21	0.15	0.39	-0.01	-0.03	0.04
																0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.60	0.58	0.35
CISS																			-5.89	-6.66	-3.66	-4.89	-6.39	-4.65	-4.88	-6.15	-4.57	-2.34	-5.42	-0.50
																			0.00	0.00	0.05	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.57
Exports																						0.06	0.03	0.03	0.06	0.06	0.02	-0.03	0.00	-0.03
																						0.01	0.41	0.40	0.01	0.07	0.57	0.04	0.98	0.22
BRENT																									0.00	-0.01	0.00	0.01	0.00	0.01
																									0.78	0.10	0.68	0.04	0.83	0.14
GDP																												0.88	0.79	0.91
																												0.00	0.00	0.00

4-quarters ahead

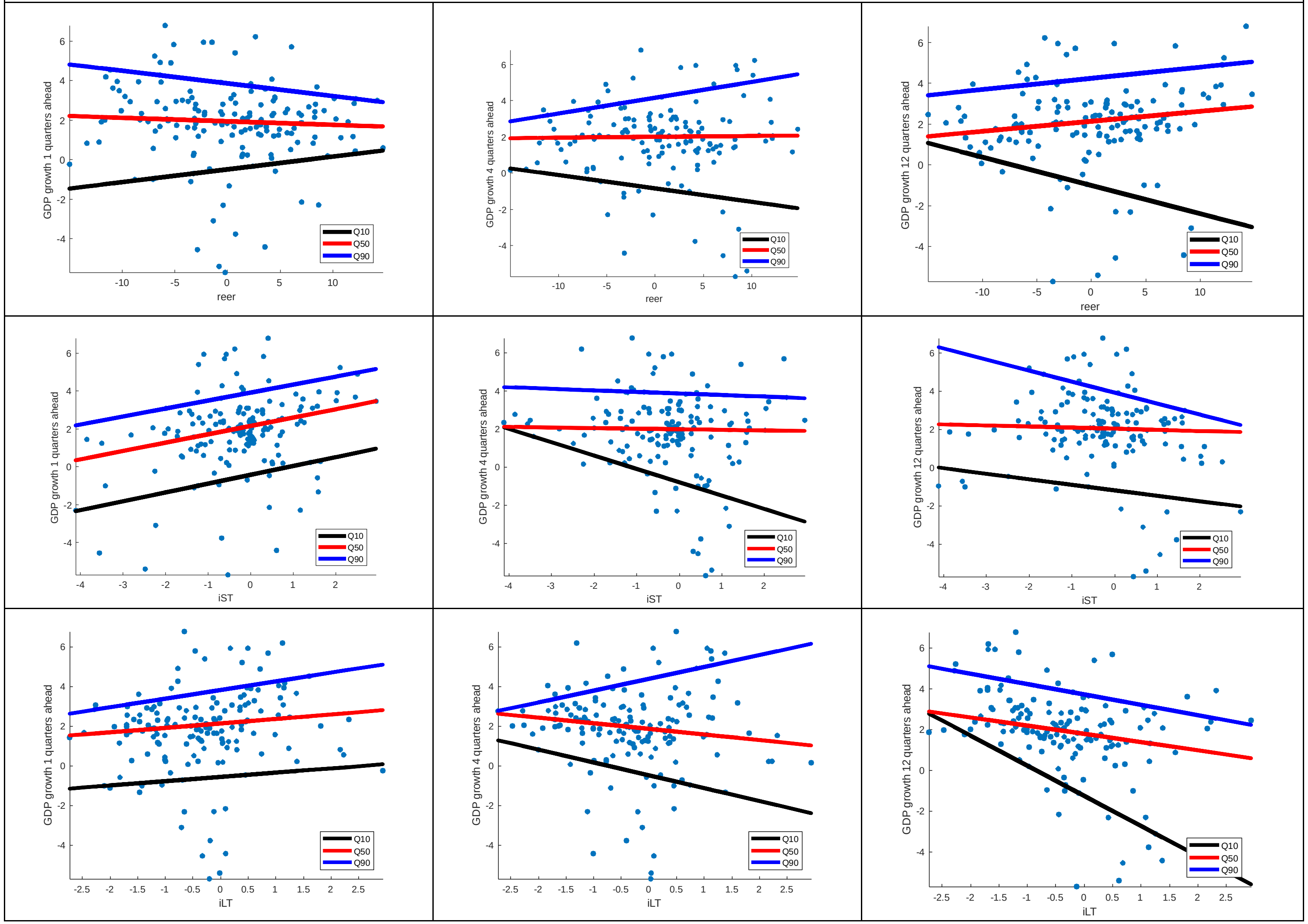
	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	-0.01	-0.07	0.09	0.00	0.03	0.09	0.00	0.04	0.07	-0.01	-0.11	0.07	0.02	-0.02	0.07	0.01	-0.03	0.00	-0.02	-0.09	0.05	-0.05	-0.11	0.00	-0.05	-0.11	-0.06	-0.05	-0.11	-0.09
	0.85	0.10	0.04	0.92	0.46	0.05	0.91	0.39	0.13	0.68	0.01	0.08	0.55	0.54	0.08	0.76	0.42	0.95	0.49	0.03	0.18	0.09	0.04	0.99	0.14	0.06	0.24	0.13	0.06	0.10
Short-term rate				-0.20	-0.73	-0.08	-0.18	-0.72	-0.37	-0.20	-0.63	-0.19	-0.35	-0.69	-0.36	-0.42	-0.64	-0.53	-0.47	-0.65	-0.59	-0.38	-0.62	-0.57	-0.38	-0.67	-0.62	-0.46	-0.67	-0.48
				0.16	0.00	0.72	0.22	0.00	0.12	0.17	0.01	0.42	0.01	0.00	0.11	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.06
Long-term rate							-0.06	-0.09	0.75	0.04	0.13	0.60	0.23	0.39	0.73	-0.05	0.10	-0.16	0.15	0.79	0.21	0.26	0.82	0.25	0.33	0.92	0.50	0.32	0.92	0.17
							0.71	0.75	0.01	0.80	0.63	0.03	0.17	0.11	0.01	0.76	0.70	0.56	0.39	0.01	0.47	0.15	0.01	0.42	0.10	0.01	0.15	0.09	0.01	0.63
Private sector credit										0.11	0.18	0.09	0.08	0.12	0.02	0.01	0.14	-0.14	0.07	0.15	-0.05	0.09	0.16	-0.12	0.10	0.17	-0.17	0.09	0.17	-0.22
										0.00	0.00	0.14	0.02	0.01	0.66	0.72	0.01	0.01	0.08	0.03	0.43	0.02	0.03	0.08	0.02	0.02	0.02	0.03	0.02	0.00
Euro Stoxx 50													0.04	0.05	0.02	0.04	0.04	0.03	0.02	0.02	0.00	0.02	0.03	0.01	0.02	0.03	0.03	0.02	0.03	0.04
													0.00	0.00	0.11	0.00	0.00	0.03	0.06	0.15	0.84	0.04	0.09	0.45	0.03	0.08	0.10	0.02	0.09	0.02
House prices																0.21	0.18	0.33	0.14	0.03	0.21	0.11	-0.02	0.27	0.11	-0.02	0.30	0.06	-0.02	0.23
																0.00	0.01	0.00	0.01	0.71	0.01	0.03	0.87	0.00	0.03	0.82	0.00	0.30	0.84	0.03
CISS																			-4.53	-11.12	-4.00	-5.37	-11.84	-4.17	-5.33	-11.30	-4.58	-4.74	-11.30	-0.70
																			0.00	0.00	0.05	0.00	0.00	0.06	0.00	0.00	0.04	0.00	0.00	0.76
Exports																						-0.05	-0.04	-0.04	-0.04	-0.03	-0.07	-0.07	-0.03	-0.16
																						0.06	0.39	0.36	0.13	0.52	0.19	0.03	0.55	0.00
BRENT																									0.00	0.00	-0.01	0.00	0.00	0.00
																									0.35	0.78	0.42	0.51	0.79	0.95
GDP																												0.20	0.00	0.50
																												0.06	1.00	0.01

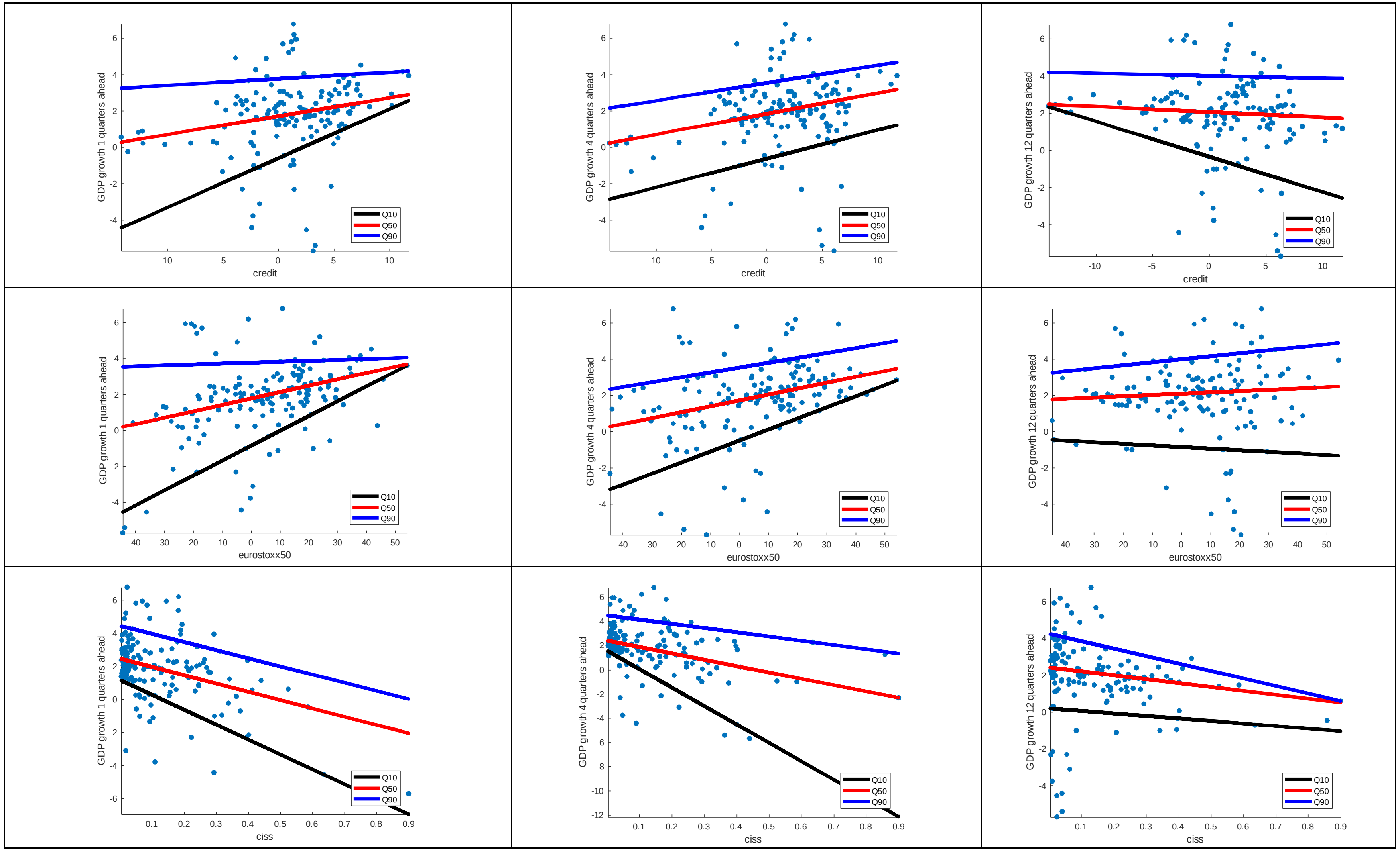
12-quarters ahead

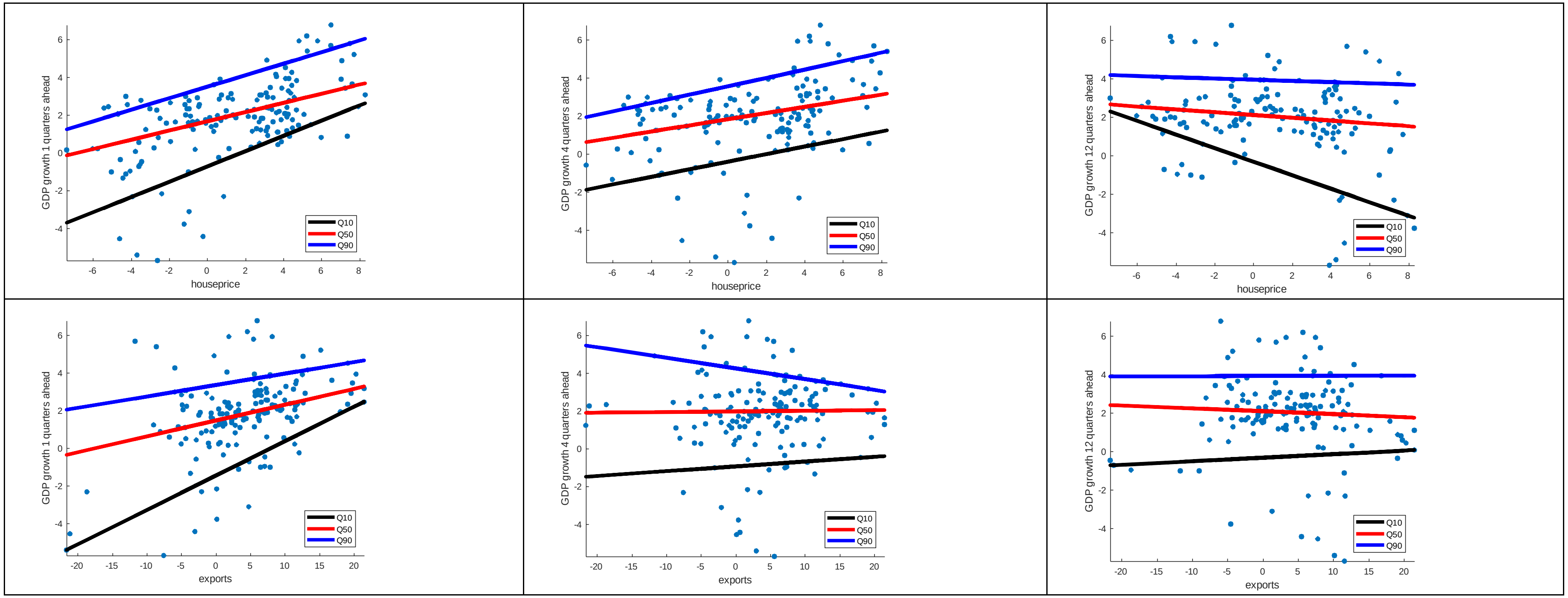
	Model #1			Model #2			Model #3			Model #4			Model #5			Model #6			Model #7			Model #8			Model #9			Model #10		
Explanatory variable	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**	**OLS**	**10th pct**	**90th pct**
REER	0.03	-0.14	0.05	0.03	-0.19	0.02	0.03	-0.03	0.03	0.03	-0.02	0.01	0.04	-0.01	0.08	0.04	-0.01	0.05	0.02	-0.03	0.01	0.05	0.13	0.07	0.06	0.14	0.06	0.06	0.13	0.09
	0.32	0.01	0.18	0.25	0.00	0.57	0.31	0.54	0.40	0.18	0.63	0.76	0.18	0.86	0.05	0.16	0.88	0.16	0.39	0.53	0.72	0.13	0.05	0.19	0.09	0.04	0.22	0.07	0.05	0.07
Short-term rate				-0.33	-0.28	-0.53	-0.17	0.25	-0.22	-0.15	0.20	-0.24	-0.16	0.37	-0.42	-0.15	0.38	-0.40	-0.18	0.36	-0.30	-0.26	0.09	-0.21	-0.26	0.06	-0.21	-0.46	-0.08	-0.52
				0.02	0.29	0.01	0.23	0.29	0.24	0.27	0.40	0.27	0.26	0.15	0.05	0.30	0.14	0.05	0.20	0.16	0.16	0.09	0.75	0.35	0.09	0.85	0.36	0.00	0.79	0.02
Long-term rate							-0.62	-1.63	-0.39	-0.72	-1.52	-0.52	-0.71	-2.01	-0.43	-0.66	-1.87	-0.39	-0.54	-1.95	-0.63	-0.63	-1.78	-0.72	-0.54	-1.78	-0.74	-0.54	-2.10	-0.35
							0.00	0.00	0.09	0.00	0.00	0.05	0.00	0.00	0.09	0.00	0.00	0.15	0.01	0.00	0.03	0.00	0.00	0.02	0.02	0.00	0.03	0.01	0.00	0.23
Private sector credit										-0.10	-0.14	-0.19	-0.10	-0.07	-0.16	-0.09	-0.08	-0.14	-0.06	-0.06	-0.07	-0.08	-0.09	-0.14	-0.07	-0.12	-0.14	-0.09	-0.07	-0.18
										0.00	0.02	0.00	0.00	0.27	0.00	0.02	0.29	0.01	0.16	0.45	0.24	0.08	0.29	0.04	0.12	0.18	0.04	0.03	0.38	0.00
Euro Stoxx 50													0.00	-0.03	0.02	0.00	-0.03	0.01	-0.01	-0.05	-0.01	-0.01	-0.04	0.00	-0.01	-0.04	-0.01	0.00	-0.04	0.01
													0.79	0.03	0.17	0.72	0.04	0.31	0.47	0.01	0.40	0.40	0.03	0.76	0.48	0.03	0.71	0.66	0.06	0.38
House prices																-0.04	-0.03	-0.11	-0.08	-0.03	-0.04	-0.06	-0.17	0.04	-0.06	-0.14	0.03	-0.18	-0.23	-0.10
																0.45	0.75	0.15	0.16	0.74	0.61	0.34	0.15	0.67	0.35	0.21	0.74	0.00	0.07	0.26
CISS																			-2.65	-1.58	-5.20	-1.96	-0.16	-2.81	-1.88	-0.04	-2.91	-0.40	1.62	0.06
																			0.05	0.52	0.01	0.17	0.95	0.19	0.19	0.99	0.18	0.77	0.56	0.97
Exports																						0.04	0.07	0.08	0.05	0.08	0.08	0.00	0.01	0.00
																						0.18	0.21	0.09	0.10	0.20	0.11	0.92	0.82	0.94
BRENT																									-0.01	0.00	0.00	0.00	0.00	0.00
																									0.24	0.80	0.95	0.52	0.96	0.73
GDP																												0.49	0.54	0.65
																												0.00	0.02	0.00

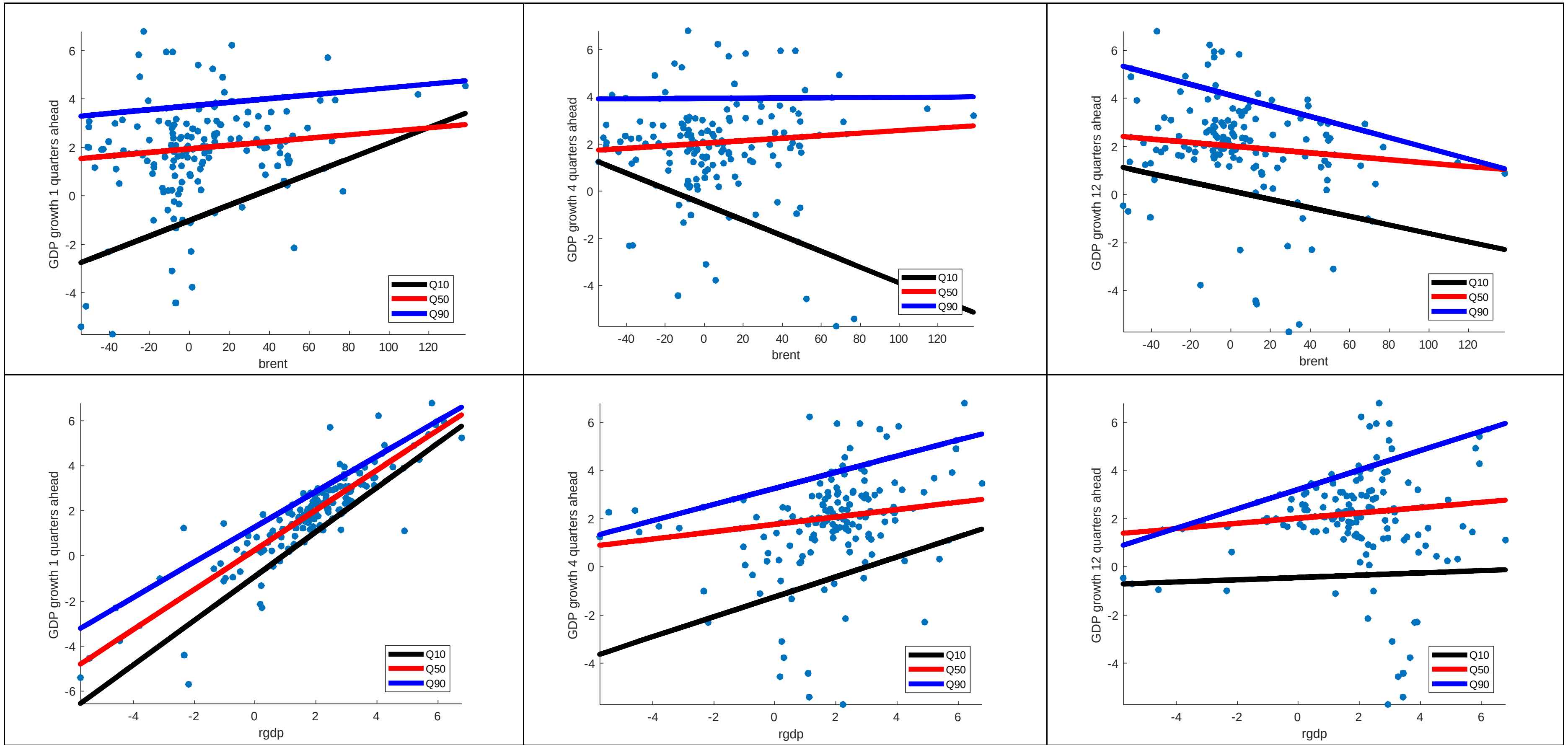
Note: Coefficients and p-values are based on OLS regressions and quantile regressions of growth distributions at the 10th and 90the percentiles. The estimation period is Q1:1986-Q4:2019.

Appendix Figure [1]. Univariate quantile regressions between future GDP growth and the contemporaneous dependent variable



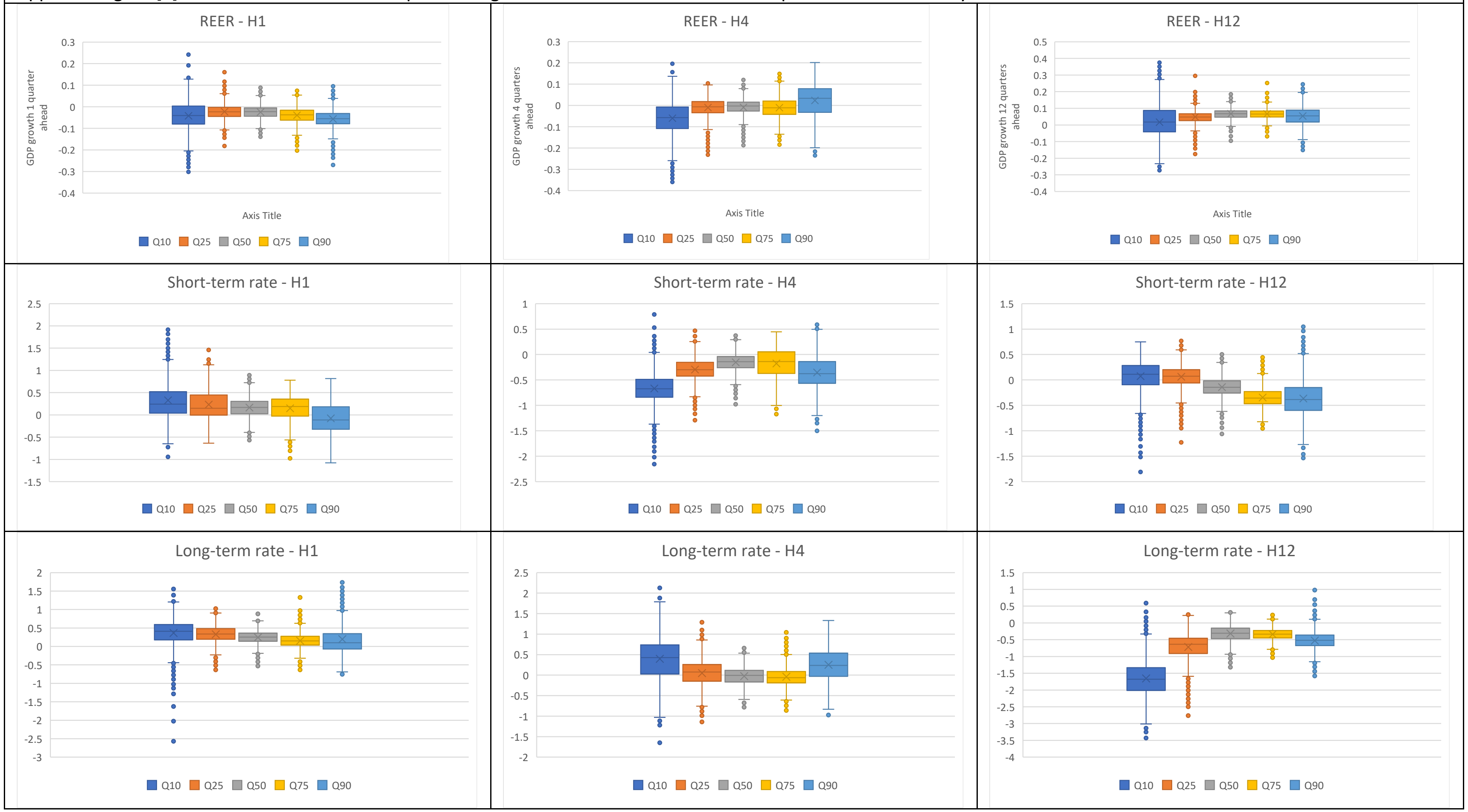

GDP growth 1 quarters ahead
GDP growth 4 quarters ahead
GDP growth 12 quarters ahead
credit
eurostoxx50
ciss
Q10
Q50
Q90

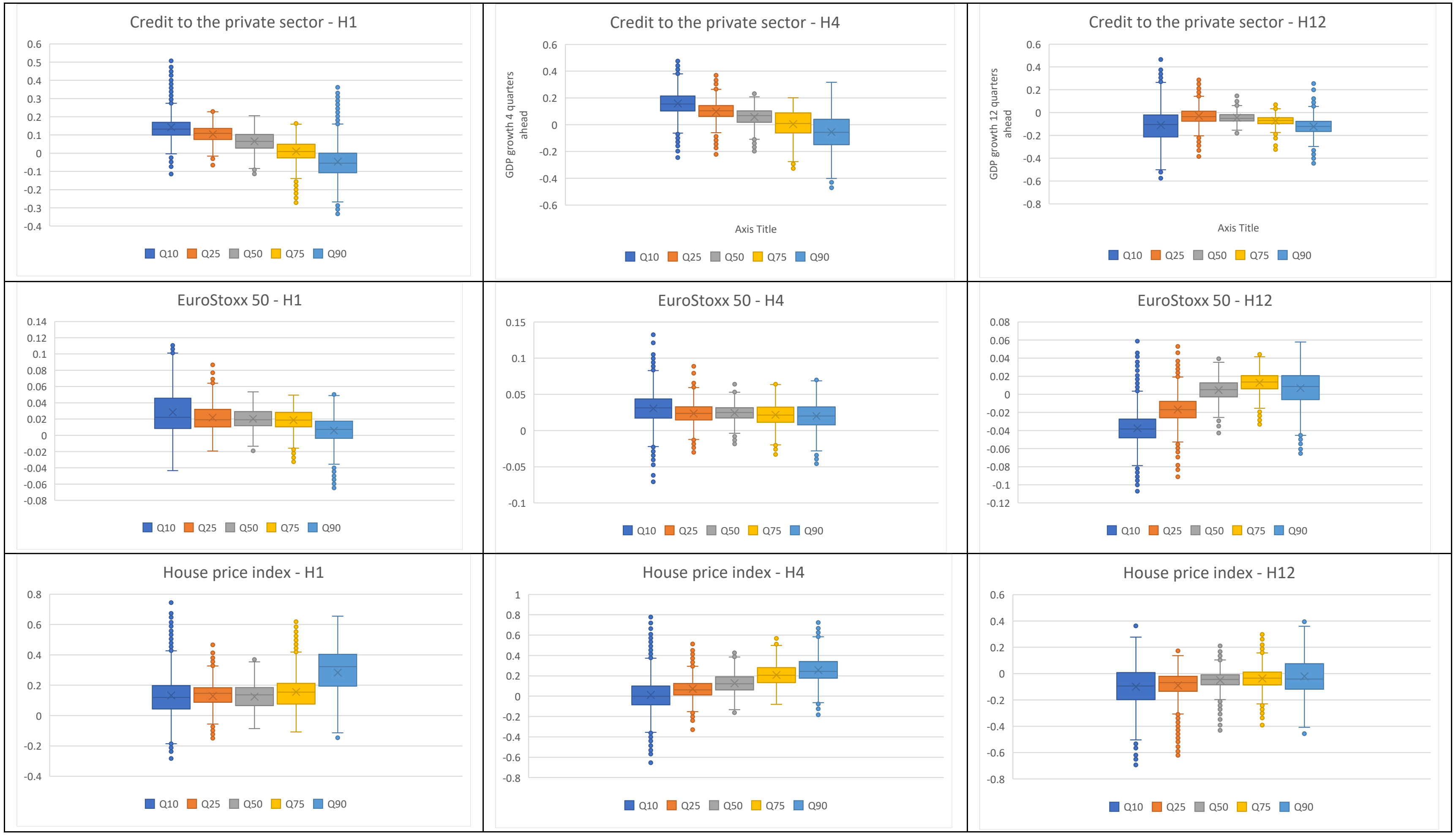

GDP growth 1 quarters ahead
houseprice
Q10
Q50
Q90
GDP growth 4 quarters ahead
houseprice
Q10
Q50
Q90
GDP growth 12 quarters ahead
houseprice
Q10
Q50
Q90
GDP growth 1 quarters ahead
exports
Q10
Q50
Q90
GDP growth 4 quarters ahead
exports
Q10
Q50
Q90
GDP growth 12 quarters ahead
exports
Q10
Q50
Q90



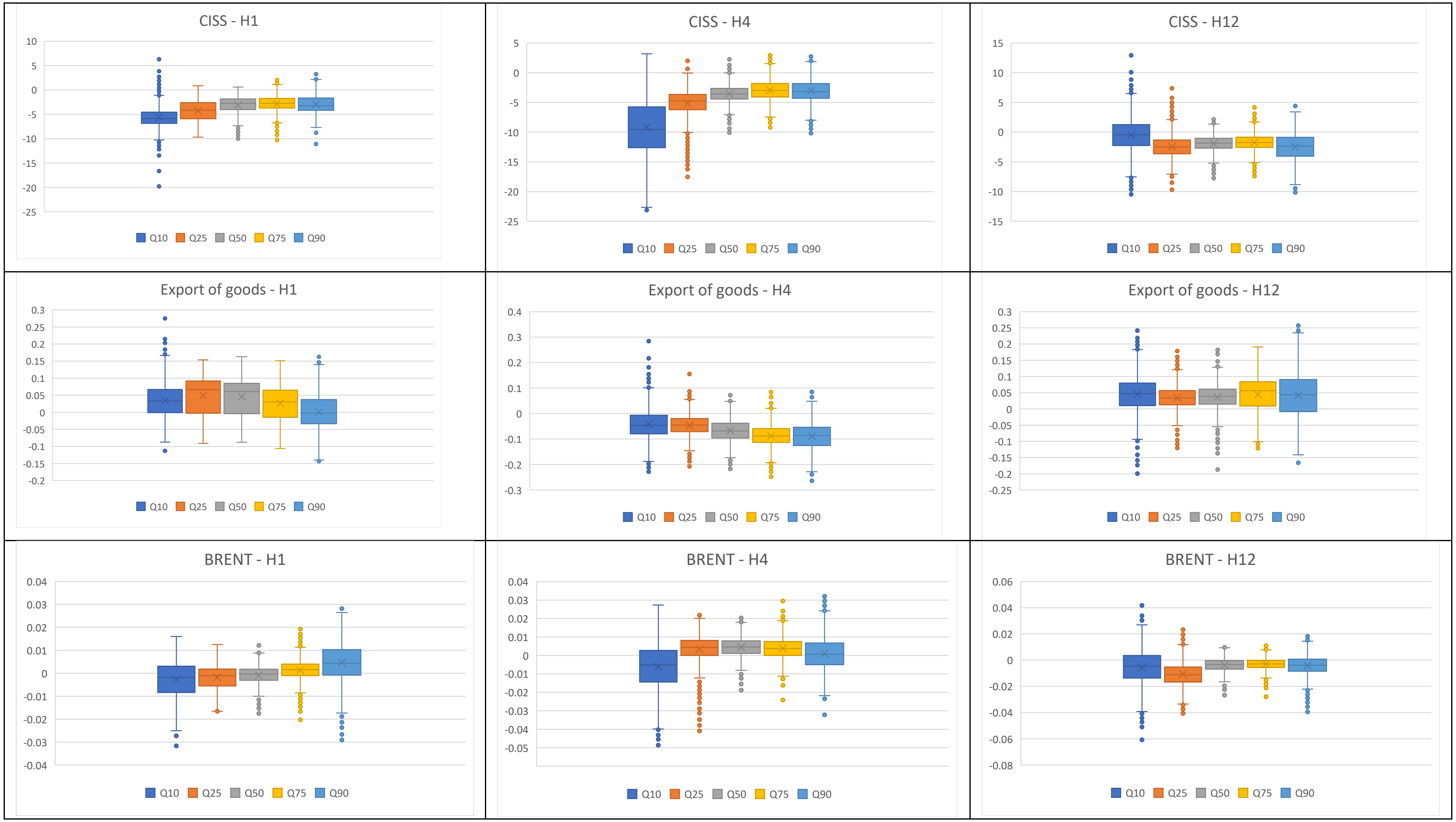
Notes: GDP growth 1-, 4-, and 12-quarters ahead (vertical axis) versus contemporaneous control variable (horizontal axis). Black, red, and blue lines represent three univariate quantile regressions fitted around the 10th, 50th and 90th percentiles of the GDP growth distribution, respectively. The estimation period is Q1:1986-Q4:2019.

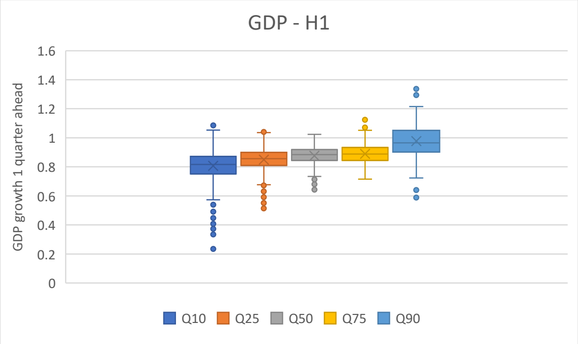
Appendix Figure [2]. Distribution of estimated quantile regressions coefficients – Model and parameter uncertainty

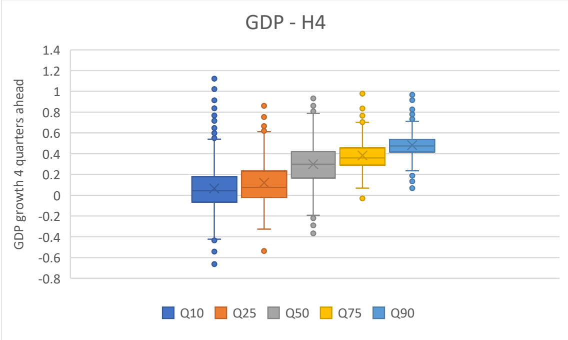


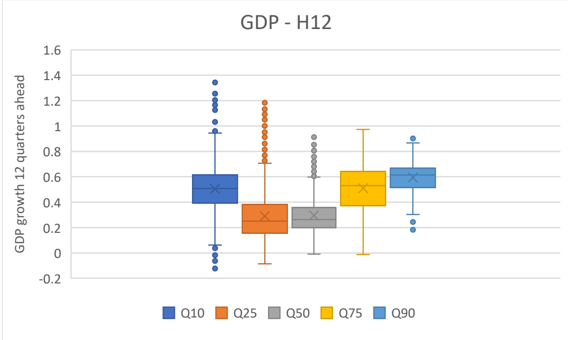


Credit to the private sector - H1
Q10 Q25 Q50 Q75 Q90
Credit to the private sector - H4
GDP growth 4 quarters ahead
Axis Title
Q10 Q25 Q50 Q75 Q90
Credit to the private sector - H12
GDP growth 12 quarters ahead
Axis Title
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H1
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H4
Q10 Q25 Q50 Q75 Q90
EuroStoxx 50 - H12
Q10 Q25 Q50 Q75 Q90
House price index - H1
Q10 Q25 Q50 Q75 Q90
House price index - H4
Q10 Q25 Q50 Q75 Q90
House price index - H12
Q10 Q25 Q50 Q75 Q90


CISS - H1
CISS - H4
CISS - H12
Export of goods - H1
Export of goods - H4
Export of goods - H12
BRENT - H1
BRENT - H4
BRENT - H12
Q10 Q25 Q50 Q75 Q90





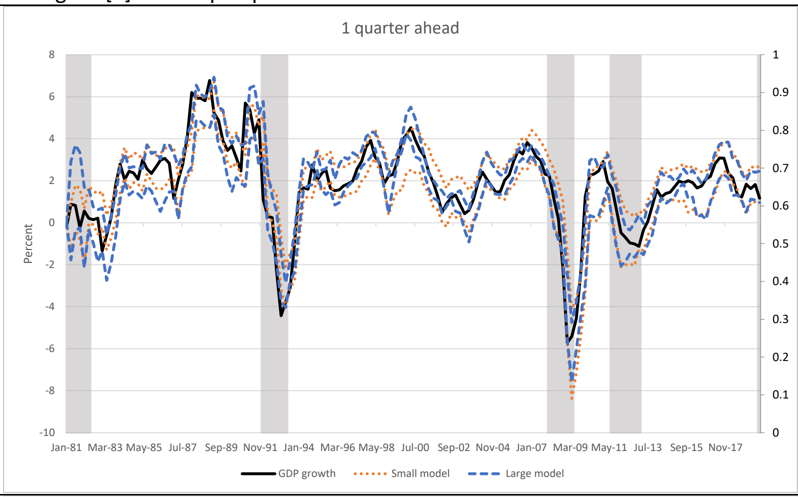


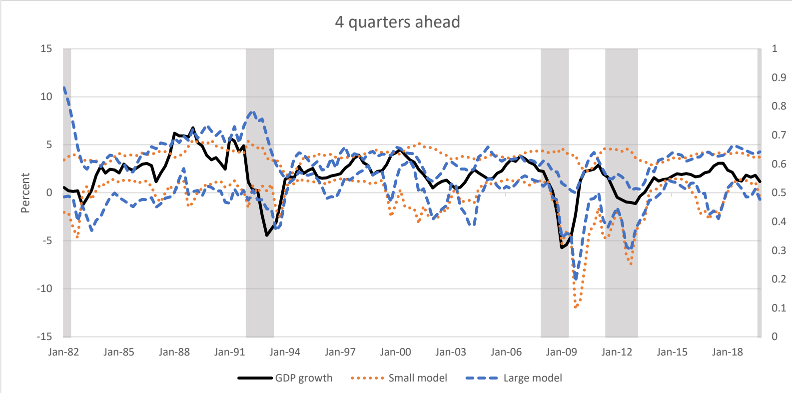
Notes: Estimated coefficients (rows) at 1-, 4-, and 12-quarters horizons (columns) for different percentiles. The boxplots reflect model uncertainty from the alternative regression models listed in Table [2] (from #1 to #10), as well as parameter uncertainty from 1000 bootstrapped replication of the estimated regression coefficient. The estimation period is Q1:1986-Q4:2019.

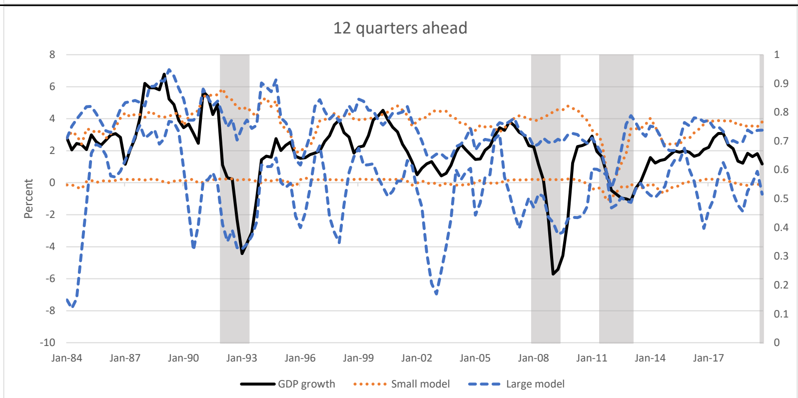
Appendix Figure [3]. Standardized quantile regression coefficients

Notes: Standardized coefficients across percentiles from the benchmark regression model (i.e., model #10 in Appendix Table [1]). The estimation period is Q1:1986-Q4:2019.

Appendix Figure [4]. In-sample quantile forecasts







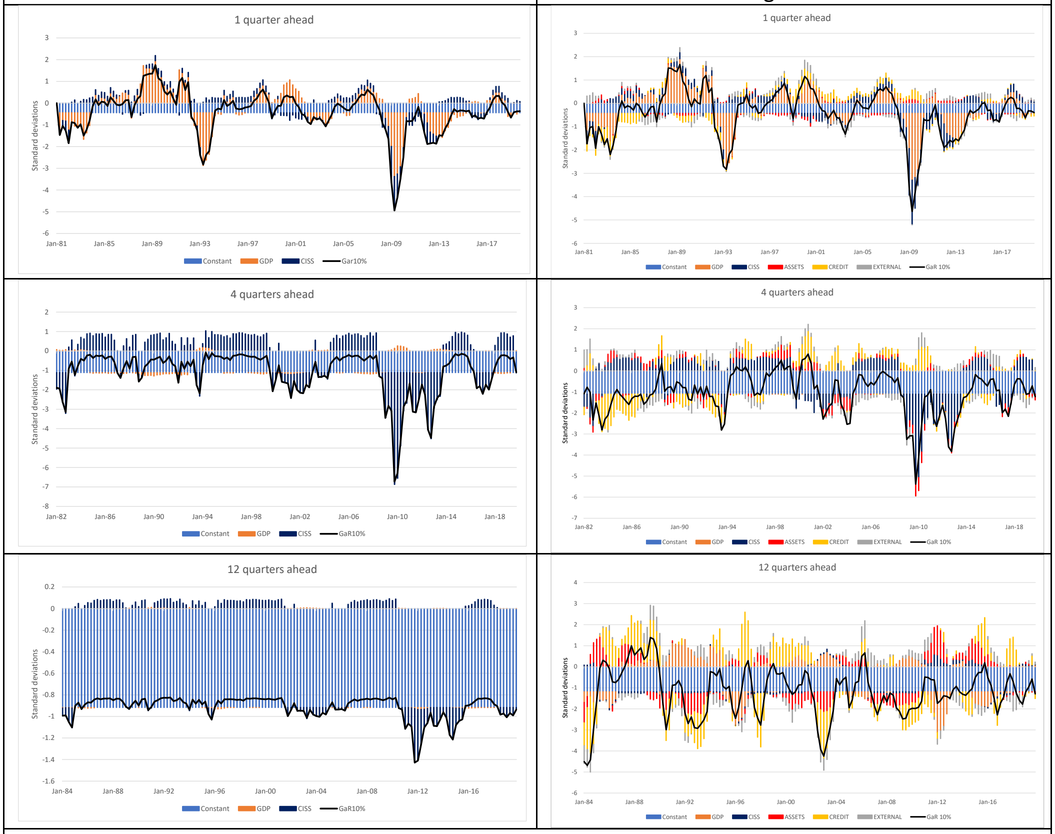
Notes: In-sample quantile forecasts obtained from the model with GDP and CISS (small model) as well as the model with the full set of regressors (large model). In each panel, the black line represents realized GDP growth; the orange dotted lines the forecasts for the upper (90th percentile) and lower (10th percentile) tails of the small model; and the blue dashed line those for the large model. CEPR recession bands are in light grey. The estimation period is Q1:1986-Q4:2019.

Appendix Figure [5]. Recession probabilities

Notes: Probability that annual GDP growth is below zero, as estimated using the small (orange dotted line) and large (blue dashed line) models. CEPR recession bands are in light grey.

Appendix Figure [6]. Growth-at-Risk decomposition

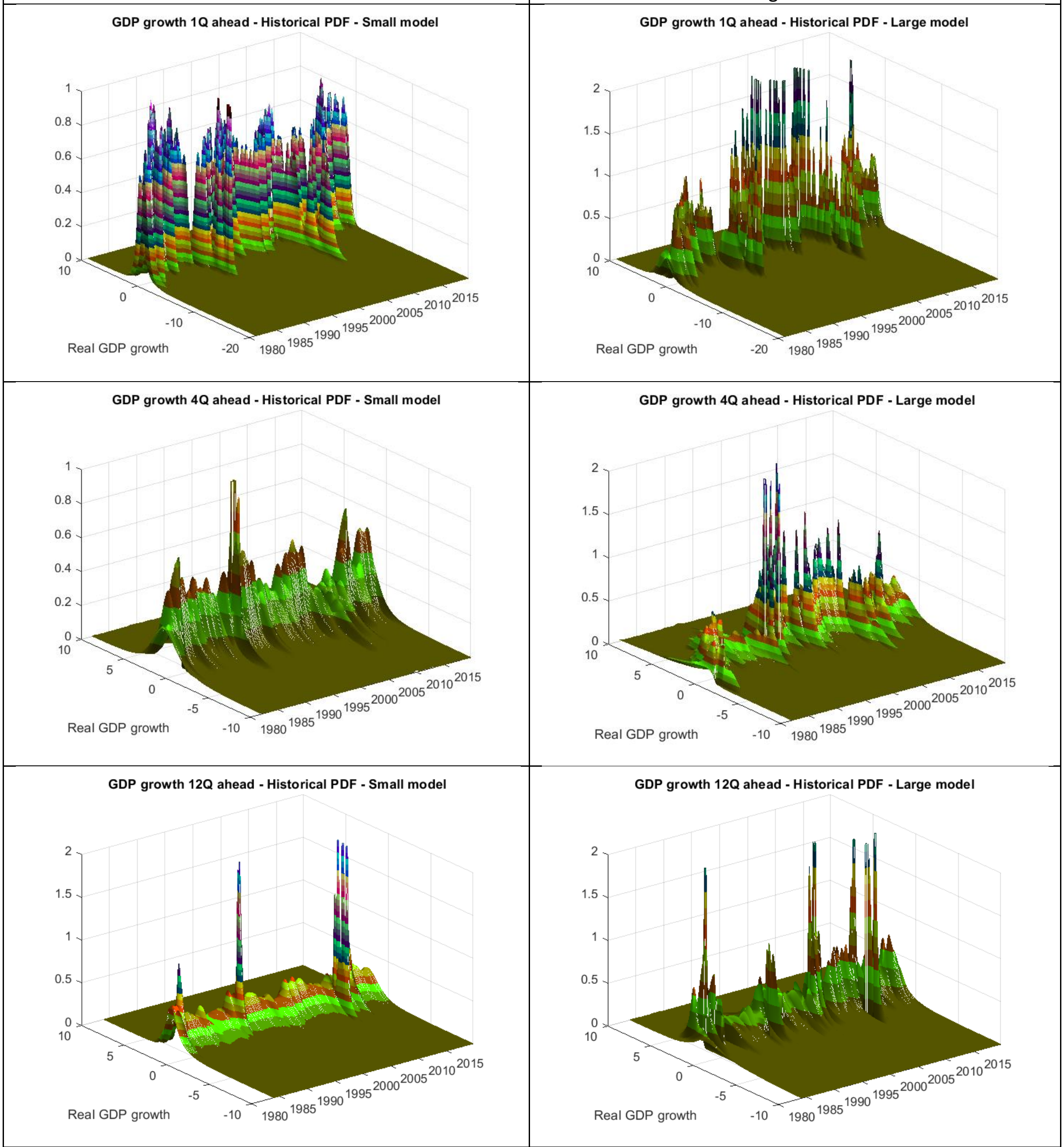
Small model	Large model



Notes: Contributions of the explanatory variables to Growth-at-Risk (GaR) in both the small and large models. In the large model, some regressors have been grouped for clarity. Specifically, the "assets factor" includes the coefficients associated with the Euro Stoxx 50 and house prices; the "credit factor" combines the coefficients of short- and long-term interest rates, as well as private sector credit; finally, the "external factor" combines the real effective exchange rate, goods exports and oil prices.

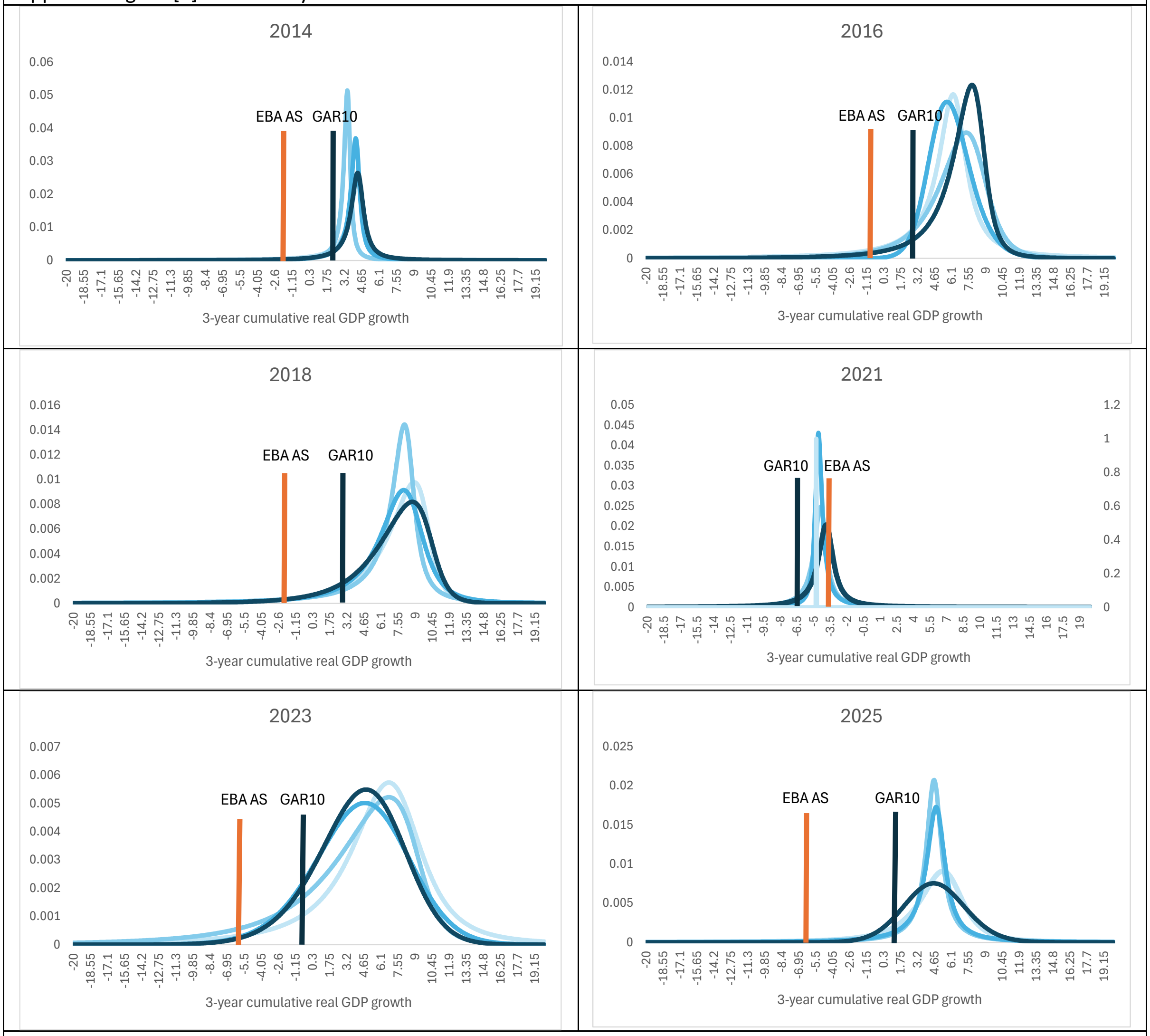
Appendix Figure [7]. Historical conditional probabilities of GDP growth

Small model	Large model



Notes: Fitted conditional probability density function of future GDP growth one-, four- and twelve-quarter ahead in each year through the estimation sample, using both the small (left) and large (right) GaR models.

Appendix Figure [8]. Probability Distribution of 3-Year Cumulative real GDP Growth



Notes: The forecast distributions are based on an out-of-sample projection, with cutoff date set at average values during Q1-Q3 of the year preceding the EBA stress test exercise. The figure illustrates the probability distribution of three-year cumulative GDP growth across four different models. The small GaR model (light blue) includes GDP and CISS. The large GaR model (dark blue) incorporates all available regressors. Two intermediate models are also presented: one (medium blue) includes GDP, CISS, long-term interest rates, private sector credit, and house prices, while the other (darker medium blue) extends this set by adding the stock market index and the REER. The EBA Adverse Scenario (AS) represents the severity of the adverse scenario used in the European Systemic Risk Board reports. The GaR10 metric captures the worst potential cumulative GDP growth over a given horizon (three years in this case) that is expected to occur with a 10% probability, based on the estimated probability distribution of growth outcomes. The figure reports the median GaR10 across the four models.