



# **A Macroeconomic Uncertainty Index for Euro Area Countries: Construction and Applications to Tail Risk Forecasting**

*Master's Thesis*

in partial fulfillment of the requirements for the degree of  
**Master of Science (M.Sc.) in Quantitative Economics**

|                            |                                          |
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## **Abstract**

This thesis constructs macroeconomic uncertainty indices for ten euro area countries and evaluates their usefulness for macroeconomic tail-risk forecasting. Following the forecast-based concept of uncertainty in [Jurado, Ludvigson, and Ng \(2015\)](#), uncertainty is defined as the conditional volatility of the unpredictable component of future macroeconomic outcomes. Using the EA-MD-QD dataset by [Barigozzi and Lissona \(2024\)](#), I extract country-specific factors from large mixed-frequency macroeconomic panels and estimate factor-augmented forecasting equations for individual variables. Then, the stochastic volatility of forecast errors is modeled, and the resulting uncertainty estimates are aggregated into standardized country-level indices. The indices capture major stress episodes such as the Global Financial Crisis, the euro-area sovereign debt crisis, the COVID-19 pandemic, and the energy-price shock following Russia's invasion of Ukraine, while remaining distinct from standard financial-stress indicators.

The empirical analysis assesses whether the constructed macroeconomic uncertainty indices contain information for adverse macroeconomic outcomes beyond established benchmarks such as Composite Indicator of Systemic Stress ([CISS](#)) and Country-Level Index of Financial Stress ([CLIFS](#)). In quantile regressions and pseudo-out-of-sample forecasting exercises, the index improves tail-risk forecasts particularly for upper-tail inflation and lower-tail GDP growth. The gains for inflation are statistically significant in Diebold-Mariano tests, while the evidence for GDP growth is economically meaningful but less precise. Forecasting improvements for unemployment are more limited. As a second application, the thesis develops a decomposable composite policy-risk index that combines macroeconomic uncertainty with financial stress, sovereign stress, geopolitical risk, energy stress, and trade stress using a correlation-adjusted aggregation scheme. The composite index provides an interpretable narrative tool for country-specific stress episodes, and local projections suggest that innovations to the index could be followed by weaker real activity, higher inflation, and rising unemployment. Overall, the thesis shows that forecast-based macroeconomic uncertainty measures can add useful information to euro-area risk monitoring and tail-risk forecasting.

# List of Abbreviations

**AT** Austria

**BE** Belgium

**CISS** Composite Indicator of Systemic Stress

**CLIFS** Country-Level Index of Financial Stress

**DE** Germany

**DM** Diebold-Mariano

**EL** Greece

**EPU** Economic Policy Uncertainty Index

**ES** Spain

**FR** France

**GPR** Geopolitical Risk Index

**GSCPI** Global Supply Chain Pressure Index

**HICP** Harmonised Index of Consumer Prices

**IE** Ireland

**IT** Italy

**JLN** [Jurado et al. \(2015\)](#) uncertainty framework

**KCFSI** Kansas City Financial Stress Index

**MCMC** Markov Chain Monte Carlo

**MUI** Macroeconomic Uncertainty Index

**NFCI** Chicago Fed National Financial Conditions Index

**NL** Netherlands

**PT** Portugal

**SovCISS** Composite Indicator of Sovereign Stress

**TPU** Trade Policy Uncertainty Index

**VDAX** Volatility index for the German DAX stock index

**VIX** CBOE Volatility Index

**WUI** World Uncertainty Index

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# 1 Introduction

Macroeconomic policy is increasingly conducted in an environment in which average outcomes are insufficient to characterize the risks faced by households, firms, and policymakers. Over the past two decades, euro area economies have been exposed to a sequence of large and heterogeneous shocks: the Global Financial Crisis, the sovereign debt crisis, the COVID-19 pandemic, the post-pandemic inflation surge, the energy price shock following Russia's invasion of Ukraine, and, more recently, geopolitical and trade policy tensions. These events differed not only in their origin but also in their cross-country incidence. While some shocks were broadly shared across the euro area, others were concentrated in individual countries or transmitted through particular channels such as sovereign bond markets, energy prices, or international demand. This makes the measurement of country-level macroeconomic uncertainty particularly relevant.

A central difficulty is that macroeconomic uncertainty is not directly observable *ex post*. Commonly used proxies, such as stock-market volatility, financial stress indices, survey disagreement, or news-based uncertainty measures, capture important dimensions of the economic environment, but they do not necessarily measure macroeconomic uncertainty itself. Following the conceptual contribution of [Jurado et al. \(2015\)](#), this thesis defines macroeconomic uncertainty as the conditional volatility of the unpredictable component of future macroeconomic outcomes. Under this view, uncertainty is high when macroeconomic variables become difficult to forecast using the available information set. It is therefore distinct from market volatility, since large movements in macroeconomic variables do not necessarily imply high uncertainty if they are predictable, and distinct from financial stress, since financial-market tensions need not fully summarize uncertainty in the broader macroeconomy.

For the United States, the construction of such forecast-based uncertainty measures can be facilitated by large and long-running macroeconomic datasets such as FRED-MD and FRED-QD ([McCracken & Ng, 2015, 2020](#)). For euro area countries, comparable measurement is more challenging. Country-level macroeconomic data are collected by different national and supranational institutions, and the common sample is shorter partly because many euro area countries have undergone substantial systemic changes. As a result, there is less evidence on comparable country-specific macroeconomic uncertainty measures for euro area economies, although country-level heterogeneity is central to many euro area crises ([Shambaugh, 2012](#)).

This thesis addresses this gap by constructing a Macroeconomic Uncertainty Index (MUI) for ten euro area countries: Austria, Belgium, Germany, Greece, Spain, France, Ireland, Italy, the Netherlands, and Portugal. The construction uses the EA-MD-QD dataset of [Barigozzi and Lissona \(2024\)](#), which provides large monthly and quarterly macroeconomic panels for the euro area and its member countries. The empirical strategy adapts the uncertainty framework of [Jurado et al. \(2015\)](#) to all countries. For each country, I first summarize the high-dimensional macroeconomic panel using a factor-based approach that accommodates missing observations and mixed frequencies. I then estimate factor-augmented forecasting equations for individual macroeconomic variables and model the conditional volatility of the

resulting forecast errors using stochastic volatility. The individual uncertainty estimates are finally aggregated into a country-level **MUI**.

The first objective of the thesis is, therefore, measurement-oriented: to construct a comparable set of country-specific **MUIs** for major euro area economies. The resulting indices are intended to capture overall macroeconomic forecast uncertainty rather than stress in a single market or sector. Since the indices are standardized country by country, they are best interpreted as deviations from each country's own historical uncertainty. This makes them suitable for studying the timing and intensity of uncertainty episodes within countries, while still allowing for comparisons of common dynamics across the euro area.

The second objective is to evaluate whether the constructed indices can be useful for macroeconomic tail-risk forecasting. Tail outcomes are especially relevant in stress episodes because policymakers and forecasters are often less concerned with the conditional mean than with the probability and severity of adverse outcomes. I therefore assess the predictive content of the **MUI** using quantile regressions for lower-tail GDP growth and upper-tail inflation and unemployment outcomes. The analysis compares the proposed index with established financial-stress benchmarks, in particular **CISS** and **CLIFS**, and evaluates forecast performance using pinball loss.

The empirical results suggest that the proposed **MUI** contains signals beyond standard financial-stress measures. In-sample quantile regressions indicate that the index is strongly associated with adverse GDP outcomes and, in particular, with high inflation outcomes. Out-of-sample forecasts show that specifications including the **MUI** generally reduce pinball losses relative to models using only financial-stress indicators. The gains are most robust for upper-tail inflation forecasts, where Diebold-Mariano (**DM**)-tests indicate statistically significant improvements when the proposed index is added to a benchmark model containing **CISS** and **CLIFS**. For GDP growth, the index also produces economically meaningful reductions in tail-forecast losses, although the statistical evidence is weaker. For unemployment, the forecasting gains are more limited. Because the underlying macroeconomic panel is not available in full real-time vintages, the forecasting represents pseudo-out-of-sample evidence on predictive signals instead of a strict real-time policy-forecasting exercise.

In a final step, the thesis extends the **MUI** into a broader decomposable policy-risk index. While the **MUI** is useful as a forecast-based measure, it is not directly decomposable into distinct sources of risk and does not explicitly separate macroeconomic, financial, sovereign, geopolitical, energy, and trade-related stress. I therefore construct a composite index that combines the **MUI** with **CLIFS**, Composite Indicator of Sovereign Stress (**SovCISS**), the Geopolitical Risk Index (**GPR**) of [Caldara and Iacoviello \(2022\)](#), a country-level energy stress index, and a global trade stress index based on supply-chain pressure and trade-policy uncertainty. The components are aggregated using a correlation-adjusted weighting scheme inspired by the systemic-stress logic of [Holló, Kremer, and Lo Duca \(2012\)](#). This preserves the interpretability of component contributions while allowing the aggregate index to increase more strongly when several stress dimensions move together.

Several studies have adapted data-rich measures of macroeconomic uncertainty to the European context. [Rossi and Sekhposyan \(2017\)](#) construct uncertainty indices for the euro area and its individual member countries based on the dispersion of forecast errors, distinguishing between uncertainty concerning upside and downside risks. More closely related to the present analysis, [Fortin, Hlouskova, and Sögner \(2023\)](#) develop economic uncertainty measures in the style of [Jurado et al. \(2015\)](#) for the euro area, Germany, France, and Austria and examine

their macroeconomic and forecasting implications alongside measures of financial uncertainty. [Comunale and Nguyen \(2025\)](#) propose a comprehensive euro area uncertainty measure derived from the conditional volatility of the unforecastable components of a large dataset, explicitly accounting for cross-country heterogeneity, and study its macroeconomic effects during the COVID-19 period. Together, these contributions demonstrate the relevance of data-rich uncertainty measurement in the European context. However, scope remains for a harmonized framework that covers a broader set of member countries, reconstructs the resulting measures recursively, and evaluates their usefulness specifically for forecasting macroeconomic tail risks.

Against this background, this thesis makes three main contributions. First, it applies a common forecast-based methodology and harmonized database to construct comparable [MUIs](#) for ten euro area economies. Second, it reconstructs these indices recursively and evaluates their incremental value for predicting country-specific downside risks to economic growth and upside risks to inflation and unemployment in a pseudo-out-of-sample setting. This analysis benchmarks the indices against established financial-stress measures and thereby examines whether macroeconomic uncertainty contains predictive information beyond conventional stress indicators. Third, the thesis develops a decomposable composite policy-risk index that combines macroeconomic uncertainty with financial, sovereign, geopolitical, energy, and trade-related stress. The resulting framework thus complements the existing literature by linking harmonized multi-country uncertainty measurement with recursive tail-risk forecasting and a transparent monitoring tool for interpreting the sources of country-specific stress.

The remainder of the thesis is structured as follows. Chapter [2](#) reviews the related literature. Chapter [3](#) describes the dataset. Chapter [4](#) explains the construction of the country-level [MUIs](#). Chapter [5](#) discusses the resulting index dynamics. Chapter [6](#) evaluates the indices in quantile-based tail-risk forecasting exercises. Chapter [7](#) constructs and interprets the decomposable composite policy-risk index. Chapter [8](#) concludes.

## 2 Literature

The literature on macroeconomic uncertainty and risk has expanded substantially over the last two decades. This development has been driven by improvements in data availability, advances in textual analysis, and a growing recognition that macroeconomic fluctuations are shaped not only by conventional business-cycle forces, but also by financial stress, geopolitical tensions, trade disruptions, energy shocks, and broader policy-related risks. Against this background, this thesis builds on three related strands of literature. The first strand studies the measurement of macroeconomic uncertainty. The second focuses on financial stress, sovereign stress, and external risk indicators. The third links uncertainty and financial conditions to predictive distributions, in particular through Growth-at-Risk and tail-risk forecasting frameworks.

### 2.1 Macroeconomic uncertainty measurement

A seminal contribution to the modern uncertainty literature is [Bloom \(2009\)](#). He studies the macroeconomic effects of uncertainty shocks using stock-market volatility as a proxy for uncertainty. In a VAR framework, uncertainty shocks identified through the CBOE Volatility Index ([VIX](#)) generate a sharp short-run decline in output, investment, employment, and productivity, followed by a rebound once uncertainty subsides. The paper also documents large increases in uncertainty around major events such as the assassination of John F. Kennedy, the Cuban Missile Crisis, and the terrorist attacks of September 11, 2001. The underlying mechanism is described as a temporary “wait-and-see” effect: when uncertainty is high, firms postpone partially irreversible decisions such as investment and hiring. This finding is central to this thesis, since it suggests that uncertainty is not merely a symptom of economic crises, but can itself contribute to downturns.

A second influential approach measures uncertainty using textual information. [Baker, Bloom, and Davis \(2016\)](#) construct the Economic Policy Uncertainty Index ([EPU](#)) index from newspaper coverage. Their index is based on the relative frequency of articles containing terms related to the economy, policy, and uncertainty. The intuition is that periods with more newspaper discussion of economic policy uncertainty are also periods in which agents face greater uncertainty about future policy and economic conditions. The [EPU](#) index rises around elections, wars, fiscal disputes, and financial crises, and the authors show that higher policy uncertainty is associated with lower investment, employment, and output.

The main methodological reference for this thesis is [Jurado et al. \(2015\)](#), who develop an [MUI](#) for the United States. Their central argument is that many common proxies, such as stock-market volatility, forecast disagreement, or news-based indicators, may capture risk, volatility, disagreement, or salience, but do not necessarily measure macroeconomic uncertainty itself. They define uncertainty as the conditional volatility of the unpredictable component of future macroeconomic outcomes. Their procedure uses a large panel of macroeconomic and financial variables. For each variable, they estimate forecasting equations based on a rich information set. The forecast errors represent the unpredictable components of the series, and time-varying

volatility in these errors is then used to construct variable-specific uncertainty measures. These are aggregated into **MUIs** at different forecast horizons.

The key conceptual contribution of [Jurado et al. \(2015\)](#) is the distinction between realized volatility and forecast uncertainty. A large, realized movement in a macroeconomic variable does not necessarily imply high uncertainty if that movement was predictable or expected. Conversely, uncertainty is high when many variables become difficult to forecast. This distinction is particularly important for this thesis, since the proposed **MUIs** are also based on forecastability and not on realized volatility alone.

A related real-time forecasting perspective is provided by [Rossi and Sekhposyan \(2015\)](#). Their measure is based on nowcast and forecast error distributions. Uncertainty is high when realized forecast errors are unusually large relative to their historical distribution. While [Jurado et al. \(2015\)](#) estimate conditional volatility for many individual variables, [Rossi and Sekhposyan \(2015\)](#) focus more directly on the behavior of macroeconomic forecast errors. Their approach is conceptually close to the idea that uncertainty should be linked to unpredictability and real-time forecasting performance.

Similarly, [Scotti \(2016\)](#) constructs an uncertainty measure from deviations of real-time data releases from market expectations or consensus forecasts. The idea is that macroeconomic uncertainty is elevated when data releases repeatedly deviate from consensus expectations. This approach again links uncertainty to forecast errors, but it relies on the gap between realized releases and professional expectations in contrast to the unpredictability of a large macroeconomic panel.

Another important contribution is [Ludvigson, Ma, and Ng \(2021\)](#), who study the relationship between macroeconomic and financial uncertainty. Their paper distinguishes between different types of uncertainty and asks whether uncertainty should be interpreted as an exogenous driver of business cycles or as an endogenous response to deteriorating economic and financial conditions. They show that macroeconomic and financial uncertainty behave differently and have different relationships with real activity. Financial uncertainty is more closely related to disruptions in financial markets, while macroeconomic uncertainty is more directly connected to uncertainty about real economic outcomes. This distinction is directly relevant for this thesis, which separately considers macroeconomic uncertainty, financial stress, and broader composite risk measures.

Finally, [Carriero, Clark, and Marcellino \(2018\)](#) study uncertainty using large Bayesian vector autoregressions with stochastic volatility. Their approach models time-varying volatility directly within a multivariate macroeconomic system, allowing them to extract uncertainty measures and study the effects of uncertainty shocks. This contribution links uncertainty measurement to Bayesian methods and supports the view that uncertainty can be understood as time-varying conditional volatility. It is therefore closely related to the methodology used in this thesis, although the [Jurado et al. \(2015\)](#) uncertainty framework (**JLN**)-approach estimates uncertainty from individual forecast errors rather than from a large BVAR system.

## 2.2 Financial stress, sovereign stress, and external risk indicators

A second strand of literature develops indicators of financial stress, sovereign stress, and external risks. These measures are relevant because macroeconomic uncertainty is only one

dimension of the broader risk environment faced by households, firms, and policymakers. In the euro area in particular, country-level risk can arise from financial-market tensions, sovereign-debt stress, geopolitical shocks, trade disruptions, and energy-price movements.

One of the most influential euro area stress indicators is the [CISS](#) developed by [Holló et al. \(2012\)](#). The [CISS](#) summarizes financial stress across several market segments, including money markets, bond markets, equity markets, financial intermediaries, and foreign exchange markets. Its main methodological contribution is that it does not simply average stress indicators. Instead, it uses a correlation-weighted aggregation scheme. The index increases more strongly when stress occurs simultaneously across several market segments when these are highly correlated. This logic is important for the composite risk index developed later in this thesis, since it provides a way to capture not only the level of stress in individual components, but also the extent to which different risk dimensions co-move.

An adaptation of this framework to sovereign-debt markets is provided by [Garcia-de Andoain and Kremer \(2017\)](#). The authors argue that sovereign stress cannot be fully captured by government bond yield spreads alone. Sovereign-market stress also involves volatility, liquidity conditions, and broader market functioning. They therefore construct the [SovCISS](#) for euro area countries. Like the [CISS](#), the [SovCISS](#) uses a correlation-weighted aggregation logic. It is relevant for this thesis because sovereign-market tensions are a key source of country-level risk in the euro area and may affect macroeconomic outcomes through financing conditions, fiscal accommodation, and expectations.

[Duprey, Klaus, and Peltonen \(2017\)](#) extend systemic-stress measurement to the country level by constructing the [CLIFS](#) for euro area economies. [CLIFS](#) is designed as a country-specific, financial-market adaptation of the systemic stress logic of [CISS](#). It combines six mainly market-based stress indicators from three financial-market segments: equity markets, sovereign bond markets, and foreign exchange markets. Within each segment, indicators capture both volatility and persistent downturns. The individual series are transformed into unit-free stress measures using empirical distribution functions and then aggregated into segment-specific subindices. Because [CLIFS](#) varies across countries, it is particularly suitable for euro area applications in which financial stress differs substantially across member states. In this thesis, [CLIFS](#) and [CISS](#) serve as important benchmarks for the proposed composite risk index.

An earlier contribution to financial-stress measurement is provided by [Illing and Liu \(2006\)](#), who construct a financial stress index for Canada using indicators from banking, foreign exchange, debt, and equity markets. Their paper is useful because it discusses the challenge of measuring financial stress and compares alternative aggregation methods. A central message is that financial stress is multidimensional and cannot be captured adequately by a single variable alone.

Several prominent financial-stress indices were also developed in the United States after the global financial crisis. The Kansas City Financial Stress Index ([KCFSI](#)) by [Hakkio and Keeton \(2009\)](#) combines financial variables that capture risk premia, liquidity conditions, uncertainty, and investor behavior. It defines financial stress as a situation in which financial markets function less efficiently, credit becomes constrained, risk premia rise, and investors shift toward safer assets. The Chicago Fed National Financial Conditions Index ([NFCI](#)), developed by [Brave and Butters \(2012\)](#), summarizes a large set of financial indicators using factor methods. Unlike the [CISS](#), which is explicitly designed to capture systemic stress, the [NFCI](#) and [KCFSI](#) measure broader financial conditions, including risk, credit, and leverage, and are more comparable to [CLIFS](#).

Beyond financial stress, several recent indicators measure external or policy-related risks. [Caldara and Iacoviello \(2022\)](#) construct a [GPR](#) using newspaper articles that refer to geopolitical tensions, war threats, terrorist threats, military buildups, and adverse geopolitical events. The index is relevant because geopolitical risk may not be immediately reflected in financial stress or macroeconomic variables. It can affect the economy through investment postponement, energy prices, trade disruptions, risk premia, and confidence. For this reason, geopolitical risk represents an external and policy-relevant dimension that may not be fully captured by macroeconomic uncertainty or financial stress indicators alone.

Trade-policy uncertainty is measured by [Caldara, Iacoviello, Molligo, Prestipino, and Raffo \(2020\)](#). Their index is based on newspaper coverage that jointly refers to trade policy and uncertainty. It captures uncertainty about tariffs, trade agreements, protectionism, and related policy decisions. The paper provides evidence that trade-policy uncertainty can reduce investment and economic activity. This channel is particularly relevant for open euro area economies, where trade exposure is high and external demand conditions play an important role. Both the Trade Policy Uncertainty Index ([TPU](#)) and [GPR](#) use newspaper-based textual methodologies similar to that underlying the [EPU](#) by [Baker et al. \(2016\)](#).

A complementary measure of trade-related disruption is the Global Supply Chain Pressure Index ([GSCPI](#)) introduced by [Benigno, di Giovanni, Groen, and Noble \(2022\)](#). The [GSCPI](#) combines information from global transportation costs and supply-chain-related survey indicators, such as delivery times and backlogs. Its components are standardized and summarized using a common-factor approach. Unlike the trade-policy uncertainty index, which captures uncertainty about policy decisions, the [GSCPI](#) captures bottlenecks in global production and transportation networks. In this thesis, trade-policy uncertainty and supply-chain pressure are combined to represent a broader trade-risk component of the composite index.

A broader international measure is the World Uncertainty Index ([WUI](#)) by [Ahir, Bloom, and Furceri \(2022\)](#). The [WUI](#) is constructed from Economist Intelligence Unit country reports by counting references to uncertainty and related terms. Its wide coverage makes it useful for international comparisons. However, because it is based on broad textual analysis, it captures a general uncertainty environment.

Energy risk is another important dimension of the composite risk environment. [Kilian \(2009\)](#) provides evidence that the macroeconomic effects of oil price movements depend strongly on the underlying source of the shock. Oil price increases caused by increased global demand have different implications from oil price increases caused by supply disruptions or geopolitical restrictions. This distinction is important because energy-price movements can affect both inflation and real activity, especially in energy-importing economies. To capture this dimension at the country level, this thesis constructs an energy-stress component based on country-level energy contributions to Harmonised Index of Consumer Prices ([HICP](#)) inflation.

## 2.3 Uncertainty and tail-risk forecasting

The third strand of literature links uncertainty, financial conditions, and other risk indicators to distributional and quantile forecasting, going beyond simpler conditional mean estimation. This is important because risk indicators may be especially informative about adverse outcomes even when their effect on average outcomes is limited. [Koenker and Bassett](#)

(1978) introduce quantile regression, which estimates conditional quantiles of the outcome distribution. [Gneiting \(2011\)](#) formalizes the evaluation of quantile forecasts by showing that the pinball loss is a strictly consistent scoring rule for quantile predictions.

The most prominent macroeconomic application of quantile forecasting is the Growth-at-Risk framework developed by [Adrian, Boyarchenko, and Giannone \(2019\)](#). Growth-at-Risk uses financial conditions to forecast the lower tail of future GDP growth. The main idea is that financial conditions may have only moderate effects on average growth in normal times, but they can contain substantial information about downside risks. This framework is extended by [Adams, Adrian, Boyarchenko, and Giannone \(2021\)](#), who use forecast errors from the Survey of Professional Forecasters together with the NFCI to model the predictive distribution of GDP growth. Related work by the [Federal Reserve Bank of New York \(2023\)](#) generalizes the tail-risk perspective to other macroeconomic variables, including inflation and unemployment.

The tail-risk perspective has also been extended to inflation. [López-Salido and Loria \(2024\)](#) study how macroeconomic drivers affect the full predictive distribution of inflation and emphasize that the conditional mean can miss important changes in inflation risks. In particular, the tails of the inflation distribution may shift substantially even when average inflation appears stable. This motivates the analysis in this thesis, which studies not only downside risks to GDP growth, but also upside risks to inflation and unemployment.

A related motivation comes from the monetary-policy literature on robustness under model uncertainty. [A. T. Levin, Wieland, and Williams \(1999\)](#) show that the performance of simple monetary-policy rules can vary across alternative macroeconomic models, implying that policy prescriptions should not be evaluated only within a single preferred model. [A. Levin, Wieland, and Williams \(2003\)](#) extend this argument to forecast-based monetary-policy rules and study how such rules perform when the policymaker faces uncertainty about the correct model of the economy. Their central implication for this thesis is not methodological in the narrow sense, since this thesis does not derive optimal policy rules. Rather, it is conceptual; indicators intended for policy use should provide robust predictive information about future macroeconomic risks, more than merely fitting one empirical specification. This perspective motivates the emphasis on pseudo-out-of-sample quantile forecasting, benchmark comparisons against [CISS](#) and [CLIFS](#), and robustness checks across alternative samples and factor choices.

This thesis contributes to the literature in three ways. First, it adapts the methodology of [Jurado et al. \(2015\)](#) to individual euro area countries using the novel dataset of [Barigozzi and Lissona \(2024\)](#). Second, it evaluates whether the resulting [MUIs](#) improve quantile forecasts for key macroeconomic variables. Third, it constructs a broader composite risk index that combines macroeconomic uncertainty with financial stress, sovereign stress, geopolitical risk, trade risk, and energy stress. The empirical analysis then studies whether increases in these risk measures are associated with weaker GDP growth, higher inflation, and higher unemployment, with particular attention to the tails of the predictive distribution.

### 3 Data

Creating an MUI similar to [Jurado et al. \(2015\)](#) for euro area countries is challenging, as the methodology requires a large macroeconomic panel dataset. For the United States, such datasets have been available for some time in the form of FRED-MD and FRED-QD ([McCracken & Ng, 2015, 2020](#)), which provide a rich set of monthly and quarterly macroeconomic indicators with long time-series coverage and, in the case of vintages, a history dating back to 1999 for FRED-MD, which is one of the sources for the original estimation for the US by [Jurado et al. \(2015\)](#). Both datasets date back to 1959 and contain 120 monthly (FRED-MD) or 250 quarterly (FRED-QD) variables.

Since no comparable real-time vintage history is available for the full set of euro area country-level variables<sup>1</sup>, the analysis abstracts from data revisions, publication lags, and real-time data availability.

For the major euro area economies, the EA-MD-QD dataset by [Barigozzi and Lissona \(2024\)](#) provides a suitable basis for constructing country-level uncertainty indices. The dataset contains up to 120 mixed-frequency macroeconomic series from January 2000 onward for the euro area aggregate as well as Germany, France, Italy, Spain, the Netherlands, Portugal, Ireland, Greece, Belgium and Austria. Although the dataset is smaller than the one used by [Jurado et al. \(2015\)](#), both in terms of cross-sectional dimension and time-series length, it is sufficiently rich to implement a country-level version of the JLN-approach. The smaller size mainly reflects the shorter common history of harmonized euro area data.

EA-MD-QD consists of approximately 85 to 120 variables, depending on the country or region. The variables cover the categories *National Accounts*, *Labor Market Indicators*, *Credit Aggregates*, *Labor Costs*, *Financial Markets*, *Interest Rates*, *Industrial Production and Turnover*, *Prices*, *Confidence Indicators*, and *Monetary Aggregates*. The dataset contains both monthly and quarterly series. Since the uncertainty index is constructed at a monthly frequency, the quarterly variables are embedded into the monthly panel and treated as series with missing observations in months for which no quarterly observation is available. This allows the factor extraction step to exploit information from both monthly and quarterly indicators.

Since the individual transformed series are not the main object of interest, interpretability at the level of single variables is less important than obtaining a stable high-dimensional panel for factor extraction and forecasting. I therefore use the standard transformation routines provided by [Barigozzi, Lissona, and Tonni \(2024\)](#) selected on the basis of unit-root tests. This choice prioritizes stationarity and numerical stability, at the cost of potentially reducing the direct comparability of individual transformed series across countries, since the selected transformations may differ across countries.

The uncertainty construction requires two ingredients from the high-dimensional macroeconomic panel. First, missing observations must be imputed to obtain a usable monthly

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<sup>1</sup>EA-MD-QD is only available in real-time since 2024

dataset. Second, the information in the large panel must be summarized by a small number of common factors, which serve as predictors in the forecasting equations used to construct variable-specific forecast uncertainty. To achieve this, I use a low-rank approximate factor model with matrix completion.

Let  $X_c = x_{c,t,i}$  denote the monthly macroeconomic panel for country  $c$ , where  $t = 1, \dots, T_c$  indexes months and  $i = 1, \dots, N_c$  indexes macroeconomic variables. Since the country-level panels are unbalanced and contain both monthly and quarterly indicators, the data matrix contains missing entries. Before factor extraction, each series is standardized using its available observations. Series with too few available observations are excluded from the factor extraction step.

The standardized panel is assumed to admit an approximate factor representation,

$$\tilde{x}_{c,t,i} = \lambda'_{c,i} f_{c,t} + e_{c,t,i},$$

or, in matrix notation,

$$\tilde{X}_c = F_c \Lambda'_c + E_c,$$

where  $F_c = (f_{c,1}, \dots, f_{c,T_c})'$  is a  $T_c \times r$  matrix of latent common factors,  $\Lambda_c$  is an  $N_c \times r$  matrix of factor loadings,  $E_c$  contains idiosyncratic components, and  $r$  denotes the number of retained factors. This specification follows the approximate factor model literature, in which a small number of latent factors summarizes the common variation in a large macroeconomic dataset (Bai & Ng, 2002; Stock & Watson, 2002). As a baseline, I choose the number of factors to be extracted from the dataset to be six. Robustness checks with a different number of factors will be provided in Appendix B.2.2.

Because  $\tilde{X}_c$  is incomplete, factors are not extracted by applying principal components to a balanced panel. Instead, the common component is estimated from the observed entries using a low-rank matrix-completion approach. Let  $\Omega_c$  denote the set of observed entries in the standardized data matrix. In general, low-rank matrix completion can be formulated as

$$\hat{M}_c = \arg \min_{M_c} \left\{ \frac{1}{2} \sum_{(t,i) \in \Omega_c} (\tilde{x}_{c,t,i} - M_{c,t,i})^2 + \lambda \|M_c\|_* \right\},$$

where  $\|M_c\|_*$  denotes the nuclear norm, which penalizes the sum of singular values and encourages a low-rank solution (Hastie, Mazumder, Lee, & Zadeh, 2015; Mazumder, Hastie, & Tibshirani, 2010). In the implementation used here, the rank is fixed at  $r$ , and the shrinkage parameter is set to  $\lambda = 0$ . The estimator therefore reduces to fitting a rank- $r$  common component to the observed entries of the standardized panel,

$$\hat{M}_c = \arg \min_{\text{rank}(M_c) \leq r} \frac{1}{2} \sum_{(t,i) \in \Omega_c} (\tilde{x}_{c,t,i} - M_{c,t,i})^2.$$

The estimated low-rank matrix can be written as

$$\hat{M}_c = \hat{U}_c \hat{D}_c \hat{V}_c',$$

where  $\hat{U}_c$  and  $\hat{V}_c$  contain left and right singular vectors and  $\hat{D}_c$  is the diagonal matrix of

retained singular values. The estimated factors are then defined as

$$\widehat{F}_c = \widehat{U}_c \widehat{D}_c.$$

Equivalently, the estimated common component can be written as

$$\widehat{M}_c = \widehat{F}_c \widehat{\Lambda}'_c, \quad \widehat{\Lambda}_c = \widehat{V}_c.$$

As is standard in factor models, the factors and loadings are only identified up to an invertible rotation: for any nonsingular  $r \times r$  matrix  $H$ ,

$$F_c \Lambda'_c = (F_c H)(\Lambda_c H^{-1})'.$$

Hence, only the factor space is identified. For numerical convenience and interpretability, the estimated factors are centered, orthogonalized, and scaled to have unit variance.

The completed standardized data matrix is obtained by using the estimated low-rank common component to fill missing entries. For missing observations, the imputed standardized value is

$$\widehat{\tilde{x}}_{c,t,i} = \widehat{M}_{c,t,i} = \widehat{\lambda}'_{c,i} \widehat{f}_{c,t}.$$

The completed data are then transformed back to the original units by

$$\widehat{x}_{c,t,i} = \widehat{\mu}_{c,i} + \widehat{\sigma}_{c,i} \widehat{\tilde{x}}_{c,t,i}.$$

Thus, missing observations are imputed using the estimated common macroeconomic component.

## 4 Constructing an Uncertainty Index from Large Panel Data

The **MUI** is constructed in the spirit of [Jurado et al. \(2015\)](#). The central idea is that macroeconomic uncertainty should not be measured by the unconditional volatility of macroeconomic variables, but by the conditional volatility of their unpredictable components. In other words, uncertainty is defined as the degree of variation in future economic outcomes that cannot be forecast using the available information set.

For each country  $c$ , let

$$X_c = (x_{c,t,i})$$

denote the completed and transformed monthly macroeconomic panel, where  $t = 1, \dots, T_c$  indexes months and  $i = 1, \dots, N_c$  indexes the macroeconomic variables. The panel has previously been transformed to induce stationarity and completed using factor-based matrix completion. Let

$$F_{c,t} = (f_{c,t,1} \ \cdots \ f_{c,t,K})'$$

denote the  $K$ -dimensional vector of static factors extracted from the country-level macroeconomic panel. These factors summarize the common macroeconomic variation in the high-dimensional dataset and are treated as observed predictors in the subsequent uncertainty estimation step.

The procedure is implemented separately for each country. The resulting index is therefore a country-specific measure of macroeconomic uncertainty. Relative to [Jurado et al. \(2015\)](#), the construction is adapted to the available country-level euro area data, but the central econometric structure is retained: variable-specific forecast errors are obtained from factor-augmented forecasting equations, their conditional variances are estimated using stochastic volatility, and the resulting individual uncertainty estimates are aggregated into a country-level **MUI**.

### 4.1 Predictor Set

The first step is to construct the predictor set used in the forecasting equations. Following the logic of [Jurado et al. \(2015\)](#), the information set contains both factors and proxies for time variation in volatility. Specifically, define the vector of predictors;

$$Z_{c,t} = \left( F'_{c,t} \ f_{c,t,1}^2 \ g_{c,t,1} \right)',$$

where  $F_{c,t}$  contains the static macroeconomic factors,  $f_{c,t,1}^2$  denotes the squared first factor, and  $g_{c,t,1}$  denotes the first principal component extracted from the squared standardized macroeconomic panel. The inclusion of  $f_{c,t,1}^2$  and  $g_{c,t,1}$  allows the forecasting equations to condition not only on the level of the macroeconomic state, but also on common movements in second moments.

Let  $q$  denote the dimension of  $Z_{c,t}$ . For notational convenience, write

$$Z_{c,t} = (z_{c,t,1} \ \cdots \ z_{c,t,q})'.$$

## 4.2 Forecasting Equations for Individual Macroeconomic Variables

For each macroeconomic variable  $x_{c,t,i}$ , a one-step-ahead forecasting equation is estimated. The baseline specification uses four own lags of the dependent variable and the predictor vector  $Z_{c,t}$ :

$$x_{c,t+1,i} = \alpha_{c,i} + \sum_{\ell=1}^4 \rho_{c,i,\ell} x_{c,t+1-\ell,i} + \gamma'_{c,i} Z_{c,t} + u_{c,t+1,i}.$$

Here,  $u_{c,t+1,i}$  is the one-step-ahead forecast error for variable  $i$  in country  $c$ . The elements of  $Z_{c,t}$  are selected using a hard-thresholding rule: after estimating the full regression, only those factor-based predictors whose absolute  $t$ -statistic exceeds a pre-specified threshold are retained. This follows the empirical strategy of [Jurado et al. \(2015\)](#), where the forecasting model is allowed to differ across individual series and only the own lags are always kept.

Let  $S_{c,i} \subseteq \{1, \dots, q\}$  denote the set of selected predictors for series  $i$ . The final forecasting equation can then be written as

$$x_{c,t+1,i} = \alpha_{c,i} + \sum_{\ell=1}^4 \rho_{c,i,\ell} x_{c,t+1-\ell,i} + \sum_{k \in S_{c,i}} \gamma_{c,i,k} z_{c,t,k} + u_{c,t+1,i}.$$

The residual  $u_{c,t+1,i}$  is interpreted as the unpredictable component of series  $i$ , conditional on its own history and the estimated macroeconomic factor information set.

## 4.3 Stochastic Volatility of Target Forecast Errors

The next step is to estimate the time-varying conditional variance of the forecast errors  $u_{c,t,i}$ . For each country  $c$  and macroeconomic variable  $i$ , the residuals from the selected forecasting equation are modeled using a univariate stochastic volatility process:

$$u_{c,t,i} = \exp\left(\frac{h_{c,t,i}}{2}\right) \varepsilon_{c,t,i}, \quad \varepsilon_{c,t,i} \sim \mathcal{N}(0, 1),$$

where  $h_{c,t,i}$  is the latent log-volatility of the forecast error. The latent log-volatility follows an autoregressive process,

$$h_{c,t,i} = \mu_{c,i} + \phi_{c,i} (h_{c,t-1,i} - \mu_{c,i}) + \sigma_{h,c,i} \eta_{c,t,i}, \quad \eta_{c,t,i} \sim \mathcal{N}(0, 1).$$

The conditional variance of the forecast error is therefore

$$\text{Var}_{t-1}(u_{c,t,i}) = \exp(h_{c,t,i}).$$

The stochastic volatility model is estimated by Markov Chain Monte Carlo ([MCMC](#)). In the implementation, posterior means of the latent log-volatility states and parameters are used to

construct the time-varying innovation variances.

This step is central to the interpretation of the index. The uncertainty measure does not capture periods in which macroeconomic variables move strongly in a predictable way. Instead, it captures periods in which the unforecastable component of many macroeconomic variables becomes more volatile.

## 4.4 Dynamics of the Predictor Variables

For horizons  $h > 1$ , uncertainty about  $x_{c,t+h,i}$  depends not only on the innovation variance of the target variable, but also on uncertainty about future values of the predictors. Therefore, each element of the predictor vector  $Z_{c,t}$  is modeled using an autoregressive process with four lags:

$$z_{c,t+1,k} = a_{c,k} + \sum_{\ell=1}^4 \varphi_{c,k,\ell} z_{c,t+1-\ell,k} + v_{c,t+1,k}, \quad k = 1, \dots, q.$$

The predictor innovation  $v_{c,t,k}$  is also modeled using stochastic volatility:

$$v_{c,t,k} = \exp\left(\frac{h_{c,t,k}^z}{2}\right) \xi_{c,t,k}, \quad \xi_{c,t,k} \sim \mathcal{N}(0, 1),$$

with

$$h_{c,t,k}^z = \mu_{c,k}^z + \phi_{c,k}^z \left( h_{c,t-1,k}^z - \mu_{c,k}^z \right) + \sigma_{h,c,k}^z \zeta_{c,t,k}, \quad \zeta_{c,t,k} \sim \mathcal{N}(0, 1).$$

This produces time-varying innovation variances.

$$\text{Var}_{t-1}(v_{c,t,k}) = \exp(h_{c,t,k}^z)$$

for all predictors. These variances enter the multi-step uncertainty calculation.

## 4.5 Horizon-Specific Forecast Uncertainty

The uncertainty index is constructed for a given forecast horizon  $h$ . For each target variable  $i$ , the forecasting equation, and the predictor dynamics are combined into a companion-form system. The state vector contains the current and lagged values of the target variable, as well as the current and lagged values of the predictor vector:

$$s_{c,t,i} = \begin{pmatrix} x_{c,t,i} \\ x_{c,t-1,i} \\ x_{c,t-2,i} \\ x_{c,t-3,i} \\ Z_{c,t} \\ Z_{c,t-1} \\ Z_{c,t-2} \\ Z_{c,t-3} \end{pmatrix}.$$

The state evolves according to

$$s_{c,t+1,i} = B_{c,i} s_{c,t,i} + \varepsilon_{c,t+1,i}^s,$$

where  $B_{c,i}$  is the companion matrix implied by the selected target forecasting equation and the AR(4) equations for the predictors. The innovation vector  $\varepsilon_{c,t+1,i}^s$  contains the target innovation  $u_{c,t+1,i}$  and the predictor innovations  $v_{c,t+1,k}$ .

Starting from the current state, the  $h$ -step-ahead forecast-error covariance matrix is obtained recursively:

$$P_{c,t+1|t,i} = \Sigma_{c,t+1,i},$$

and, for  $j = 2, \dots, h$ ,

$$P_{c,t+j|t,i} = B_{c,i}P_{c,t+j-1|t,i}B'_{c,i} + \Sigma_{c,t+j,i}.$$

The horizon- $h$  uncertainty estimate for variable  $i$  is then defined as the standard deviation of the forecast error for the target variable:

$$U_{c,t,i}(h) = \sqrt{e'_1 P_{c,t+h|t,i} e_1},$$

where  $e_1$  is a selection vector that extracts the first element of the state vector, corresponding to  $x_{c,t+h,i}$ .

Thus,  $U_{c,t,i}(h)$  measures the conditional uncertainty surrounding the  $h$ -step-ahead forecast of macroeconomic variable  $i$ . It incorporates both the stochastic volatility of the target variable's own forecast error and the uncertainty transmitted through future values of the common macroeconomic predictors.

## 4.6 Aggregation into a Country-Level Index

The previous steps produce a panel of individual uncertainty estimates.

$$\{U_{c,t,i}(h)\}_{i=1}^{N_c}$$

for each country  $c$ , month  $t$ , and horizon  $h$ . Following [Jurado et al. \(2015\)](#), the individual series are first transformed into log uncertainty measures:

$$\ell_{c,t,i}(h) = \log U_{c,t,i}(h).$$

The log transformation reduces the influence of extreme values and makes the cross-sectional aggregation more stable.

In the baseline specification, the country-level uncertainty index is defined as the first principal component of the standardized individual log-uncertainty series. Let

$$L_c(h) = (\ell_{c,t,i}(h))_{t=1,\dots,T_c; i=1,\dots,N_c}$$

denote the  $T_c \times N_c$  matrix of log individual uncertainty estimates. Each column is standardized over time:

$$\tilde{\ell}_{c,t,i}(h) = \frac{\ell_{c,t,i}(h) - \bar{\ell}_{c,i}(h)}{s_{\ell,c,i}(h)},$$

where  $\bar{\ell}_{c,i}(h)$  and  $s_{\ell,c,i}(h)$  are the time-series mean and standard deviation of  $\ell_{c,t,i}(h)$ . The standardized matrix is denoted by  $\tilde{L}_c(h)$ .

The baseline **MUI** is then obtained from the first principal component of  $\tilde{L}_c(h)$ :

$$\tilde{L}_c(h) = A_c(h)D_c(h)R_c(h)',$$

and

$$U_{c,t}^{PC1}(h) = A_{c,t,1}(h)D_{c,1}(h),$$

where  $A_{c,t,1}(h)$  is the first left singular vector and  $D_{c,1}(h)$  is the largest singular value. The sign of the first principal component is normalized such that higher values correspond to higher average uncertainty across the underlying individual series.

Finally, the index is standardized to facilitate interpretation:

$$\mathcal{U}_{c,t}(h) = \frac{U_{c,t}^{PC1}(h) - \bar{U}_c^{PC1}(h)}{s_c^{PC1}(h)}.$$

The resulting series  $\mathcal{U}_{c,t}(h)$  is the baseline macroeconomic uncertainty index for country  $c$  at horizon  $h$ . Since it is standardized, the index is measured in country-specific standard deviations from its historical mean.

As a robustness check, I also compute an equal-weighted aggregation of the individual log-uncertainty estimates:

$$U_{c,t}^{AVG}(h) = \frac{1}{N_c} \sum_{i=1}^{N_c} \ell_{c,t,i}(h).$$

This average index is also standardized over time:

$$\mathcal{U}_{c,t}^{AVG}(h) = \frac{U_{c,t}^{AVG}(h) - \bar{U}_c^{AVG}(h)}{s_c^{AVG}(h)}.$$

The equal-weighted version is closer to the baseline aggregation in [Jurado et al. \(2015\)](#), while the first-principal-component version emphasizes the common component in uncertainty across the individual macroeconomic series. Since the empirical analysis primarily focuses on broad country-level movements in uncertainty, the PC1-based index is used as the main measure, and the equal-weighted index is reported as a robustness check in [Appendix A.1](#).

The resulting **MUI** captures common variation in the forecast uncertainty of a large set of macroeconomic variables. A high value of  $\mathcal{U}_{c,t}(h)$  indicates that many variables in country  $c$  exhibit elevated uncertainty in their unpredictable components at horizon  $h$ . The index, therefore, differs from both simple realized volatility measures and financial stress indicators. It is explicitly macroeconomic, since it is constructed from a broad panel of macroeconomic variables, and it is explicitly forecast-based, since it measures uncertainty after conditioning on the available macroeconomic information set.

## 5 Results

For tables and graphs, I use the EU country abbreviations: *Austria (AT)*, *Belgium (BE)*, *Germany (DE)*, *Greece (EL)*, *Spain (ES)*, *France (FR)*, *Ireland (IE)*, *Italy (IT)*, *Netherlands (NL)*, *Portugal (PT)*. While I report the index for the horizons 1-month-ahead, 3-month-ahead, and 12-month-ahead for robustness in Figure 1, the thesis will focus on the 3-month-ahead version. Similarly, I choose  $K = 6$  for the number of factors. However, indices for  $h=3$  using other  $K$  are reported in Appendix A.2. For each target series, I estimate a one-step-ahead forecasting regression containing four autoregressive lags and the common predictors. Candidate predictors are retained through a one-time hard-thresholding rule, with coefficients retained when their absolute unrestricted OLS t-statistic exceeds 2.575 (consistent with a two-sided test at 1%); the selected specification is subsequently re-estimated without further selection iterations. Stochastic volatility is estimated separately for each target and predictor innovations with 5,000 burn-in iterations, 5,000 sampling iterations, and thinning factors of 10 for both parameter and latent-state draws. I employ the *stochvol* package (Kastner, 2016) default priors, which place a Normal prior on the level of log-volatility, a Beta prior on the persistence parameter, and an Inverse-Gamma prior on the volatility-of-volatility, constituting weakly informative yet proper priors that facilitate efficient MCMC sampling via the ancillarity-sufficiency interweaving strategy (ASIS). Multi-period innovation variances are obtained analytically from AR(1) log-volatility forecasts evaluated at posterior-mean parameters and latent states, including the lognormal variance correction. These variances enter a diagonal state innovation covariance matrix, thereby imposing zero contemporaneous covariance between target and predictor innovations, and forecast uncertainty is propagated through the companion-form state system. The computation time of the whole process is around six minutes per country.

The result is an index over 26 years with 312 observations per country. For a better comparison, all indices are standardized to a mean of 0 and a standard deviation of 1. In Figure 1, it can be seen that in high uncertainty periods, the index peaks at around 4-6 standard deviations higher than the mean, presenting substantial differences in macro uncertainty over time.

Also, while most countries' MUIs are highly correlated between 0.6 and 0.8, Ireland and Greece are relative outliers, most likely due to their large exposure to the euro area crisis, which, at least in macroeconomic terms, left other economies like Germany more unaffected (International Monetary Fund, 2012). In general, the indices look plausible; the global maxima are almost always reached during COVID-19. For most countries, we can also see a spike during Russia's invasion of Ukraine, with the underlying energy crisis. Surprisingly, the Great Recession is a major peak, but much lower than other crises. An explanation for this can be that while it was a large crisis, the uncertainty regarding variables such as prices was not as elevated. To further show that the index comprises elements that current risk and uncertainty indices do not capture, I also look at the correlation of my German MUI against the CISS, CLIFS, and the Volatility index for the German DAX stock index (VDAX) in Table 3. While the latter three are highly correlated with each other, they are only weakly correlated with the MUI, with a maximum of 0.325 for CLIFS. While this observation alone is certainly not

an index of quality or information richness, it provides evidence that it introduces variation where other indices do not.

**Table 1:** Summary Statistics of Standardized Country-Specific MUIs

| Country | <i>N</i> | Min.   | P5     | P25    | Median | P75   | P95   | Max.  |
|---------|----------|--------|--------|--------|--------|-------|-------|-------|
| AT      | 312      | -1.599 | -1.119 | -0.740 | -0.293 | 0.618 | 2.019 | 3.708 |
| BE      | 312      | -1.306 | -1.057 | -0.679 | -0.321 | 0.453 | 2.053 | 4.757 |
| DE      | 312      | -1.356 | -1.077 | -0.729 | -0.217 | 0.337 | 1.866 | 5.093 |
| EL      | 312      | -2.076 | -1.300 | -0.715 | -0.113 | 0.553 | 1.578 | 4.145 |
| ES      | 312      | -1.184 | -1.071 | -0.630 | -0.186 | 0.279 | 1.658 | 5.671 |
| FR      | 312      | -0.992 | -0.836 | -0.617 | -0.284 | 0.327 | 1.527 | 6.102 |
| IE      | 312      | -1.682 | -1.272 | -0.723 | -0.200 | 0.499 | 1.835 | 5.313 |
| IT      | 312      | -0.911 | -0.793 | -0.587 | -0.327 | 0.239 | 1.914 | 5.775 |
| NL      | 312      | -1.233 | -1.043 | -0.601 | -0.308 | 0.213 | 2.507 | 3.855 |
| PT      | 312      | -1.250 | -1.005 | -0.629 | -0.240 | 0.319 | 1.471 | 6.420 |

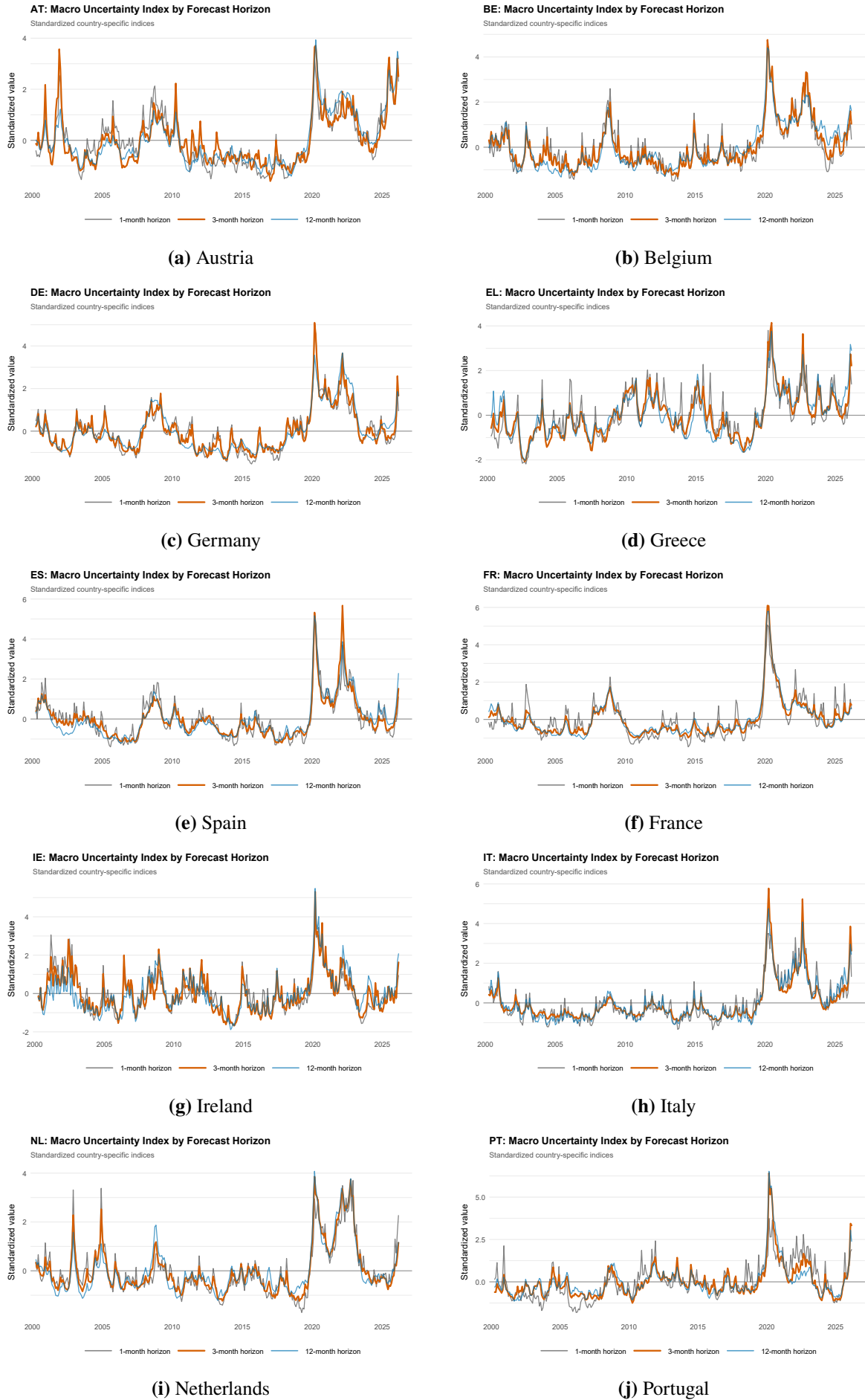
*Notes:* Since each index is standardized country-by-country, values should be interpreted as deviations from the respective country's historical distribution rather than as absolute cross-country uncertainty levels.

**Table 2:** Correlation Matrix of Country-Specific MUIs

| Country | AT    | BE    | DE    | EL    | ES    | FR    | IE    | IT    | NL    | PT    |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| AT      | 1.000 | 0.618 | 0.644 | 0.547 | 0.633 | 0.661 | 0.498 | 0.721 | 0.553 | 0.498 |
| BE      | 0.618 | 1.000 | 0.773 | 0.535 | 0.774 | 0.827 | 0.554 | 0.849 | 0.785 | 0.665 |
| DE      | 0.644 | 0.773 | 1.000 | 0.477 | 0.831 | 0.799 | 0.550 | 0.768 | 0.757 | 0.632 |
| EL      | 0.547 | 0.535 | 0.477 | 1.000 | 0.545 | 0.511 | 0.381 | 0.698 | 0.518 | 0.591 |
| ES      | 0.633 | 0.774 | 0.831 | 0.545 | 1.000 | 0.755 | 0.582 | 0.793 | 0.806 | 0.625 |
| FR      | 0.661 | 0.827 | 0.799 | 0.511 | 0.755 | 1.000 | 0.635 | 0.808 | 0.668 | 0.723 |
| IE      | 0.498 | 0.554 | 0.550 | 0.381 | 0.582 | 0.635 | 1.000 | 0.560 | 0.486 | 0.526 |
| IT      | 0.721 | 0.849 | 0.768 | 0.698 | 0.793 | 0.808 | 0.560 | 1.000 | 0.786 | 0.760 |
| NL      | 0.553 | 0.785 | 0.757 | 0.518 | 0.806 | 0.668 | 0.486 | 0.786 | 1.000 | 0.615 |
| PT      | 0.498 | 0.665 | 0.632 | 0.591 | 0.625 | 0.723 | 0.526 | 0.760 | 0.615 | 1.000 |

**Table 3:** Correlation Matrix of German Risk and Uncertainty Measures

| Variable | MUI   | CISS  | CLIFS | VDAX  |
|----------|-------|-------|-------|-------|
| MUI      | 1.000 | 0.214 | 0.325 | 0.237 |
| CISS     | 0.214 | 1.000 | 0.753 | 0.665 |
| CLIFS    | 0.325 | 0.753 | 1.000 | 0.761 |
| VDAX     | 0.237 | 0.665 | 0.761 | 1.000 |



**Figure 1: MUI by country for 1-, 3-, and 12-months ahead**

## 6 Applications to Tail-Risk Forecasting

To assess the empirical relevance of the constructed [MUI](#), I evaluate whether it contains incremental information for macroeconomic tail risks beyond standard financial-stress indicators. The analysis proceeds in two steps. First, I estimate in-sample quantile regressions to examine the conditional association between the [MUI](#) and adverse macroeconomic outcomes while controlling for [CISS](#) and [CLIFS](#). Second, I conduct a recursive pseudo-out-of-sample forecasting exercise and compare predictive accuracy using the quantile, or pinball, loss.

For a realised value  $y_{t+h}$ , a predicted conditional quantile  $q_{\tau,t+h}$ , and quantile level  $\tau \in (0, 1)$ , the pinball loss is defined as

$$L_{\tau}(y_{t+h}, q_{\tau,t+h}) = (\tau - \mathbb{1}\{y_{t+h} < q_{\tau,t+h}\}) (y_{t+h} - q_{\tau,t+h}) \quad (1)$$

Lower average pinball loss indicates a more accurate forecast of the corresponding conditional quantile. I focus on lower-tail GDP growth quantiles,  $\tau \in \{0.05, 0.10, 0.25\}$ , and upper-tail inflation and unemployment quantiles,  $\tau \in \{0.75, 0.90, 0.95\}$ .

This loss function is asymmetric: underpredictions and overpredictions receive different weights depending on the quantile level. For lower-tail quantiles, such as  $\tau = 0.05$ , observations below the predicted quantile are penalized more strongly, while for upper-tail quantiles, such as  $\tau = 0.95$ , observations above the predicted quantile receive larger penalties. Lower average pinball loss, therefore, indicates a more accurate forecast of the corresponding conditional quantile.

The relevant targets are therefore the 0.05, 0.10, and 0.25 quantiles of GDP growth and the 0.75, 0.90, and 0.95 quantiles of [HICP](#) inflation and unemployment.

Both the in-sample and the out-of-sample applications are done illustratively for Germany and the whole panel of countries; detailed results for all countries can be found in [Appendix B](#).

### 6.1 In-sample significance

To evaluate whether the [MUI](#) contains predictive information for macroeconomic tail outcomes, I estimate quantile predictive regressions for a panel of euro area countries. The dependent variables are future macroeconomic outcomes: next-quarter GDP growth, the annualized three-month-ahead inflation rate, and the three-month-ahead unemployment rate transformed as:

$$Growth_t = 400 \log\left(\frac{GDP_t}{GDP_{t-1}}\right) \quad (2)$$

$$\pi_t = 400 \log\left(\frac{\text{HICP}_t}{\text{HICP}_{t-3}}\right) \quad (3)$$

$$UR_t \rightarrow \text{Level} \quad (4)$$

The baseline panel specification is given by

$$Q_\tau(y_{i,t+h} | \mathcal{F}_{i,t}) = \alpha_i^{(\tau)} + \sum_{\ell=0}^{p_y} \rho_\ell^{(\tau)} y_{i,t-\ell} + \beta_R^{(\tau)} \text{MUI}_{i,t} + \beta_C^{(\tau)} \text{CISS}_{i,t} + \beta_L^{(\tau)} \text{CLIFS}_{i,t}, \quad (5)$$

where  $h = 3$  (or  $h = 1$  for GDP),  $Q_\tau(y_{i,t+h} | \mathcal{F}_{i,t})$  denotes the conditional  $\tau$ -quantile of the target variable for country  $i$ , and  $\alpha_i^{(\tau)}$  denotes quantile-specific country fixed effects that absorb time-invariant differences across countries.  $\text{CISS}_{i,t}$  and  $\text{CLIFS}_{i,t}$  are included as benchmark financial-stress controls. The autoregressive terms control for persistence in the respective target variable. The number of lags is target-specific: two lags are used for GDP growth, while three lags are used for inflation and unemployment due to different frequencies. All risk and financial-stress predictors are standardized within the country, so the estimated coefficients can be interpreted as the change in the conditional quantile associated with a one-standard-deviation increase in the respective index.

To assess the incremental information content of the index, the specification includes the  $\text{MUI}$ ,  $\text{CISS}$ , and  $\text{CLIFS}$  jointly. This structure allows the analysis to distinguish between predictive content that is already captured by standard financial-stress indicators and additional information contained in the newly constructed index.

In addition to the pooled panel regressions, I estimate the quantile-regression specifications separately for each country individually. They therefore serve as a robustness check and help identify whether the panel results are driven by broad cross-country patterns or by particular crisis episodes in individual countries.

The models are estimated on a common sample within each target variable and country set, requiring non-missing observations for the dependent variable, the autoregressive lags, the  $\text{MUI}$ ,  $\text{CISS}$ , and  $\text{CLIFS}$ . Predictive performance is summarized using the in-sample pinball loss, where lower values indicate more accurate quantile forecasts. It should be considered that this exercise is not merely to measure forecasting performance but rather to examine the significance and signals added by including the  $\text{MUI}$ ; a more forecasting-performance-oriented version focusing on out-of-sample pinball losses will be shown in the next section.

Table 4 reports the country-specific results for Germany. The  $\text{MUI}$  enters negatively and significantly at the 0.05 and 0.10 GDP-growth quantiles, indicating that higher macroeconomic uncertainty is associated with weaker downside growth outcomes.  $\text{CLIFS}$  shows a similar negative association, while  $\text{CISS}$  is insignificant. For upper-tail inflation, the  $\text{MUI}$  is the only risk indicator that remains statistically significant across the reported quantiles, whereas  $\text{CISS}$  and  $\text{CLIFS}$  add little explanatory content once the  $\text{MUI}$  is included. For unemployment, the evidence is weaker, with only limited significance at the 0.90 quantile. Overall, the German results suggest that the  $\text{MUI}$  contains information about lower-tail GDP risk and, more clearly, upside inflation risk beyond standard financial-stress indicators.

For unemployment in Germany, the results are more neutral, with barely any significance from any index, meaning that adding any of the indices may not improve the prediction.

To obtain a broader cross-country perspective, I additionally estimate panel quantile regressions using the full set of country-specific indices and macroeconomic observations. Inference is based on a synchronized moving-block bootstrap over calendar dates. Contiguous blocks of months are resampled while retaining the full cross-section of countries within each selected date, which allows the procedure to preserve both serial dependence over time

and contemporaneous dependence across countries. This is particularly relevant given the persistence of the regressors and the overlapping forecast horizons. The panel results provide a more differentiated picture than the country-specific evidence. For GDP growth, both **CLIFS** and the **MUI** are negatively associated with the lower conditional quantiles, although statistical significance is concentrated at selected quantiles and is weaker under the bootstrap inference than under conventional standard errors. For inflation, the **MUI** is the only index that remains positively and statistically significant in the upper tail, particularly at the 0.90 and 0.95 quantiles, whereas **CISS** and **CLIFS** carry little robust explanatory content. For unemployment, **CLIFS** and especially the **MUI** are positively associated with adverse upper-tail outcomes, with the magnitude of the **MUI** coefficient increasing toward the 0.95 quantile. Overall, the results suggest that the **MUI** contains the most consistent information about inflationary and labor-market tail risks, while the evidence for GDP is economically meaningful but less precisely estimated.

**Table 4:** Country-specific and panel quantile regression results

| Outcome                                             | $\tau$ | Germany           |                      |                      | Panel               |                     |                     |
|-----------------------------------------------------|--------|-------------------|----------------------|----------------------|---------------------|---------------------|---------------------|
|                                                     |        | CISS              | CLIFS                | MUI                  | CISS                | CLIFS               | MUI                 |
| Target A: GDP growth, next quarter                  |        |                   |                      |                      |                     |                     |                     |
|                                                     | 0.05   | 0.225<br>(0.262)  | −0.720***<br>(0.175) | −1.163***<br>(0.232) | −0.244<br>(0.154)   | −0.517*<br>(0.275)  | −1.559*<br>(0.737)  |
|                                                     | 0.10   | 0.165<br>(0.177)  | −0.771***<br>(0.273) | −1.000***<br>(0.357) | −0.153<br>(0.130)   | −0.435*<br>(0.243)  | −0.825<br>(0.555)   |
|                                                     | 0.25   | −0.001<br>(0.196) | −0.160<br>(0.294)    | −0.318<br>(0.211)    | −0.001<br>(0.070)   | −0.323**<br>(0.130) | −0.269<br>(0.266)   |
| Target B: <i>HICP</i> inflation, three months ahead |        |                   |                      |                      |                     |                     |                     |
|                                                     | 0.75   | −0.033<br>(0.098) | −0.020<br>(0.100)    | 0.172**<br>(0.079)   | −0.039<br>(0.027)   | −0.050<br>(0.048)   | 0.167<br>(0.101)    |
|                                                     | 0.90   | 0.043<br>(0.068)  | 0.032<br>(0.080)     | 0.289***<br>(0.077)  | −0.028<br>(0.034)   | 0.002<br>(0.049)    | 0.270**<br>(0.121)  |
|                                                     | 0.95   | 0.010<br>(0.063)  | 0.071<br>(0.078)     | 0.431***<br>(0.113)  | −0.018<br>(0.040)   | 0.049<br>(0.061)    | 0.312**<br>(0.131)  |
| Target C: Unemployment rate, three months ahead     |        |                   |                      |                      |                     |                     |                     |
|                                                     | 0.75   | 0.000<br>(0.003)  | 0.000<br>(0.004)     | 0.000<br>(0.002)     | −0.016**<br>(0.007) | 0.037***<br>(0.010) | 0.033**<br>(0.015)  |
|                                                     | 0.90   | −0.003<br>(0.012) | 0.002<br>(0.013)     | 0.017*<br>(0.009)    | −0.017<br>(0.012)   | 0.046***<br>(0.014) | 0.079***<br>(0.026) |
|                                                     | 0.95   | −0.004<br>(0.008) | −0.001<br>(0.011)    | 0.005<br>(0.008)     | −0.009<br>(0.015)   | 0.066***<br>(0.020) | 0.122***<br>(0.037) |

*Notes:* The table reports coefficient estimates from country-specific quantile regressions for Germany and panel quantile regressions with country fixed effects. All specifications include autoregressive controls and jointly include **CISS**, **CLIFS**, and the **MUI**. Standard errors are reported in parentheses. For Germany, the number of observations is 101 for GDP growth and 308 for inflation and unemployment. Panel standard errors are obtained from a synchronized moving-block bootstrap over calendar dates, retaining the complete cross-section within each selected date. Panel significance levels are based on centered bootstrap  $p$ -values. Significance is denoted by \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ . Increasingly dark shading denotes significance at the 10, 5, and 1 percent levels, respectively.

## 6.2 Out-of-sample expanding forecasts

As the in-sample regressions suggest that the **MUI** is associated with higher predictive value for macroeconomic tail outcomes, the next step is to evaluate whether this association translates into improved out-of-sample quantile forecasts. To assess whether the proposed **MUI** improves tail-risk forecasting performance, I conduct a recursive out-of-sample quantile forecasting exercise for the panel of countries. The exercise is designed to compare the predictive content of the index against standard financial-stress indicators, both individually and jointly. This provides a more performance-focused and rigorous extension of the in-sample analysis.

### 6.2.1 Setup

For each target variable, country  $c$ , forecast origin  $t$ , and quantile  $\tau$ , I estimate a country-specific quantile regression using the observations available for that country up to the forecast origin. The fitted model is then used to generate one out-of-sample forecast of the conditional quantile of  $y_{c,t+h}$ . The forecasting regression is re-estimated recursively as the forecast origin moves forward. Formally, the country-specific forecasting model is

$$Q_\tau(y_{c,t+h} \mid \mathcal{F}_{c,t}) = \alpha_c^{(\tau)} + \delta_{c,m(t)}^{(\tau)} + \sum_{\ell \in \mathcal{L}_y} \rho_{c,\ell}^{(\tau)} y_{c,t-\ell} + \sum_{\ell \in \mathcal{L}_x} \gamma_{c,\ell}^{(\tau)'} x_{c,t-\ell} + \theta_c^{(\tau)'} z_{c,t}. \quad (6)$$

where  $Q_\tau(y_{c,t+h} \mid \mathcal{F}_{c,t})$  denotes the conditional  $\tau$ -quantile of the target variable for country  $c$ ,  $\alpha_c^{(\tau)}$  is the country-specific intercept, and  $\delta_{c,m(t)}^{(\tau)}$  captures month-of-year effects within the country-specific regression. The autoregressive controls include lags of the target variable, while  $x_{c,t-\ell}$  contains parsimonious cross-variable macroeconomic controls. For GDP growth, the cross-controls are lagged inflation and unemployment; for inflation, they are lagged GDP growth and unemployment; and for unemployment, they are lagged GDP growth and inflation. The vector  $z_{c,t}$  contains the risk or financial-stress indicators included in the respective specification.

The pooled results reported below are therefore pooled forecast-evaluation results; pinball losses are first computed from country-specific forecasts and then aggregated across countries.

The quantile and horizon structure mirrors the setup of the in-sample exercise. To ensure minimal look-ahead bias, arising from future observations and full-sample estimation, is present in the index creation, the **MUI** is reconstructed at every month using only data available up until the month, including the factor extraction and index standardization. Since no real-time vintages are available for most of the periods, this means that the stochastic volatility models in reconstructing the index are reconstructed with data up to that month from the latest vintage to prevent leakage. In practice, this means that I end up with a matrix of separate country-level **MUIs** at every vintage month. The first estimation window contains at least 8 years of data, so 96 months or 32 quarters, after which the model is re-estimated recursively at each forecast origin. This leaves us with an out-of-sample period of April 2008–March 2026 (N=215 for unemployment and **HICP**, N=76 for GDP).

I compare six main forecasting specifications. The baseline model contains autoregressive controls, cross-variable macro controls, a country-specific intercept, and month-of-year effects. The remaining specifications augment this baseline with different combinations of risk and

financial-stress indicators:

$$\begin{aligned}
\mathcal{M}_0 &: \text{Baseline,} \\
\mathcal{M}_1 &: \text{Baseline} + \text{MUI}_{i,t}, \\
\mathcal{M}_2 &: \text{Baseline} + \text{CISS}_{i,t}, \\
\mathcal{M}_3 &: \text{Baseline} + \text{CLIFS}_{i,t}, \\
\mathcal{M}_4 &: \text{Baseline} + \text{CISS}_{i,t} + \text{CLIFS}_{i,t}, \\
\mathcal{M}_5 &: \text{Baseline} + \text{MUI}_{i,t} + \text{CISS}_{i,t} + \text{CLIFS}_{i,t}.
\end{aligned} \tag{7}$$

Here,  $\text{MUI}_{i,t}$  denotes the proposed **MUI**, while  $\text{CISS}_{i,t}$  and  $\text{CLIFS}_{i,t}$  are benchmark financial-stress indicators. This set of models allows for three comparisons. First, the individual specifications  $\mathcal{M}_1$ – $\mathcal{M}_3$  compare the stand-alone forecasting content of the **MUI**, **CISS**, and **CLIFS**. Second,  $\mathcal{M}_4$  evaluates the joint predictive content of the two benchmark financial-stress indicators. Third,  $\mathcal{M}_5$  tests whether the **MUI** adds forecasting value beyond the combined information contained in **CISS** and **CLIFS**. All index variables are standardized recursively within a country using only the estimation sample available at each forecast origin. Thus, for each country and forecast origin, the index values are transformed into expanding-window  $z$ -scores based on past information only.

## 6.2.2 Germany

**Table 5:** Out-of-sample pinball losses for Germany

| Outcome                                                          | Quantile $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
|------------------------------------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| <i>Target A: GDP growth – 1Q-ahead, <math>N = 76</math></i>      |                 |                 |                 |                 |                 |                 |                 |
|                                                                  | 0.05            | 0.809           | <b>0.447</b>    | 0.770           | 0.676           | 0.802           | 0.537           |
|                                                                  | 0.10            | 0.943           | <b>0.605</b>    | 0.882           | 0.709           | 0.868           | 0.617           |
|                                                                  | 0.25            | 1.063           | 0.822           | 1.054           | 0.881           | 0.961           | <b>0.801</b>    |
| <i>Target B: HICP inflation – 3M-ahead, <math>N = 215</math></i> |                 |                 |                 |                 |                 |                 |                 |
|                                                                  | 0.75            | 0.681           | <b>0.567</b>    | 0.693           | 0.692           | 0.696           | 0.577           |
|                                                                  | 0.90            | 0.491           | <b>0.329</b>    | 0.511           | 0.469           | 0.473           | 0.347           |
|                                                                  | 0.95            | 0.311           | <b>0.235</b>    | 0.330           | 0.269           | 0.295           | 0.252           |
| <i>Target C: Unemployment – 3M-ahead, <math>N = 215</math></i>   |                 |                 |                 |                 |                 |                 |                 |
|                                                                  | 0.75            | 0.070           | 0.070           | 0.072           | 0.070           | 0.069           | <b>0.069</b>    |
|                                                                  | 0.90            | 0.040           | 0.043           | 0.041           | 0.043           | <b>0.039</b>    | 0.039           |
|                                                                  | 0.95            | <b>0.026</b>    | 0.027           | 0.028           | 0.028           | 0.031           | 0.029           |

Notes: The table reports out-of-sample pinball losses for Germany. Lower values indicate better quantile forecast performance. Bold entries denote the best-performing specification within each outcome–quantile combination. Shaded columns indicate specifications that include the proposed **MUI**. Model definitions are as follows:  $\mathcal{M}_0$  = baseline model;  $\mathcal{M}_1$  = baseline + **MUI**;  $\mathcal{M}_2$  = baseline + **CISS**;  $\mathcal{M}_3$  = baseline + **CLIFS**;  $\mathcal{M}_4$  = baseline + **CISS** + **CLIFS**;  $\mathcal{M}_5$  = baseline + **CISS** + **CLIFS** + **MUI**.

In Table 5, the average pinball loss is reported for all six specifications for Germany. It can be inferred that the **MUI** can provide additional forecast precision for low quantiles of GDP. For

the 0.05 quantile, pinball loss can be reduced by 33% in  $\mathcal{M}_5$  over  $\mathcal{M}_4$  when including the **MUI** or even 34% for  $\mathcal{M}_1$  over  $\mathcal{M}_3$ , also outperforming the benchmark specification without any index. The effect persists but gets weaker for higher quantiles. For inflation, it appears similar to the in-sample analysis that **CISS** and **CLIFS** both only hold marginal information value, whereas the **MUI** increases tail forecasting substantially. It is even preferred to use the **MUI** on its own than to combine it with **CISS** and **CLIFS**. Just using an **MUI** reduces pinball losses by 31% over  $\mathcal{M}_4$  for the 0.9 inflation quantile. This confirms previous significance findings of the **MUI** in-sample versus the benchmark indices.

For unemployment, none of the models seem to be overly helpful for prediction, and the baseline specification  $\mathcal{M}_0$  can even be the best choice. This confirms the result of a weak unemployment relation to the indices from the in-sample analysis.

In Figures 2a and 2b, it can be seen that the gains in pinball loss for the selected quantiles over time, also using the **MUI** or just **CISS** and **CLIFS**. Unsurprisingly, most of the gains are coming during periods of high stress. For GDP, the largest gains occur during the financial crisis, COVID-19, as well as the post-pandemic weakness in 2024-2025. For inflation, the timing is even more striking. For most of the sample, there are only marginal gains as inflation remained fairly stable around the 2% target from 2000-2019. The substantial gains occur during the inflation surge of 2021-2023, which is not surprising given the extraordinary inflation increase that **CISS** and **CLIFS** seem to provide less signal than the **MUI**.

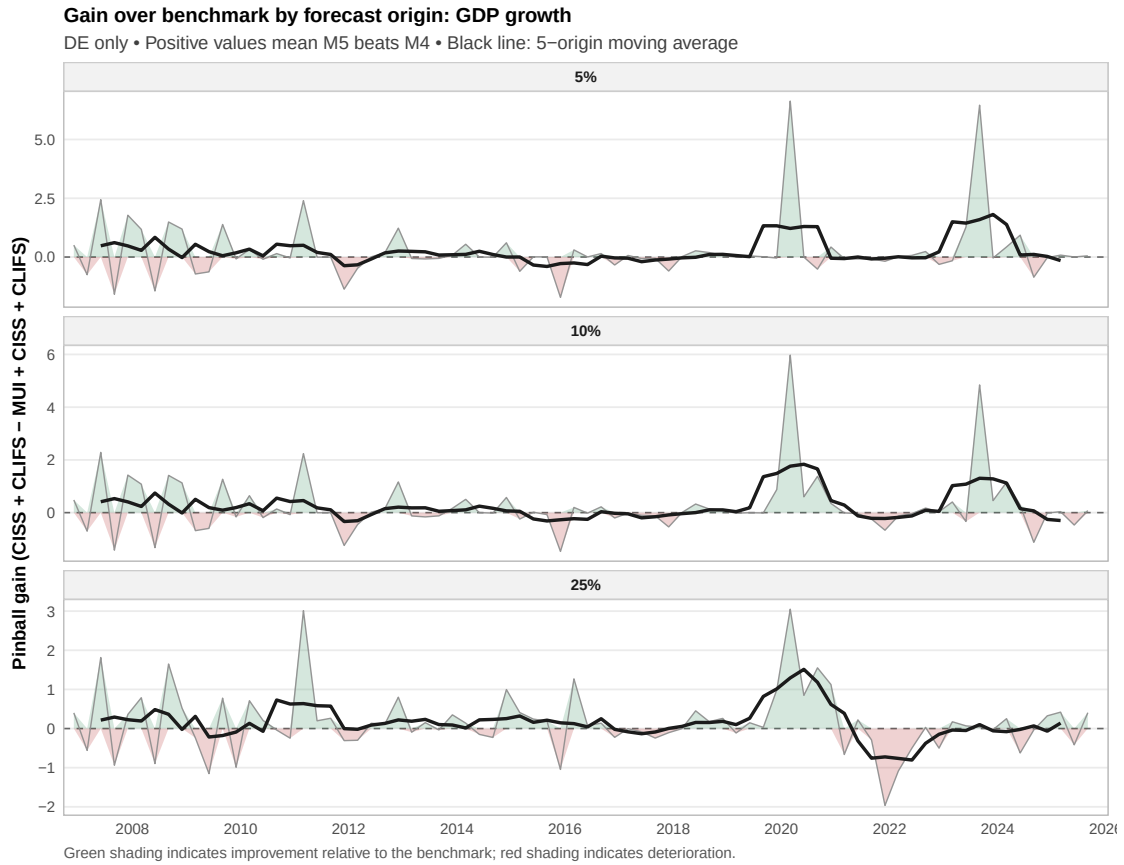
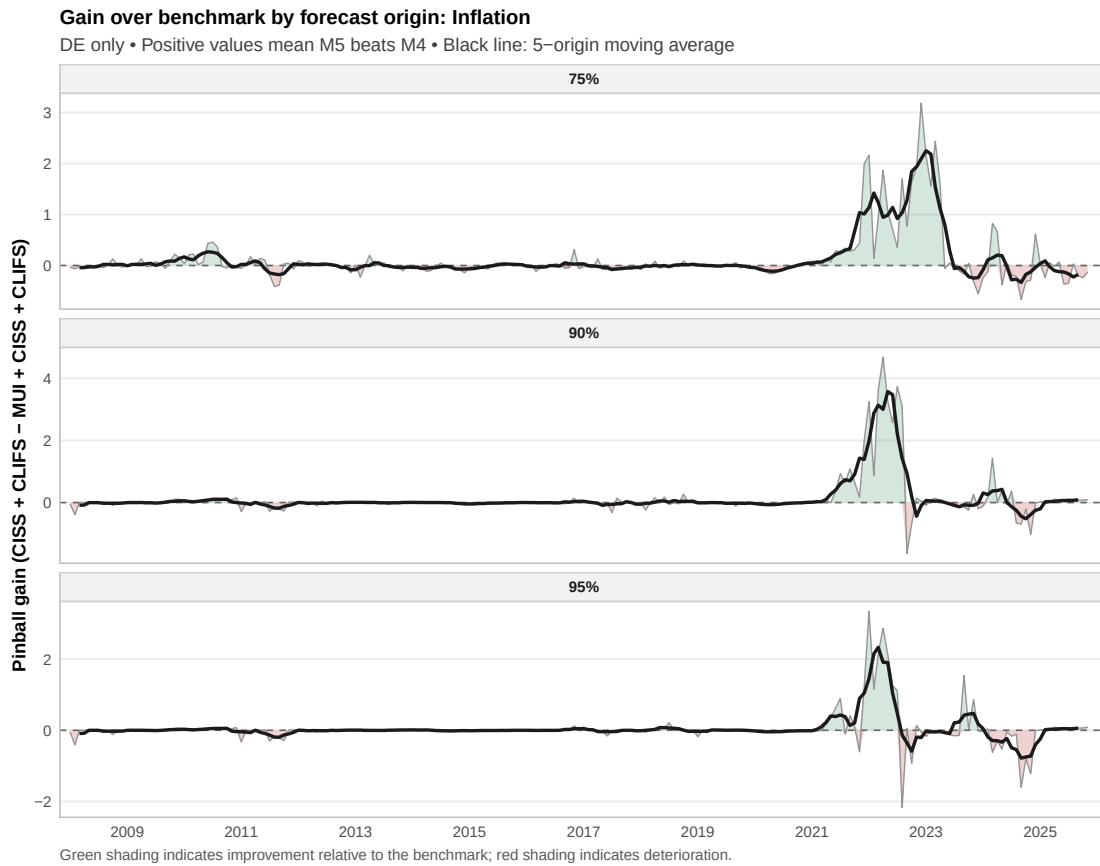
As a robustness check, I repeat the complete recursive out-of-sample forecasting exercise using **MUIs** constructed with  $K=3$  and  $K=8$  factors, in addition to the baseline choice of  $K=6$ . The results, reported in Appendix Table 32, are qualitatively stable across specifications. Choosing  $\mathcal{M}_5$  over  $\mathcal{M}_4$  reduces panel pinball loss by 13.3-19.6% for the 0.05 GDP-growth quantile and by 8.4-13.8% for the 0.10 quantile. The gains at the 0.25 GDP quantile are smaller and less uniform. For upper-tail inflation, the improvements are particularly robust: the corresponding gains range from 4.6 to 6.2% at the 0.75 quantile, from 14.9 to 16.6% at the 0.90 quantile, and from 15.8 to 18.3% at the 0.95 quantile. The inflation improvements remain statistically significant for every value of  $K$ , while unemployment gains remain comparatively small. Thus, the main forecasting conclusions are not driven by the baseline choice of six factors: the **MUI** contributes most consistently to upper-tail inflation forecasts, provides additional information for lower-tail GDP forecasts, and adds little to unemployment forecasts.

### 6.2.3 Panel Results

The panel forecast results in Table 6 for all countries confirm the results for Germany. GDP tail forecasts for the 0.05 quantile can be improved by 13% when including an **MUI**, whereas 0.9 quantile inflation forecasts can be improved by 17% over  $\mathcal{M}_4$ . Unemployment tails, however, can only be improved marginally by the **MUI**. This is in line with the in-sample significance of both **CLIFS** and the **MUI** for the panel specification.

To assess whether the gains from including the proposed index are driven by a small number of crisis observations, Table 7 compares the **CISS+CLIFS** benchmark to the full specification under several sample restrictions.

The relative performance of  $\mathcal{M}_5$  is robust across most sample restrictions. In the full sample,  $\mathcal{M}_5$  produces lower pinball losses than the  $\mathcal{M}_4$  for both pooled and German forecasts of downside GDP risk and upside inflation risk. These gains remain clearly visible after excluding COVID-19 target periods. They also persist after excluding the 2021–2023 inflation surge for

(a) Gains of  $\mathcal{M}_5$  over  $\mathcal{M}_4$  over time for GDP in Germany(b) Gains of  $\mathcal{M}_5$  over  $\mathcal{M}_4$  over time for Inflation in Germany**Figure 2:** Timing of gains for  $\mathcal{M}_5$  over  $\mathcal{M}_4$

**Table 6:** Out-of-sample pinball losses for the panel

| Outcome                                                           | Quantile $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
|-------------------------------------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| <i>Target A: GDP growth – 1Q-ahead, <math>N = 760</math></i>      |                 |                 |                 |                 |                 |                 |                 |
|                                                                   | 0.05            | 1.015           | 0.807           | 0.921           | 0.868           | 0.916           | <b>0.794</b>    |
|                                                                   | 0.10            | 1.113           | 0.980           | 0.984           | 0.938           | 1.007           | <b>0.911</b>    |
|                                                                   | 0.25            | 1.374           | 1.284           | 1.210           | <b>1.150</b>    | 1.193           | 1.174           |
| <i>Target B: HICP inflation – 3M-ahead, <math>N = 2150</math></i> |                 |                 |                 |                 |                 |                 |                 |
|                                                                   | 0.75            | 0.673           | 0.620           | 0.647           | 0.652           | 0.646           | <b>0.605</b>    |
|                                                                   | 0.90            | 0.468           | 0.379           | 0.459           | 0.452           | 0.445           | <b>0.371</b>    |
|                                                                   | 0.95            | 0.321           | 0.261           | 0.322           | 0.322           | 0.318           | <b>0.260</b>    |
| <i>Target C: Unemployment – 3M-ahead, <math>N = 2150</math></i>   |                 |                 |                 |                 |                 |                 |                 |
|                                                                   | 0.75            | 0.202           | 0.195           | 0.182           | 0.176           | 0.174           | <b>0.173</b>    |
|                                                                   | 0.90            | 0.135           | 0.120           | 0.120           | <b>0.114</b>    | 0.115           | 0.114           |
|                                                                   | 0.95            | 0.100           | 0.083           | 0.089           | 0.084           | 0.088           | <b>0.082</b>    |

Notes: The table reports out-of-sample pinball losses for the panel. Lower values indicate better quantile forecast performance. Bold entries denote the best-performing specification within each outcome–quantile combination. Shaded columns indicate specifications that include the proposed MUI. Model definitions are as follows:  $\mathcal{M}_0$  = baseline model;  $\mathcal{M}_1$  = baseline + MUI;  $\mathcal{M}_2$  = baseline + CISS;  $\mathcal{M}_3$  = baseline + CLIFS;  $\mathcal{M}_4$  = baseline + CISS + CLIFS;  $\mathcal{M}_5$  = baseline + CISS + CLIFS + MUI.

**Table 7:** Robustness of pinball losses to crisis exclusions

| Sample                        | Sample restriction                  | GDP growth      |                 | HICP inflation  |                 |                 |                 |
|-------------------------------|-------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                               |                                     | $\tau = 0.05$   |                 | $\tau = 0.90$   |                 | $\tau = 0.95$   |                 |
|                               |                                     | $\mathcal{M}_4$ | $\mathcal{M}_5$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| <i>Target A: Pooled panel</i> |                                     |                 |                 |                 |                 |                 |                 |
| Panel                         | Full sample                         | 0.916           | <b>0.794</b>    | 0.445           | <b>0.371</b>    | 0.318           | <b>0.260</b>    |
| Panel                         | Excluding COVID target periods      | 0.763           | <b>0.690</b>    | 0.448           | <b>0.373</b>    | 0.322           | <b>0.262</b>    |
| Panel                         | Excluding 2021–2023 inflation surge | 0.877           | <b>0.832</b>    | 0.249           | <b>0.220</b>    | 0.188           | <b>0.155</b>    |
| Panel                         | Pre-2020 only                       | <b>0.642</b>    | 0.673           | <b>0.200</b>    | 0.202           | <b>0.140</b>    | 0.143           |
| <i>Target B: Germany</i>      |                                     |                 |                 |                 |                 |                 |                 |
| DE                            | Full sample                         | 0.802           | <b>0.537</b>    | 0.473           | <b>0.347</b>    | 0.295           | <b>0.252</b>    |
| DE                            | Excluding COVID target periods      | 0.704           | <b>0.522</b>    | 0.483           | <b>0.352</b>    | 0.302           | <b>0.256</b>    |
| DE                            | Excluding 2021–2023 inflation surge | 0.771           | <b>0.576</b>    | <b>0.182</b>    | 0.191           | <b>0.109</b>    | 0.141           |
| DE                            | Pre-2020 only                       | 0.702           | <b>0.589</b>    | <b>0.144</b>    | 0.152           | <b>0.087</b>    | 0.097           |

Notes: The table reports out-of-sample pinball losses under alternative sample restrictions. Lower values indicate better quantile forecast performance. The GDP columns refer to lower-tail forecasts at  $\tau = 0.05$ , while the HICP columns refer to upper-tail inflation forecasts at  $\tau = 0.90$  and  $\tau = 0.95$ . Bold entries denote the lower pinball loss within each  $\mathcal{M}_4$ – $\mathcal{M}_5$  comparison. Shaded columns indicate the specification that includes the proposed MUI in addition to CISS and CLIFS. Model definitions are:  $\mathcal{M}_4$  = baseline + CISS + CLIFS;  $\mathcal{M}_5$  = baseline + CISS + CLIFS + MUI.

pooled forecasts and for German lower-tail GDP forecasts, indicating that the improvement in GDP tail prediction is not driven exclusively by crisis observations. The results are less uniform for inflation once the inflation surge is excluded: although  $\mathcal{M}_5$  continues to outperform in the pooled panel,  $\mathcal{M}_4$  yields lower losses for Germany. A similar distinction emerges in the pre-2020 sample. There,  $\mathcal{M}_5$  retains a meaningful advantage for German downside GDP forecasts, but its advantage disappears for pooled GDP and for upper-tail inflation forecasts, for which the two specifications perform very similarly or  $\mathcal{M}_4$  performs slightly better. Overall, the evidence suggests that the **MUI** contributes robustly to forecasting downside GDP risk, particularly for Germany, whereas its gains for upper-tail inflation forecasts are concentrated more strongly in the post-2020 period.

### 6.2.4 Calibration

While the pinball loss provides a strictly consistent scoring rule for evaluating quantile forecasts, it summarizes forecast accuracy in a single loss measure and does not directly show whether the predicted quantiles are empirically well calibrated. In the context of tail-risk forecasting, calibration is important because a conditional  $\tau$ -quantile should be violated with frequency  $\tau$  in the lower tail. For example, if the predicted 0.05 quantile of GDP growth is well calibrated, realized GDP growth should fall below this forecast in approximately 5% of the out-of-sample observations. Similarly, for upper-tail forecasts of inflation and unemployment, realized outcomes should exceed the predicted  $\tau$ -quantile with frequency approximately  $1 - \tau$ .

I therefore complement the pinball-loss evaluation with a simple empirical coverage check. For lower-tail GDP growth forecasts, I compute the violation frequency.

$$\widehat{v}_\tau = \frac{1}{T} \sum_{t=1}^T \mathbf{1}\{y_{t+h} < \widehat{q}_{\tau,t+h}\},$$

where  $y_{t+h}$  is the realized outcome and  $\widehat{q}_{\tau,t+h}$  denotes the predicted conditional  $\tau$ -quantile. A well-calibrated lower-tail forecast should satisfy  $\widehat{v}_\tau \approx \tau$ . For upper-tail inflation and unemployment forecasts, I compute the corresponding exceedance frequency

$$\widehat{e}_\tau = \frac{1}{T} \sum_{t=1}^T \mathbf{1}\{y_{t+h} > \widehat{q}_{\tau,t+h}\},$$

which should be close to  $1 - \tau$  under correct calibration.

Importantly, the calibration exercise alone is not intended to replace the pinball-loss comparison, since coverage alone does not measure the sharpness or distance of forecast errors. Instead, it provides a diagnostic check on whether the gains in pinball loss are accompanied by plausible empirical tail coverage. I report calibration results for the baseline model, the benchmark financial-stress model, and the full model including the **MUI**.

Across all quantiles and targets, the exceedance rate is closest to the nominal level, for either  $\mathcal{M}_1$  or  $\mathcal{M}_5$ , suggesting that specifications augmented with the **MUI** tend to be better calibrated. This is corroborated by the average absolute exceedance errors in Table 9, which are almost uniformly lower for  $\mathcal{M}_1$  and  $\mathcal{M}_5$  than for the baselines  $\mathcal{M}_0$  and  $\mathcal{M}_4$ . Since exceedance rates exceed their nominal counterparts for almost all models and quantiles, the averaging is not distorted by offsetting errors, lending the summary measure some additional credibility.

**Table 8:** Empirical tail exceedance rates

| Sample                        | Target | Quantile | Nominal | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
|-------------------------------|--------|----------|---------|-----------------|-----------------|-----------------|-----------------|
| <i>Target A: Pooled panel</i> |        |          |         |                 |                 |                 |                 |
| Panel                         | GDP    | 0.05     | 0.05    | 0.129           | 0.112           | 0.133           | <b>0.102</b>    |
| Panel                         | GDP    | 0.10     | 0.10    | 0.170           | 0.156           | 0.180           | <b>0.143</b>    |
| Panel                         | GDP    | 0.25     | 0.25    | 0.296           | <b>0.295</b>    | 0.313           | 0.302           |
| Panel                         | HICP   | 0.75     | 0.25    | 0.288           | 0.278           | 0.282           | <b>0.275</b>    |
| Panel                         | HICP   | 0.90     | 0.10    | 0.206           | 0.181           | 0.206           | <b>0.174</b>    |
| Panel                         | HICP   | 0.95     | 0.05    | 0.168           | 0.145           | 0.160           | <b>0.137</b>    |
| <i>Target B: Germany</i>      |        |          |         |                 |                 |                 |                 |
| DE                            | GDP    | 0.05     | 0.05    | <b>0.094</b>    | <b>0.094</b>    | 0.176           | 0.141           |
| DE                            | GDP    | 0.10     | 0.10    | 0.141           | <b>0.118</b>    | 0.247           | 0.176           |
| DE                            | GDP    | 0.25     | 0.25    | 0.447           | <b>0.329</b>    | 0.412           | 0.400           |
| DE                            | HICP   | 0.75     | 0.25    | 0.227           | 0.220           | 0.235           | <b>0.239</b>    |
| DE                            | HICP   | 0.90     | 0.10    | 0.182           | <b>0.155</b>    | 0.205           | 0.174           |
| DE                            | HICP   | 0.95     | 0.05    | 0.170           | <b>0.140</b>    | 0.193           | 0.152           |

*Notes:* The table reports empirical exceedance rates. For GDP, exceedances are lower-tail events,  $y_{t+h} \leq \hat{q}_{\tau,t+h|t}$ . For HICP, exceedances are upper-tail events,  $y_{t+h} > \hat{q}_{\tau,t+h|t}$ , so the nominal exceedance rate is  $1 - \tau$ . Bold entries denote the model closest to the nominal exceedance rate within each row.

**Table 9:** Average absolute exceedance errors

| Sample | Target | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
|--------|--------|-----------------|-----------------|-----------------|-----------------|
| Panel  | GDP    | 0.065           | 0.054           | 0.075           | <b>0.049</b>    |
| Panel  | HICP   | 0.087           | 0.068           | 0.083           | <b>0.062</b>    |
| DE     | GDP    | 0.094           | <b>0.047</b>    | 0.145           | 0.106           |
| DE     | HICP   | 0.075           | <b>0.059</b>    | 0.088           | 0.062           |

*Notes:* The table reports the average absolute deviation between empirical and nominal exceedance rates across the target-specific quantiles. Lower values indicate better calibration. For GDP, exceedances refer to lower-tail realizations; for HICP, exceedances refer to upper-tail realizations.

That said, none of the models achieves satisfactory absolute calibration as exceedance rates consistently and substantially exceed their nominal thresholds.

**Table 10:** Quantile-score decomposition of the gains from adding the **MUI**

| Outcome                      | $\tau$ | $\Delta QS$ | $p_{\Delta QS}$ | $\Delta MCB$ | $p_{\Delta MCB}$ | $\Delta DSC$ | $p_{\Delta DSC}$ |
|------------------------------|--------|-------------|-----------------|--------------|------------------|--------------|------------------|
| <i>Panel A: Germany</i>      |        |             |                 |              |                  |              |                  |
| GDP growth                   | 0.05   | -0.264**    | 0.033           | -0.123       | 0.158            | 0.141**      | 0.025            |
| GDP growth                   | 0.10   | -0.252**    | 0.028           | -0.119       | 0.105            | 0.133**      | 0.042            |
| GDP growth                   | 0.25   | -0.160*     | 0.058           | -0.123**     | 0.034            | 0.037        | 0.292            |
| HICP inflation               | 0.75   | -0.119**    | 0.042           | -0.030       | 0.118            | 0.089        | 0.116            |
| HICP inflation               | 0.90   | -0.126*     | 0.084           | 0.022        | 0.722            | 0.148*       | 0.073            |
| HICP inflation               | 0.95   | -0.043      | 0.217           | 0.000        | 0.506            | 0.044        | 0.111            |
| <i>Panel B: Pooled panel</i> |        |             |                 |              |                  |              |                  |
| GDP growth                   | 0.05   | -0.122*     | 0.052           | -0.102*      | 0.063            | 0.021        | 0.187            |
| GDP growth                   | 0.10   | -0.096      | 0.135           | -0.058       | 0.169            | 0.037        | 0.162            |
| GDP growth                   | 0.25   | -0.019      | 0.405           | -0.020       | 0.281            | -0.002       | 0.513            |
| HICP inflation               | 0.75   | -0.040**    | 0.020           | -0.003       | 0.266            | 0.037**      | 0.029            |
| HICP inflation               | 0.90   | -0.074***   | 0.009           | -0.010       | 0.272            | 0.064***     | 0.003            |
| HICP inflation               | 0.95   | -0.058***   | 0.007           | -0.025       | 0.103            | 0.034***     | < 0.001          |

*Notes:* The table reports differences between the full specification  $\mathcal{M}_5$  and the benchmark specification  $\mathcal{M}_4$ , which contains **CISS** and **CLIFS**. The average quantile score is decomposed as  $\overline{QS} = MCB - DSC + UNC$ . Because both models are evaluated on the same realizations, the uncertainty component cancels. All differences are defined as  $\mathcal{M}_5 - \mathcal{M}_4$ . Thus,  $\Delta QS < 0$  indicates a lower quantile score,  $\Delta MCB < 0$  indicates lower miscalibration, and  $\Delta DSC > 0$  indicates greater discrimination. The reported  $p$ -values correspond to one-sided tests in the direction favoring  $\mathcal{M}_5$ . Significance is denoted by \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ . Increasingly dark shading denotes significance at the 10, 5, and 1 percent levels, respectively.

To assess whether the lower pinball losses of the specification containing the **MUI** reflect improved calibration or greater informational content, I decompose the average quantile score into miscalibration, discrimination, and uncertainty components according to **Gneiting and Resin (2023)**. The decomposition is given by

$$\overline{QS} = MCB - DSC + UNC,$$

where MCB measures the loss associated with systematic miscalibration, DSC measures the ability of the forecast to distinguish between different states of the conditional outcome distribution, and UNC depends only on the unconditional distribution of the realized target. Since  $\mathcal{M}_4$  and  $\mathcal{M}_5$  are evaluated on the same observations, the uncertainty component is identical across models and drops out of the pairwise comparison. Accordingly, a negative difference in MCB and a positive difference in DSC both favor the specification augmented with the **MUI**.

Inference for the score decomposition is based on a synchronized moving-block bootstrap over forecast-origin dates. For the pooled panel, the complete cross-section of countries is retained whenever an origin date is resampled, thereby preserving contemporaneous cross-country dependence, while resampling blocks of adjacent origins accommodates temporal dependence in the forecast evaluation sample. The quantile recalibration regressions and the resulting score, miscalibration, and discrimination components are re-estimated in each bootstrap replication.

For pairwise comparisons, differences are defined as the value for  $\mathcal{M}_5$  minus that for  $\mathcal{M}_4$ . Accordingly, the reported one-sided  $p$ -values test whether adding the **MUI** reduces the quantile

score or MCB, or increases DSC. Bootstrap standard errors are obtained from the distribution of the corresponding pairwise differences across replications, with inference based on the resulting normal approximation.

The results in Table 10 show that the source of the forecast improvements differs across outcomes. For Germany, adding the MUI significantly lowers the quantile score at the 0.05 and 0.10 GDP-growth quantiles. These gains are driven primarily by greater discrimination, with increases in DSC of 0.141 and 0.133, respectively. This suggests that the MUI helps the model distinguish periods of especially elevated downside growth risk rather than merely shifting the predicted quantiles toward their unconditional coverage frequencies. At the 0.25 quantile, the score improvement is weaker and statistically significant only at the 10% level, while the decomposition points mainly to a reduction in miscalibration. For German inflation, the score improvement is statistically significant at the 0.75 quantile and weaker at the 0.90 quantile. At the latter, the point estimates again suggest that the gain is mainly associated with higher discrimination. No statistically significant improvement is found at the 0.95 quantile.

The pooled inflation results provide the clearest evidence. The full specification achieves significantly lower quantile scores than the CISS–CLIFS benchmark at all three upper-tail quantiles. These improvements are driven predominantly by greater discrimination:  $\Delta\text{DSC}$  equals 0.037, 0.064, and 0.034 at the 0.75, 0.90, and 0.95 quantiles, respectively, and is statistically significant in each case. By contrast, the corresponding changes in MCB are small and statistically insignificant. Thus, the MUI appears to add state-dependent information about when upside inflation risks are elevated, instead of just improving calibration. For panel GDP growth, the strongest evidence is concentrated in the most adverse tail. At the 0.05 quantile, the score improvement is significant at approximately the 10% level and is associated mainly with lower miscalibration. At the 0.10 and 0.25 quantiles, the point estimates continue to favor  $\mathcal{M}_5$ , but the differences are not statistically significant.

Overall, the decomposition qualifies the empirical coverage results. Specifications including the MUI do not achieve perfect absolute calibration, but they generally produce more informative conditional quantile forecasts. In particular, the gains for upper-tail inflation arise mainly from increased discrimination, while the improvements for extreme downside GDP risk reflect a combination of greater discrimination and lower miscalibration.

### 6.2.5 Diebold–Mariano Tests

To assess whether the reductions in pinball loss translate into statistically significant improvements in predictive accuracy, I conduct one-sided Diebold–Mariano (DM) tests (Diebold & Mariano, 1995). The comparison focuses on  $\mathcal{M}_5$ , which augments CISS and CLIFS with the proposed MUI, relative to  $\mathcal{M}_4$ , which contains CISS and CLIFS only. This comparison directly tests the incremental forecasting value of the MUI conditional on the two financial-stress measures. Results are reported for GDP growth and inflation, for which the preceding loss comparisons indicate the clearest improvements. The more limited gains for unemployment are not considered further in the formal DM-analysis.

For each forecast origin, define the loss differential as

$$d_t = L_{\mathcal{M}_4,t} - L_{\mathcal{M}_5,t}, \quad (8)$$

where  $L_{\mathcal{M}_4,t}$  and  $L_{\mathcal{M}_5,t}$  denote the pinball losses of the two competing specifications. Hence,  $\bar{d} > 0$  indicates that  $\mathcal{M}_5$  achieves a lower average forecast loss. Given the directional research

question of whether adding the **MUI** improves forecast accuracy, the one-sided hypotheses are

$$H_0 : \mathbb{E}[d_t] \leq 0 \quad \text{against} \quad H_1 : \mathbb{E}[d_t] > 0. \quad (9)$$

Statistical inference is based on a regression of  $d_t$  on a constant with Newey–West HAC standard errors, which allow for serial dependence in the sequence of forecast losses. For the standard error calculation, the Bartlett kernel is used along a lag length of  $L = h - 1 = 2$ . For the country-specific test, this procedure is applied directly to the German loss differentials. For the panel test, pinball losses are first averaged across countries within each forecast origin, and the loss differential is subsequently constructed from these cross-country averages. This yields one panel-average loss differential per forecast origin and avoids treating contemporaneous forecast errors across countries as independent observations.

Table 11 reports the results for Germany. For GDP growth, the mean loss differential is positive at all three lower-tail quantiles. The improvement from adding the **MUI** is statistically significant at the 5% level at  $\tau = 0.05$  and  $\tau = 0.10$ , and at the 10% level at  $\tau = 0.25$ . Thus, the German results provide relatively broad evidence that the **MUI** improves forecasts of downside GDP risk beyond the information contained in **CISS** and **CLIFS**. For inflation, the gains are significant at the 5% level at  $\tau = 0.75$  and  $\tau = 0.90$ , while the improvement at the more extreme  $\tau = 0.95$  quantile is positive but not statistically significant.

**Table 11:** Diebold–Mariano tests for German quantile forecasts of  $\mathcal{M}_5$  against  $\mathcal{M}_4$

| Outcome                                    | Quantile $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM stat. | $p$ -value |
|--------------------------------------------|-----------------|-----|-----------|----------|----------|------------|
| <i>Target A: GDP growth – 1Q-ahead</i>     |                 |     |           |          |          |            |
|                                            | 0.05            | 76  | 0.264     | 0.135    | 1.957    | 0.027**    |
|                                            | 0.10            | 76  | 0.252     | 0.130    | 1.935    | 0.028**    |
|                                            | 0.25            | 76  | 0.160     | 0.098    | 1.640    | 0.053*     |
| <i>Target B: HICP inflation – 3M-ahead</i> |                 |     |           |          |          |            |
|                                            | 0.75            | 215 | 0.119     | 0.053    | 2.252    | 0.013**    |
|                                            | 0.90            | 215 | 0.126     | 0.071    | 1.785    | 0.038**    |
|                                            | 0.95            | 215 | 0.043     | 0.047    | 0.913    | 0.181      |

Notes: The table reports country-specific Diebold–Mariano tests for Germany. The loss differential is defined as  $d_t = L_{\mathcal{M}_4,t} - L_{\mathcal{M}_5,t}$ , so that a positive mean differential indicates lower average pinball loss for  $\mathcal{M}_5$ . The reported  $p$ -values correspond to the one-sided alternative that  $\mathcal{M}_5$  has lower expected pinball loss than  $\mathcal{M}_4$ . HAC standard errors are computed using the Newey–West estimator. Significance levels are denoted by  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ .

Table 12 provides the corresponding evidence for the pooled panel. The cross-country results reinforce the inflation finding while providing more selective evidence for GDP growth. At the  $\tau = 0.05$  GDP-growth quantile,  $\mathcal{M}_5$  significantly outperforms  $\mathcal{M}_4$  at the 5% level. The loss differentials at  $\tau = 0.10$  and  $\tau = 0.25$  remain positive, but are not statistically significant. For inflation, by contrast, the improvement is statistically significant across all three upper-tail quantiles. The evidence is particularly strong at  $\tau = 0.90$  and  $\tau = 0.95$ , where the null of no improvement is rejected at the 1% level.

Taken together, the German and panel results point to a differentiated but consistent pattern. The German evidence indicates that the **MUI** can add substantial information for downside

**Table 12:** Diebold–Mariano tests for panel quantile forecasts of  $M_5$  against  $M_4$ 

| Outcome                                    | Quantile $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM stat. | $p$ -value |
|--------------------------------------------|-----------------|-----|-----------|----------|----------|------------|
| <i>Target A: GDP growth – 1Q-ahead</i>     |                 |     |           |          |          |            |
|                                            | 0.05            | 77  | 0.127     | 0.073    | 1.744    | 0.043**    |
|                                            | 0.10            | 77  | 0.095     | 0.078    | 1.217    | 0.114      |
|                                            | 0.25            | 77  | 0.018     | 0.080    | 0.227    | 0.411      |
| <i>Target B: HICP inflation – 3M-ahead</i> |                 |     |           |          |          |            |
|                                            | 0.75            | 215 | 0.040     | 0.015    | 2.647    | 0.004***   |
|                                            | 0.90            | 215 | 0.074     | 0.024    | 3.120    | 0.001***   |
|                                            | 0.95            | 215 | 0.058     | 0.019    | 3.064    | 0.001***   |

Notes: For the panel tests, pinball losses are first averaged across countries within each forecast origin. The loss differential is defined as  $d_t = L_{M_4,t} - L_{M_5,t}$ , so that a positive mean differential indicates lower average pinball loss for  $M_5$ . HAC standard errors are computed using the Newey–West estimator. Significance levels are denoted by \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ .

GDP risk, whereas the panel results show that these gains are less uniform across countries. The evidence for upper-tail inflation forecasting is considerably more robust: significant improvements are found for Germany at two of the three quantiles and for the panel at all three quantiles. The remaining country-specific DM-tests, reported in Appendix B.2.1, further document the degree of cross-country heterogeneity. Overall, the results indicate that the recursively constructed MUI contains predictive information beyond CISS and CLIFS, with the most systematic gains arising for upside inflation risk.

One possible explanation for the particularly robust inflation results is that the recent inflation surge was not primarily a conventional financial-stress episode (Bernanke & Blanchard, 2025). CISS and CLIFS are designed to capture stress in financial markets, including liquidity conditions, equity-market volatility, sovereign-bond stress, and foreign-exchange pressure. These channels are highly relevant during banking and sovereign-debt crises, but may capture disruptions originating in the real economy only indirectly. By contrast, the MUI is constructed from a broad macroeconomic information set and measures changes in the conditional volatility of forecast errors across a wide range of real, nominal, and survey variables. It can therefore increase when macroeconomic relationships become more difficult to predict even in the absence of a proportional deterioration in financial-market conditions.

This distinction is particularly relevant for the 2021–2023 inflation episode, which was shaped by a combination of supply-chain disruptions, energy-price shocks, post-pandemic demand shifts, and changes in inflation dynamics. The forecasting evidence is therefore consistent with the view that macroeconomic forecast uncertainty contains information about upside inflation risk that is not fully summarized by conventional financial-stress indicators.

## 7 Creating a Decomposable Policy Risk Index

While the [MUI](#) is useful as a forecast-based measure of macroeconomic uncertainty, it is not directly decomposable into distinct sources of risk. It also does not explicitly separate macroeconomic uncertainty from financial stress, sovereign stress, geopolitical risk, energy stress, or trade-related disruptions. I therefore construct a second-layer composite policy-risk index. The purpose of this index is not to outperform the [MUI](#) as a forecasting instrument, but to provide an interpretable monitoring tool that decomposes broad macroeconomic risk into economically meaningful channels.

The composite index combines the [MUI](#) with five additional components. I use [CLIFS](#) ([Duprey et al., 2017](#)) as the financial-stress component, [SovCISS](#) ([Garcia-de Andoain & Kremer, 2017](#)) as the sovereign-stress component, the [GPR](#) index ([Caldara & Iacoviello, 2022](#)) as the geopolitical-risk component, a country-specific energy-stress index based on the energy component of [HICP](#), and a common trade-stress index combining the [TPU](#) index ([Caldara et al., 2020](#)) and the [GSCPI](#) ([Benigno et al., 2022](#)). The existing indicators are used as external inputs, while the energy and trade components are constructed below. All components are transformed to a comparable standardized scale before aggregation.

The two indices therefore serve different purposes. The [MUI](#) asks how uncertain the macroeconomic outlook is, while the composite index asks where this broader risk environment comes from and through which channels it is transmitted. This makes the two measures complementary: the [MUI](#) is forecasting-oriented, whereas the composite index is designed as a decomposable narrative and monitoring device.

### 7.1 Additional Components of the Composite Index

The composite index is based on six standardized component series,

$$\mathbf{z}_{i,t} = \left( z_{i,t}^M, z_{i,t}^F, z_{i,t}^S, z_{i,t}^G, z_{i,t}^E, z_{i,t}^T \right)',$$

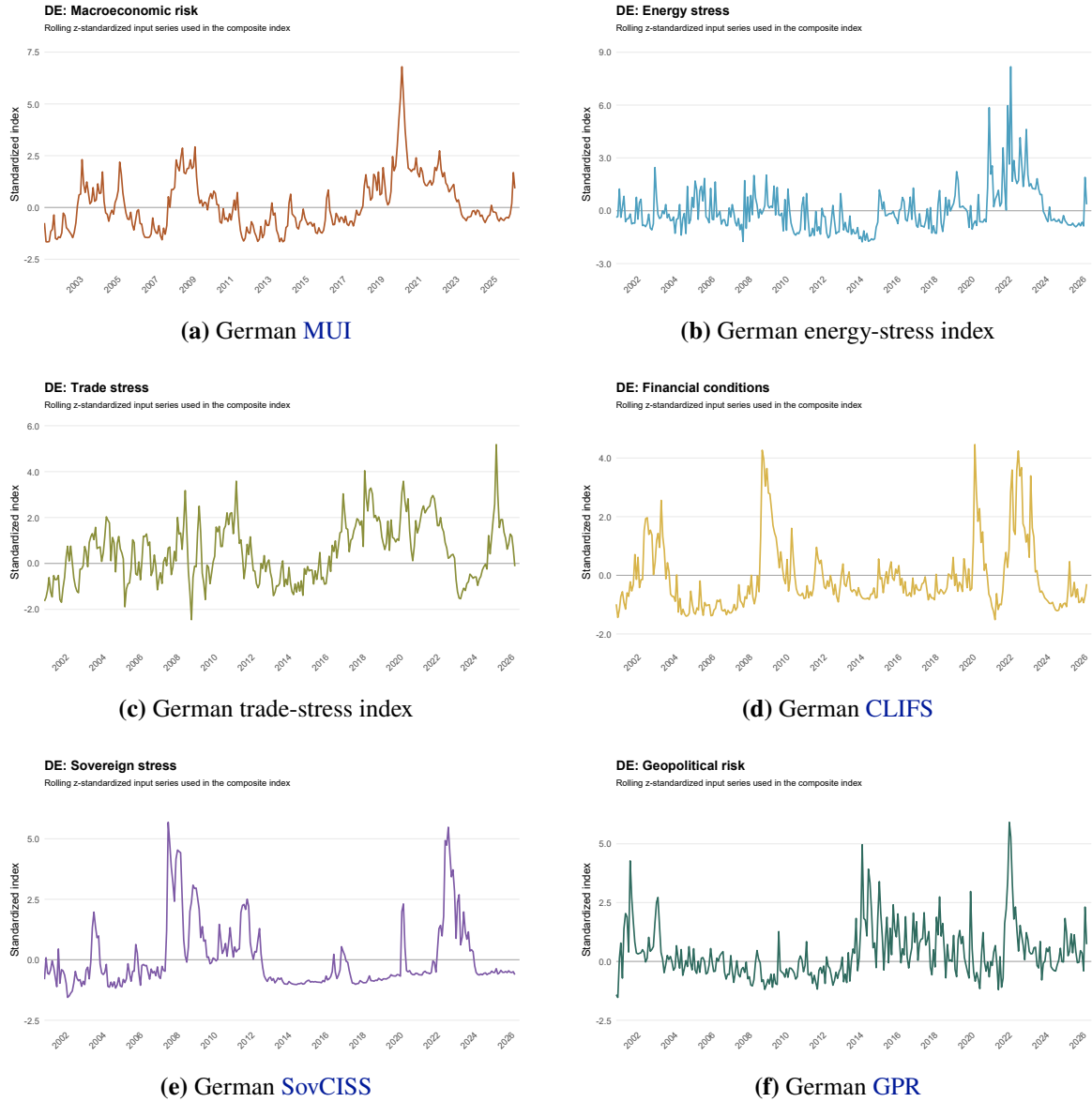
where  $z_{i,t}^M$  denotes macroeconomic uncertainty,  $z_{i,t}^F$  financial stress,  $z_{i,t}^S$  sovereign stress,  $z_{i,t}^G$  geopolitical risk,  $z_{i,t}^E$  energy stress, and  $z_{i,t}^T$  trade stress for country  $i$  in month  $t$ .

For country-specific components, I use the standardization operator.

$$\mathcal{Z}_i(a_{i,t}) = \frac{a_{i,t} - \bar{a}_i}{\sigma(a_i)},$$

where  $\bar{a}_i$  and  $\sigma(a_i)$  denote the country-specific mean and standard deviation of series  $a_{i,t}$  over the available sample at each individual estimation cutoff. For common global components, I analogously write

$$\mathcal{Z}(a_t) = \frac{a_t - \bar{a}}{\sigma(a)}.$$



**Figure 3:** Standardized input indices for the German composite risk index

Thus, all components entering the composite index are measured in standardized deviations from their respective historical distributions. The **MUI** is already standardized by country in the index-construction step; I therefore set  $z_{i,t}^M$  equal to the standardized country-specific **MUI**.

### 7.1.1 CLIFS

I use **CLIFS** as the financial-stress component. Since **CLIFS** is available at monthly frequency for euro area countries, it matches the country coverage and frequency required for the composite index (Duprey et al., 2017). Let  $F_{i,t}$  denote the raw **CLIFS** series for country  $i$ . The financial-stress block is defined as

$$z_{i,t}^F = \mathcal{Z}_i(F_{i,t}).$$

The resulting series measures financial stress relative to each country's own historical financial-stress distribution.

### 7.1.2 SovCISS

I use **SovCISS** as the sovereign-stress component. This captures a country-level sovereign-market risk dimension that is particularly relevant in the euro area (Garcia-de Andoain & Kremer, 2017). Let  $S_{i,t}$  denote the raw **SovCISS** series for country  $i$ . The sovereign-stress block is defined as

$$z_{i,t}^S = \mathcal{Z}_i(S_{i,t}).$$

A positive value of  $z_{i,t}^S$  therefore indicates elevated sovereign stress relative to normal conditions in country  $i$ .

### 7.1.3 Geopolitical Risk Index

I use the **GPR** index of Caldara and Iacoviello (2022) as the geopolitical-risk component. Where a country-specific **GPR** series is available, I use the corresponding national index. For Austria, Greece, and Ireland, where no country-specific series is available, I use the global **GPR** index as a proxy.

Let  $G_{i,t}$  denote the **GPR** series assigned to country  $i$ . The geopolitical-risk block is defined as

$$z_{i,t}^G = \mathcal{Z}_i(G_{i,t}).$$

The resulting series measures geopolitical risk relative to the historical distribution of the **GPR** measure used for that country.

### 7.1.4 Energy Stress Index

I construct a country-specific energy-stress component from the energy component of **HICP**. This captures both upward energy-price pressure and energy-price volatility at the country level. Let  $E_{i,t}$  denote the **HICP** energy index for country  $i$ . I first compute monthly log changes,

$$\Delta e_{i,t} = \log(E_{i,t}) - \log(E_{i,t-1}).$$

Since the index is intended to capture adverse energy-price pressure, only positive monthly energy-price changes are treated as direct price-pressure shocks:

$$p_{i,t} = \max(\Delta e_{i,t}, 0).$$

In addition, I compute an energy-volatility component as the rolling standard deviation of monthly energy-price changes over the previous 12 months:

$$v_{i,t} = \text{sd}(\Delta e_{i,t-11}, \dots, \Delta e_{i,t}).$$

Both subcomponents are standardized within country,

$$\tilde{p}_{i,t} = \mathcal{Z}_i(p_{i,t}), \quad \tilde{v}_{i,t} = \mathcal{Z}_i(v_{i,t}).$$

The raw energy-stress block is then defined as the equally weighted average of standardized upward price pressure and standardized volatility,

$$r_{i,t}^E = \frac{1}{2}\tilde{p}_{i,t} + \frac{1}{2}\tilde{v}_{i,t}.$$

Finally, I standardize the aggregated energy component once more,

$$z_{i,t}^E = \mathcal{Z}_i(r_{i,t}^E),$$

so that the energy-stress block has a comparable scale to the other components of the composite index.

### 7.1.5 Trade Stress Index

I construct a trade-stress component from two global indicators: the [GSCPI](#) and the [TPU](#) index. The former captures realized global supply-chain pressure, while the latter captures uncertainty about trade policy ([Benigno et al., 2022](#); [Caldara et al., 2020](#)). Since no comparable country-level trade-risk series is available for the full sample, the trade component is common across countries.

Let  $\text{GSCPI}_t$  and  $\text{TPU}_t$  denote the two raw global trade-risk series. I first standardize both series over the available sample:

$$\widetilde{\text{GSCPI}}_t = \mathcal{Z}(\text{GSCPI}_t), \quad \widetilde{\text{TPU}}_t = \mathcal{Z}(\text{TPU}_t).$$

The raw trade-stress block is then defined as the equally weighted average of the two standardized inputs,

$$r_t^T = \frac{1}{2}\widetilde{\text{GSCPI}}_t + \frac{1}{2}\widetilde{\text{TPU}}_t.$$

The equal weighting avoids imposing a hierarchy between realized supply-chain disruptions and uncertainty about future trade policy. I then standardize the aggregated trade component,

$$z_t^T = \mathcal{Z}(r_t^T).$$

Since both input series are global, the resulting trade-stress component is assigned to all countries:

$$z_{i,t}^T = z_t^T \quad \text{for all countries } i.$$

Country-specific variation in the composite index therefore comes from the [MUI](#), financial-stress, sovereign-stress, geopolitical-risk, and energy-stress components, while the trade block captures a shared external trade-risk environment.

## 7.2 Weighting Scheme

A crucial choice here is the weighting of each component. A simple choice would be to use equal weights. This has the advantage of transparency and stability, but it treats isolated stress in one component and simultaneous stress across several components in the same way. Conversely, fully dynamic weights may make the index overly volatile and can lead to episodes in which the composite is dominated by a single component. I therefore use a correlation-adjusted aggregation scheme that preserves equal anchor weights across components, while allowing the composite index to increase when stress signals co-move across blocks.

The approach is inspired by the [CISS](#) of [Holló et al. \(2012\)](#), where systemic stress is not only measured by the level of stress in individual market segments, but also by their contemporaneous correlation. Let  $z_t = (z_{1t}, \dots, z_{Nt})'$  denote the vector of standardized component indices in month  $t$ , where the components comprise macroeconomic uncertainty, financial conditions, sovereign stress, energy stress, geopolitical risk, and trade stress. Let  $w_t = (w_{1t}, \dots, w_{Nt})'$  denote the corresponding component weights, normalised such that  $\sum_{j=1}^N w_{jt} = 1$ . In the baseline specification, these weights are anchored around equal weights,  $w_j = 1/N$ , which avoids imposing an ex ante hierarchy across risk categories.

The unadjusted composite is given by the weighted sum of standardized components,

$$\tilde{C}_t = \sum_{j=1}^N w_{jt} z_{jt} = w_t' z_t. \quad (10)$$

To account for the fact that stress becomes more systemic when several components move together, I compute a rolling correlation matrix  $R_t$  of the standardized component signals. The correlation adjustment is based on the quadratic form

$$q_t = w_t' R_t w_t. \quad (11)$$

This object is analogous to the portfolio-variance logic used in the [CISS](#) framework: for a given vector of component weights, the aggregate stress contribution is larger when the underlying components are positively correlated.

To preserve the scale of the additive composite and to keep the index directly interpretable as a signed risk measure, I use the normalised correlation factor

$$\phi_t = \sqrt{\frac{w_t' R_t w_t}{w_t' I w_t}}, \quad (12)$$

where  $I$  is the identity matrix. The denominator corresponds to the benchmark case in which the components are uncorrelated. Hence,  $\phi_t = 1$  when cross-component correlations are zero on average, while  $\phi_t > 1$  when stress components co-move positively. The final composite

index is then defined as

$$C_t = \phi_t \tilde{C}_t = \phi_t w'_t z_t. \quad (13)$$

This specification has two advantages. First, it keeps the contribution of each component exactly decomposable:

$$C_t = \sum_{j=1}^N \underbrace{\phi_t w_{jt} z_{jt}}_{\text{contribution of component } j}. \quad (14)$$

Second, it distinguishes between isolated and broad-based stress episodes. A spike in a single component raises the index through  $z_{jt}$ , but the scalar  $\phi_t$  amplifies the signed average during periods in which the components have exhibited stronger positive rolling co-movement. The resulting composite, therefore, captures not only the intensity of individual stress signals but also the degree to which stress is systemic across risk categories.

Regarding the weighting scheme, Table 13 summarizes the role of the time-varying correlation multiplier  $\phi_{i,t}$ . Values above unity increase the absolute magnitude of the underlying weighted index, whereas values below unity attenuate it. For Germany, the mean value of  $\phi_{i,t}$  is 1.233, implying an average amplification of approximately 23.3%. Moreover, the multiplier exceeds unity in every period of the estimation sample. Positive amplification is also prevalent in most other countries, occurring in around 80–100% of observations, although it is less persistent in the Netherlands, where the index is amplified in only 68.1% of periods. The average pairwise correlations among the index components remain comparatively modest, ranging from 0.051 in Greece to 0.111 in Italy. Nevertheless, because the multiplier incorporates the joint correlation structure across all components, these positive correlations translate into economically non-negligible adjustments to the composite index.

**Table 13:** Summary statistics of the correlation multiplier  $\phi_t$

| Country     | Minimum | Mean  | Median | 95th pct. | Mean corr. | Amplified | Dampened |
|-------------|---------|-------|--------|-----------|------------|-----------|----------|
| Austria     | 0.942   | 1.198 | 1.156  | 1.427     | 0.092      | 91.4      | 8.6      |
| Belgium     | 0.940   | 1.200 | 1.235  | 1.358     | 0.092      | 90.3      | 9.7      |
| Germany     | 1.079   | 1.233 | 1.195  | 1.493     | 0.107      | 100.0     | 0.0      |
| Greece      | 0.905   | 1.116 | 1.091  | 1.314     | 0.051      | 82.4      | 17.6     |
| Spain       | 0.972   | 1.236 | 1.265  | 1.402     | 0.109      | 92.1      | 7.9      |
| France      | 0.938   | 1.185 | 1.211  | 1.300     | 0.082      | 96.4      | 3.6      |
| Ireland     | 0.933   | 1.174 | 1.184  | 1.354     | 0.080      | 79.2      | 20.8     |
| Italy       | 0.960   | 1.240 | 1.256  | 1.426     | 0.111      | 90.0      | 10.0     |
| Netherlands | 0.912   | 1.143 | 1.136  | 1.476     | 0.068      | 68.1      | 31.9     |
| Portugal    | 0.946   | 1.187 | 1.169  | 1.359     | 0.085      | 99.6      | 0.4      |

*Notes:* The table reports summary statistics of the time-varying correlation multiplier  $\phi_{i,t}$  used in the construction of the correlation-adjusted composite index. A value of  $\phi_{i,t} > 1$  amplifies the absolute magnitude of the underlying weighted index, whereas  $\phi_{i,t} < 1$  dampens it. “Mean corr.” denotes the time-series average of the mean pairwise correlation among the index components. “Amplified” and “Dampened” report the percentage of observations for which  $\phi_{i,t} > 1$  and  $\phi_{i,t} < 1$ , respectively. The initialization period, during which the rolling correlation matrix cannot yet be fully estimated, is excluded. The estimation sample runs from February 2003 to March 2026.

## 7.3 Results and Interpretation

Before turning to individual episodes, Table 14 provides a descriptive check of how strongly the composite index co-moves with its underlying components. The correlations are highest with the MUI and the financial-stress block in most countries, while the geopolitical-risk component is less closely aligned with the aggregate index in several cases. This pattern is unsurprising, since geopolitical shocks need not coincide with domestic macro-financial stress in every country. The correlations should not be interpreted as independent validation of the composite index, because the components enter the index mechanically. They are nevertheless useful for assessing the relative influence of the different blocks. I then illustrate the time-series behavior and component contributions using Germany as the baseline case and Greece as a contrasting country with a much stronger sovereign-debt crisis episode.

**Table 14:** Correlation of Composite Index to components by country

| Country | MUI   | CLIFS | SovCISS | Energy Index | GPR   | Trade Index |
|---------|-------|-------|---------|--------------|-------|-------------|
| AT      | 0.594 | 0.511 | 0.477   | 0.665        | 0.199 | 0.456       |
| BE      | 0.693 | 0.519 | 0.340   | 0.444        | 0.392 | 0.423       |
| DE      | 0.751 | 0.533 | 0.453   | 0.499        | 0.518 | 0.470       |
| EL      | 0.546 | 0.697 | 0.314   | 0.255        | 0.074 | 0.242       |
| ES      | 0.656 | 0.667 | 0.304   | 0.345        | 0.208 | 0.371       |
| FR      | 0.606 | 0.650 | 0.415   | 0.448        | 0.256 | 0.484       |
| IE      | 0.551 | 0.561 | 0.149   | 0.472        | 0.248 | 0.396       |
| IT      | 0.586 | 0.626 | 0.453   | 0.310        | 0.311 | 0.441       |
| NL      | 0.786 | 0.454 | 0.357   | 0.506        | 0.351 | 0.454       |
| PT      | 0.437 | 0.640 | 0.317   | 0.182        | 0.459 | 0.207       |

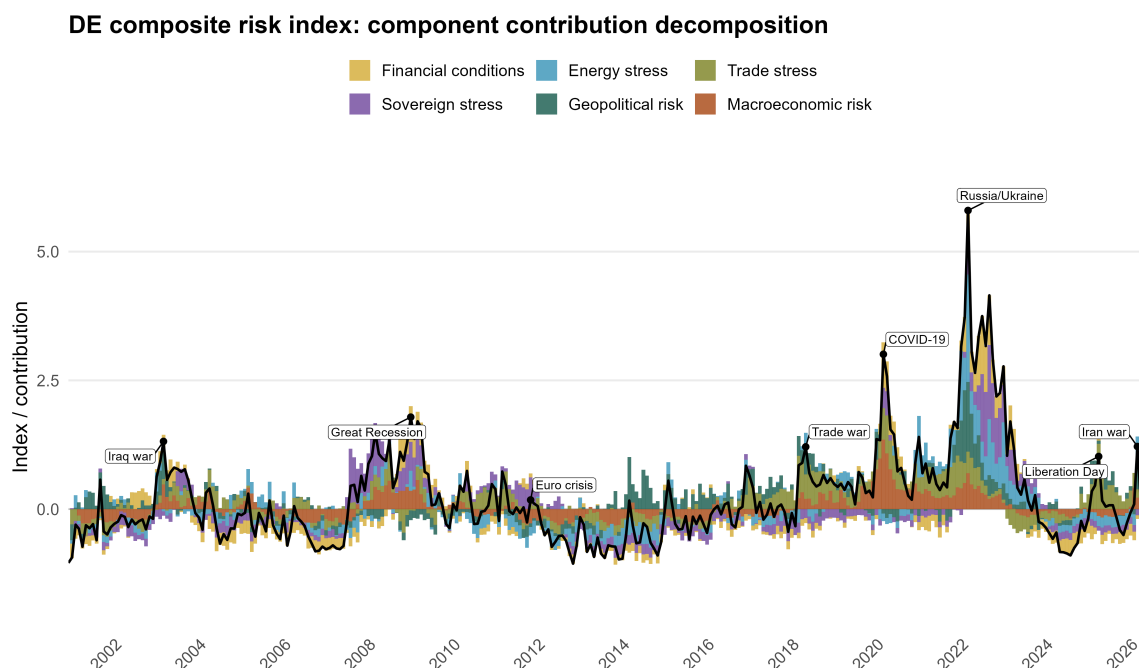
Notes: Entries report correlations between the composite index and its respective component series. Blue shading indicates positive correlations, with darker shading corresponding to larger magnitudes.

Figure 4 suggests that the German composite index captures several historically plausible stress episodes. The first visible spike occurs around the Iraq War, when geopolitical tensions and higher oil prices weakened sentiment and the euro area outlook (European Central Bank, 2003). The Great Recession is associated with a broad increase in macroeconomic risk, financial stress, and sovereign stress. The rise in 2018–2019 is consistent with the deterioration in the external environment faced by Germany’s export-oriented manufacturing sector, including trade-policy uncertainty, weaker foreign demand, Brexit-related uncertainty, and temporary disruptions in the automotive sector (German Council of Economic Experts, 2019; OECD, 2018). The COVID-19 shock is primarily reflected in macroeconomic uncertainty. The largest value of the German composite index was reached after Russia invaded Ukraine. This is consistent with the simultaneous activation of several stress channels: geopolitical risk from the war, the energy-price shock following the sharp reduction in Russian gas supplies, Germany’s exposure through energy-intensive manufacturing, supply-chain disruptions after the pandemic, and tighter financial conditions during the subsequent monetary-policy tightening cycle (Deutsche Bundesbank, 2022; European Commission, 2023; International Energy Agency, 2025; International Monetary Fund, 2024). Because several components move together during this episode, the correlation-adjusted weighting scheme amplifies the response of the aggregate index. Later spikes associated with renewed US tariff announcements and Middle East tensions

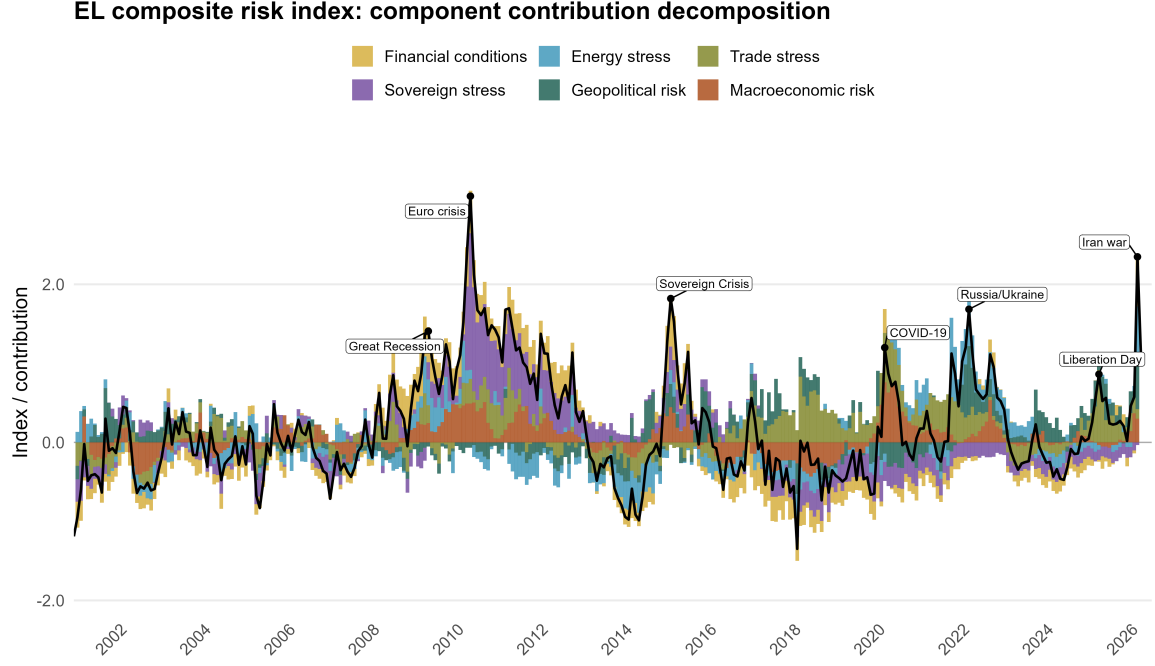
can be interpreted as trade- and energy-related stress episodes, respectively, although these very recent events should be treated primarily as contemporary event annotations (Ignatenko, Lashkaripour, Macedoni, & Simonovska, 2025; Kolev-Schaefer, Matthes, & Sultan, 2025).

At first glance, the comparatively muted response during the euro area sovereign debt crisis may appear surprising. However, this should not be interpreted as evidence that Germany was uninvolved in the crisis. Rather, Germany was primarily affected as a creditor country and policy anchor, while the acute sovereign-financial stress materialised in the euro area periphery. German sovereign risk remained comparatively contained, partly because Bunds benefited from safe-haven demand, and the domestic macroeconomic fallout was milder than in the crisis countries (Deutsche Bundesbank, 2012; van Riet, 2017). Consequently, the episode is visible in the sovereign and financial components, but it does not generate the broad-based component co-movement observed during the global financial crisis, the COVID-19 shock, or the 2021-2022 energy crisis. At the last observation, March 2026, risk is composed mostly of geopolitical risk as well as energy stress. Both could be caused by the Iran war, whereas financial and sovereign risk are lower than the average.

The contrast with Greece, shown in Figure 5, illustrates the country-specific nature of the composite index. Many global events appear in both countries, but the relative scale and component structure differ substantially. In particular, the euro area sovereign debt crisis is far more prominent for Greece, where sovereign stress, banking-sector fragility, fiscal adjustment, and macroeconomic contraction were central features of the crisis (International Monetary Fund, 2010, 2013; OECD, 2013). By contrast, episodes such as the Great Recession, COVID-19, and the Ukraine-related energy shock appear less dominant relative to Greece's own sovereign-debt crisis. This does not imply that Greece was unaffected by these later shocks, but rather that the sovereign-debt crisis constitutes the dominant country-specific stress episode in the sample.



**Figure 4:** Composite Index for Germany with major events labeled



**Figure 5:** Composite Index for Greece with major events labeled

## 7.4 Panel Local Projections to Risk-Index Innovations

As an additional exercise, I examine whether innovations in the composite risk index are followed by systematic movements in key macroeconomic variables. For this purpose, I estimate panel local projections following [Jordà \(2005\)](#). The analysis focuses on GDP growth, [HICP](#) inflation, and the unemployment rate.

The object of interest is the dynamic response of these variables to an unexpected increase in the country-specific composite risk index. Because the risk index is persistent and partly predictable from lagged macroeconomic conditions, I do not use its raw level directly. Instead, I construct an innovation to the index and standardize it separately for each country. The resulting impulse responses can therefore be interpreted as the response to a one-standard-deviation innovation in the composite risk index.

For each country  $i$ , the risk-index innovation is obtained from the auxiliary projection

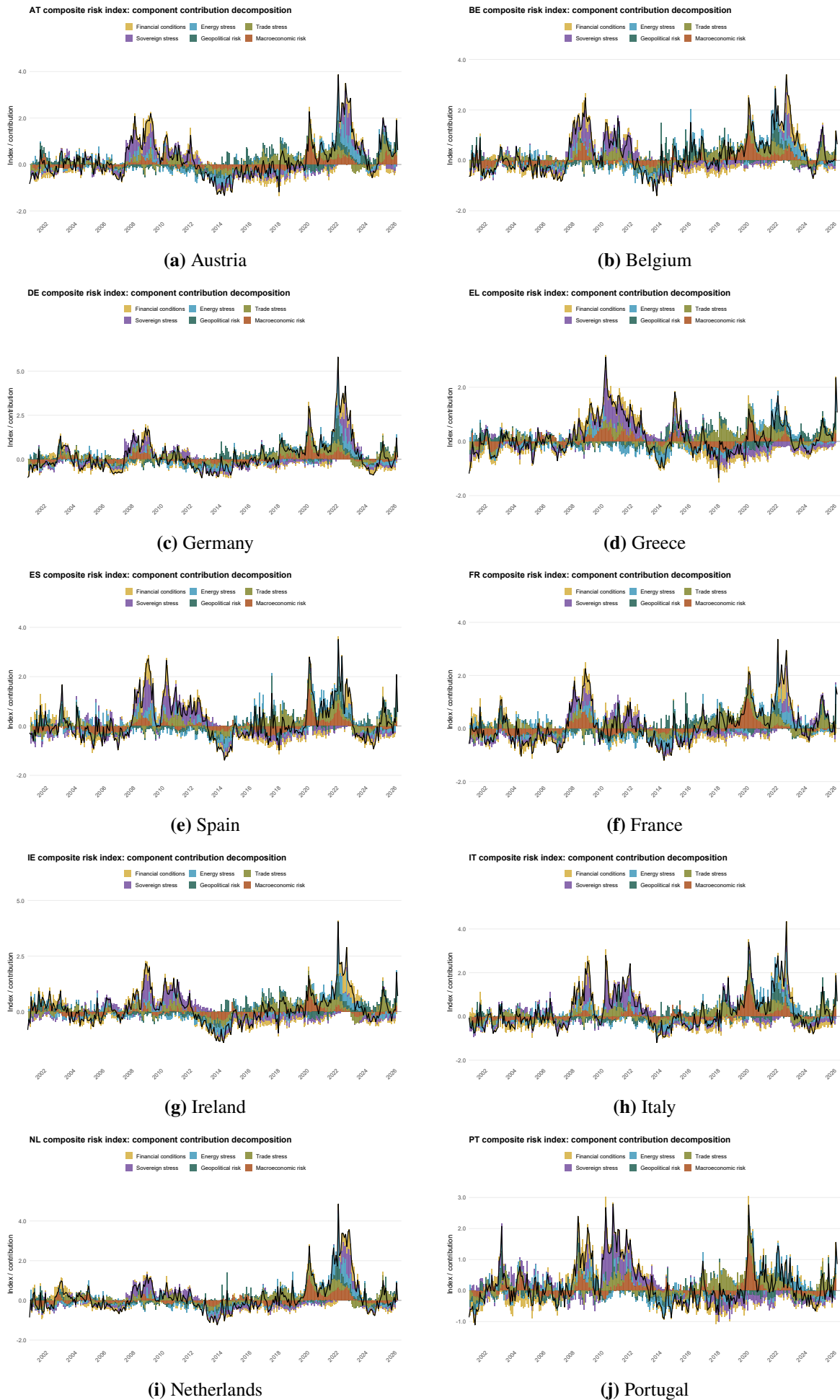
$$R_{i,t} = a_i + \sum_{\ell=1}^q \rho_{\ell} R_{i,t-\ell} + \sum_{\ell=1}^q \psi'_{\ell} \mathbf{z}_{i,t-\ell} + \eta_{i,t}, \quad (15)$$

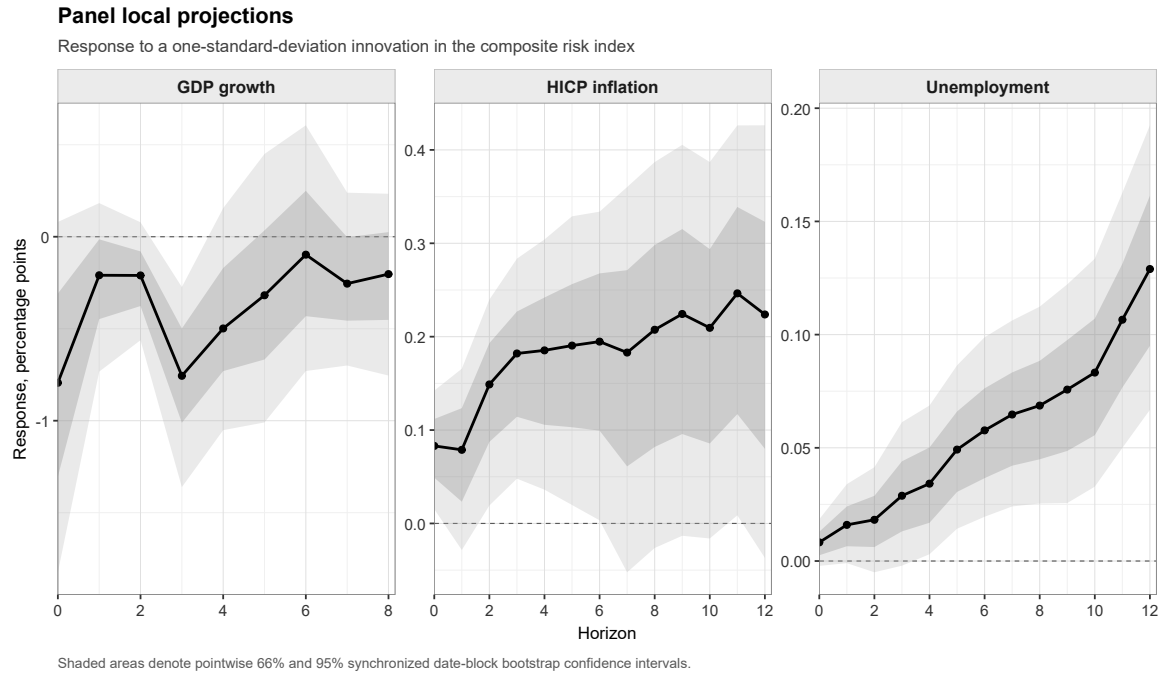
where  $R_{i,t}$  denotes the composite risk index and  $\mathbf{z}_{i,t}$  contains lagged macroeconomic controls. The residual  $\eta_{i,t}$  captures the component of the index that is not explained by its own history or by lagged macroeconomic conditions. I standardize this residual by its country-specific standard deviation,

$$\varepsilon_{i,t} = \frac{\eta_{i,t}}{\widehat{\sigma}_{\eta,i}}, \quad (16)$$

so that the shock variable  $\varepsilon_{i,t}$  has a comparable scale across countries.

The baseline panel local projection is estimated separately for each horizon  $h$  and each outcome

**Figure 6:** Contributions to a Composite Policy Risk Index per country



**Figure 7:** Panel local projection responses to a composite risk-index innovation

*Notes:* The figure reports panel local projection responses to a one-standard-deviation innovation in the country-specific composite risk index. GDP growth is estimated at quarterly frequency, while **HICP** inflation and unemployment are estimated at monthly frequency. The dark and light shaded areas denote pointwise 66% and 95% synchronized moving-block bootstrap confidence intervals, respectively. The bootstrap resamples contiguous blocks of dates while retaining the full country cross-section at each selected date and uses the same resampled dates across horizons. The baseline block lengths are six months for the monthly projections and four quarters for the quarterly projections. The intervals are based on 999 bootstrap replications and are conditional on the estimated risk-index innovations. COVID-19 observations are excluded when either the forecast origin or the horizon-specific target period falls within the excluded pandemic window, namely 2020Q2 or 2020Q3.

variable:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i^{(h)} + \beta_h \varepsilon_{i,t} + \sum_{\ell=1}^p \gamma_{\ell}^{(h)} y_{i,t-\ell} + \sum_{\ell=1}^p \delta_{\ell}^{(h)} \varepsilon_{i,t-\ell} + \sum_{\ell=1}^p \theta_{\ell}^{(h)'} \mathbf{x}_{i,t-\ell} + u_{i,t+h}^{(h)}. \quad (17)$$

Here,  $y_{i,t+h} - y_{i,t-1}$  denotes the cumulative change in the respective outcome between period  $t - 1$  and horizon  $t + h$ . The coefficient  $\beta_h$  traces the response at horizon  $h$  to a one-standard-deviation innovation in the composite risk index. Country fixed effects  $\alpha_i^{(h)}$  absorb time-invariant differences across countries.

Inference is based on a synchronized moving-block bootstrap over the time dimension. Contiguous blocks of calendar periods are resampled while retaining the complete cross-section of countries for each selected date. The same resampled sequence of dates is used across all horizons within a bootstrap replication. This procedure preserves contemporaneous dependence across countries, serial dependence over time, and the dependence across horizons induced by overlapping cumulative outcomes. The baseline bootstrap uses blocks of six months for the monthly projections and four quarters for the quarterly GDP projections. The reported 66% and 95% confidence intervals are pointwise percentile intervals based on 999 bootstrap replications. The bootstrap treats the estimated index innovations as fixed and therefore conditions on the first-stage shock construction.

The specification differs slightly across outcomes to reflect their data frequency and macroeconomic relevance. For **HICP** inflation and unemployment, the local projections are estimated at monthly frequency for horizons  $h = 0, \dots, 12$ . I include three lags of the dependent variable, three lags of the risk-index innovation, and lagged macroeconomic controls. In the inflation specification, the controls are lagged unemployment and the long-term interest rate. In the unemployment specification, the controls are lagged **HICP** inflation and the long-term interest rate. The risk-index innovation is orthogonalized with respect to three lags of the risk index, inflation, unemployment, and the long-term interest rate.

For GDP growth, the local projections are estimated at quarterly frequency for horizons  $h = 0, \dots, 8$ . The GDP specification includes two lags of GDP growth, the risk-index innovation, inflation, unemployment, and the long-term interest rate. The quarterly innovation in the composite risk index is constructed analogously using two lags of the index and two lags of the quarterly macroeconomic controls. To prevent the estimates from being dominated by exceptional pandemic observations, I exclude observations for which either the forecast origin or the horizon-specific target period falls within the COVID-19 window.

Figure 7 reports the estimated impulse responses. The GDP response is negative at all reported horizons, but the bootstrap confidence intervals are wide and include zero throughout. The point estimates are therefore consistent with a decline in real activity following a risk-index innovation, but the evidence is too imprecise to establish a statistically robust GDP response.

The inflation response is positive and persistent. The point estimate rises from approximately 0.08 percentage points on impact to around 0.20–0.25 percentage points at longer horizons. The 66% confidence interval remains above zero over most of the response path, while the 95% interval excludes zero only at some horizons and becomes wider at longer horizons.

The unemployment response is initially close to zero but increases steadily over time. After approximately five to six months, the 95% bootstrap interval lies above zero, and the estimated response reaches about 0.13 percentage points after twelve months. Among the three outcomes,

this provides the clearest evidence of a persistent macroeconomic response to an innovation in the composite risk index.

Taken together, the local projections point to an adverse macroeconomic pattern following innovations in the composite risk index. The evidence is strongest for unemployment, suggestive for inflation, and statistically inconclusive for GDP growth.

## 8 Limitations and Conclusion

This thesis constructs country-specific **MUIs** for ten euro area economies and evaluates their usefulness for macroeconomic risk monitoring and tail-risk forecasting. Following the forecast-based concept of uncertainty developed by [Jurado et al. \(2015\)](#), macroeconomic uncertainty is defined as the conditional volatility of the component of future macroeconomic outcomes that cannot be predicted using the available information set. The resulting indices therefore differ conceptually from measures of realised volatility, financial stress, or news-based uncertainty: they are designed to capture periods in which a broad range of macroeconomic variables becomes unusually difficult to forecast.

The indices are constructed from the EA-MD-QD country datasets using a factor-based approach that accommodates large, unbalanced, and mixed-frequency macroeconomic panels. Country-specific factors are extracted after completing the panels through a low-rank approximation. These factors enter forecasting equations for the individual macroeconomic variables, while stochastic-volatility models are used to estimate the time-varying conditional volatility of the resulting forecast errors. The variable-specific uncertainty estimates are subsequently aggregated into standardized country-level indices. Although the indices are estimated separately for each country, they display substantial common variation and identify the major stress episodes of the sample, including the Global Financial Crisis, the euro area sovereign debt crisis, the COVID-19 pandemic, and the energy-price shock following Russia's invasion of Ukraine. At the same time, the differences across countries illustrate the heterogeneous incidence of these episodes within the euro area.

The forecasting results suggest that the constructed **MUI** contains information about adverse macroeconomic outcomes that is not fully captured by standard financial-stress indicators. In the in-sample quantile regressions, higher macroeconomic uncertainty is associated with weaker lower-tail GDP growth and, particularly consistently, with higher upper-tail inflation outcomes. The corresponding relationship with unemployment is less uniform. These patterns remain visible when the **MUI** is included jointly with **CISS** and **CLIFS**, indicating that it captures a distinct dimension of macroeconomic risk, going beyond merely reproducing financial-market stress.

The out-of-sample exercise provides the main evidence on forecasting performance. For the pooled panel, adding the **MUI** to a benchmark containing **CISS** and **CLIFS** reduces pinball loss by approximately 13 percent for the 0.05 quantile of GDP growth and by approximately 18% for the 0.95 quantile of inflation. The improvement is especially pronounced during periods of elevated macroeconomic stress. The inflation gains remain visible under alternative sample restrictions and are statistically significant in the **DM**-tests at all considered upper-tail quantiles. For GDP growth, the average loss differentials also favour the model containing the **MUI**, but the **DM**-tests are only significant for the 0.05 quantile. Improvements in unemployment forecasts are considerably smaller. Specifications containing the **MUI** also tend to produce empirical tail-exceedance rates closer to their nominal levels, although all models continue to exhibit substantial absolute miscalibration in the most extreme tails.

As a second application, the thesis develops a decomposable composite policy-risk index combining the **MUI** with country-level financial stress, sovereign stress, geopolitical risk, energy stress, and trade-related stress. The correlation-adjusted aggregation scheme retains equal anchor weights while amplifying the composite when several risk dimensions move together. This makes it possible to distinguish between isolated disturbances and broader episodes in which multiple stress channels are activated simultaneously. The decompositions for Germany and Greece illustrate the usefulness of this approach. While the German index is dominated by broad global episodes such as the Global Financial Crisis, the pandemic, and the European energy crisis, the Greek index assigns a much larger role to the euro area sovereign debt crisis. The composite should therefore be regarded primarily as an interpretable monitoring and narrative-decomposition instrument and not as a direct substitute for the forecasting-oriented **MUI**.

The panel local projections provide complementary descriptive evidence. Innovations in the composite index are followed by lower GDP growth, higher **HICP** inflation, and a gradual increase in unemployment. These response patterns are consistent with the interpretation of the index as a measure of adverse macroeconomic risk. However, they do not establish that changes in the composite index themselves cause the subsequent macroeconomic developments. The index combines endogenous macroeconomic uncertainty with financial and external stress indicators and may respond contemporaneously to information about the future economic outlook. The local projections should consequently be interpreted as documenting dynamic conditional associations rather than structurally identified causal effects.

Several limitations qualify the results. First, the forecasting exercise is not fully real-time because a complete vintage history of the underlying country-level macroeconomic panel dataset is unavailable. At each forecast origin, the **MUI** is nevertheless reconstructed recursively using only observations dated up to that origin. This reconstruction includes the completion and standardization of the macroeconomic panel, factor extraction, estimation of the variable-specific forecasting and stochastic-volatility models, and aggregation of the resulting uncertainty estimates. The exercise therefore avoids look-ahead arising from the use of future-dated observations or a fixed full-sample index. However, because historical real-time data vintages are unavailable, it cannot account for data revisions, publication lags, or the precise information-release calendar faced by forecasters at the time.

Second, both the forecasting and local-projection results are predictive and descriptive in nature. The quantile regressions document conditional associations between the risk measures and future macroeconomic outcomes, while the local projections trace the dynamics following innovations that are orthogonal only to the included lagged controls. Neither exercise provides structural identification of an exogenous uncertainty or policy-risk shock. Reverse causality and omitted common shocks may therefore contribute to the estimated relationships.

Third, the available sample is relatively short and contains several exceptionally large events. Although the crisis-exclusion exercises indicate that the forecasting results are not entirely driven by the pandemic or the recent inflation surge, extreme observations remain important for evaluating tail forecasts. Statistical inference remains constrained by the relatively short time dimension, the limited number of distinct crisis episodes, and the sensitivity of extreme-quantile estimates to a small number of tail realizations. The significance levels in the panel quantile regressions should consequently be interpreted cautiously. Similarly, estimates for the most extreme quantiles are based on comparatively few tail realizations,

which contributes to the remaining calibration errors and uncertainty surrounding forecast-performance comparisons.

Fourth, a key caveat of the forecasting framework is the absolute calibration failure observed across several nominal thresholds, where actual exceedance rates consistently surpass their theoretical targets. This pattern may reflect that during periods of extreme macroeconomic stress, the transmission of uncertainty into tail risks could be highly non-linear. Because the linear quantile regression framework assumes a stable, linear relationship between the predictors and the conditional quantiles, it underpredicts the severity of tail events when the economy undergoes structural breaks. Future research could address this by augmenting the current framework with time-varying parameters or non-linear quantile mappings to better capture these shifting tail dynamics.

Finally, the composite index necessarily incorporates modeling choices concerning the selection, transformation, and aggregation of its components. Some inputs, particularly the trade-risk measure and the geopolitical-risk series for countries without a national index, are common global proxies and therefore cannot reflect all differences in country-specific exposure. The correlation adjustment captures broad co-movement across components but does not provide a structural measure of the transmission mechanisms linking the individual risk categories.

Extending the country coverage and the historical sample would permit more precise evaluation across different crisis types and institutional settings. Further work could also compare the current aggregation method with alternative dynamic-factor, Bayesian, or shrinkage-based approaches and evaluate complete predictive distributions rather than selected quantiles. For the composite index, country-specific measures of trade and geopolitical exposure and a more explicit structural identification strategy would help distinguish the macroeconomic consequences of the individual risk channels.

Overall, the results indicate that forecast-based macroeconomic uncertainty measures provide information that is complementary to conventional financial-stress indicators. Their contribution is clearest for upper-tail inflation risk, while the evidence for downside GDP risk is economically relevant but less statistically precise and the gains for unemployment are limited. Combined with the decomposable composite index, the proposed framework offers two complementary perspectives: a forecasting-oriented measure of how uncertain the macroeconomic outlook has become and an interpretable account of the financial, sovereign, geopolitical, energy, and trade-related forces associated with that risk. Subject to the stated real-time, inferential, and data limitations, these tools can contribute to a more distribution-sensitive assessment of macroeconomic risks across euro area countries.

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## A Alternative Specifications

### A.1 Equal-weighted Average Index

As a comparison to the original specification by [Jurado et al. \(2015\)](#), I also report the indices based on equal-weighted stochastic volatilities instead of taking the first PCA factor to construct the index in Figure 8. The observed differences are rather minor. The PC1 version has more volatility, which is to be expected as principal component methods concentrate variation onto the dominant common factor rather than smoothing movements uniformly across components. The trends, however, are almost exactly mirrored. Conclusively, the aggregation choice does not ultimately matter. As an example, for Germany, the correlation of both variants lies at 0.966, meaning that they are highly similar in dynamics.

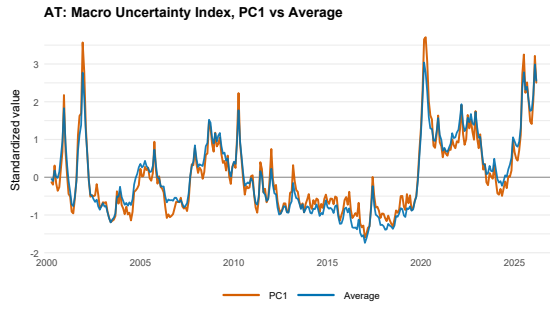
### A.2 Indices for a different number of factors

As a robustness check, I benchmark the original index specification for a different value of  $K$ , the number of factors used in the regression equation for constructing the index in Figure 9. Here, I also consider  $K = 3, 6, 8$ . While the index deviates slightly depending on  $K$ , overall trends are the same, and only small differences arise. In general, the lower  $K$ , the smoother the index is, but it also reacts less prominently. Hence,  $K = 6$  seems to be a reasonable middle ground. If we look at the correlations, we can see that the choice of a low vs a high or medium  $K$  is quite significant, whereas choosing  $K = 6$  or  $K = 8$  seems rather secondary given correlations around 0.9.

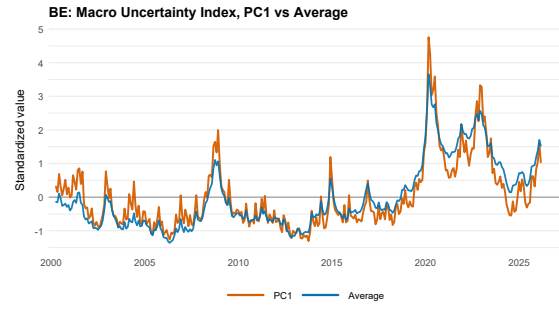
**Table 15:** Correlation between [MUIs](#) across different numbers of factors

| Country | $K = 3$ vs. $K = 6$ | $K = 3$ vs. $K = 8$ | $K = 6$ vs. $K = 8$ |
|---------|---------------------|---------------------|---------------------|
| AT      | 0.765               | 0.735               | 0.941               |
| BE      | 0.913               | 0.908               | 0.935               |
| DE      | 0.834               | 0.879               | 0.900               |
| EL      | 0.715               | 0.696               | 0.877               |
| ES      | 0.778               | 0.718               | 0.862               |
| FR      | 0.873               | 0.839               | 0.968               |
| IE      | 0.646               | 0.690               | 0.850               |
| IT      | 0.906               | 0.835               | 0.928               |
| NL      | 0.855               | 0.806               | 0.947               |
| PT      | 0.747               | 0.734               | 0.908               |

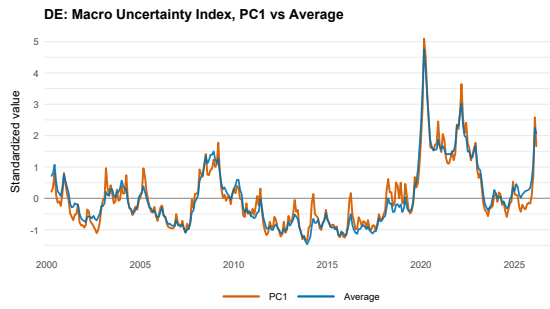
*Notes:* Entries report country-specific pairwise correlations between [MUIs](#) constructed using  $K = 3$ ,  $K = 6$ , and  $K = 8$  factors. Blue shading indicates positive correlations, with darker shading corresponding to larger magnitudes.



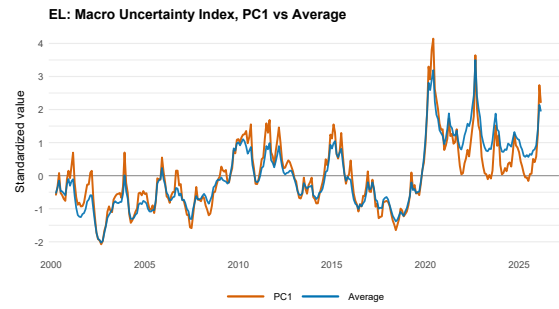
(a) Austria



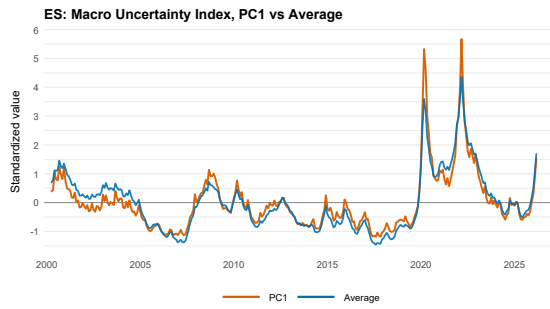
(b) Belgium



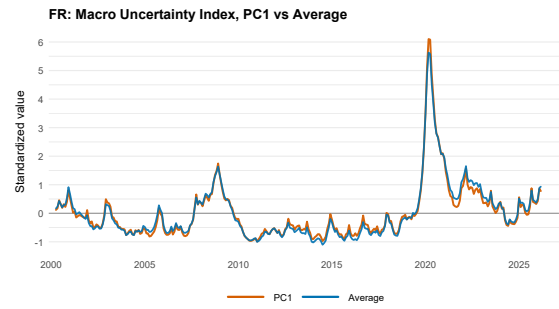
(c) Germany



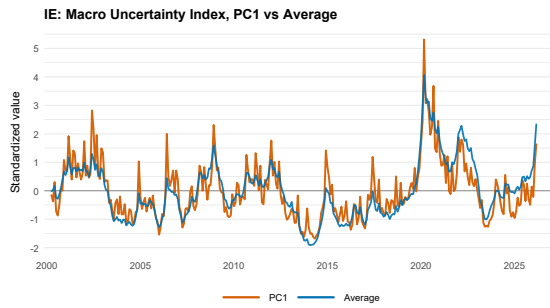
(d) Greece



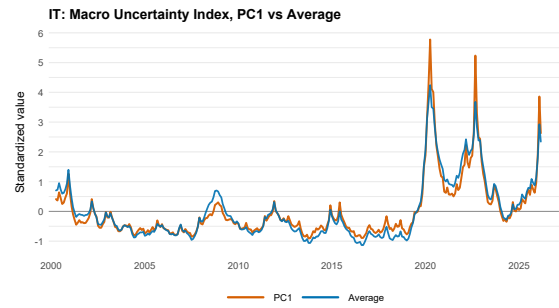
(e) Spain



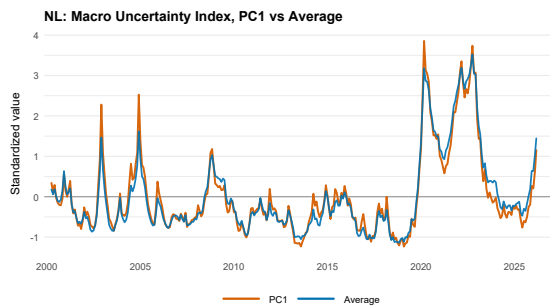
(f) France



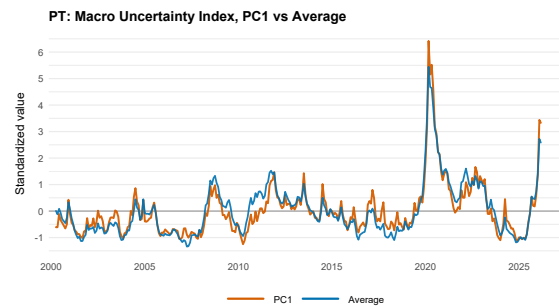
(g) Ireland



(h) Italy

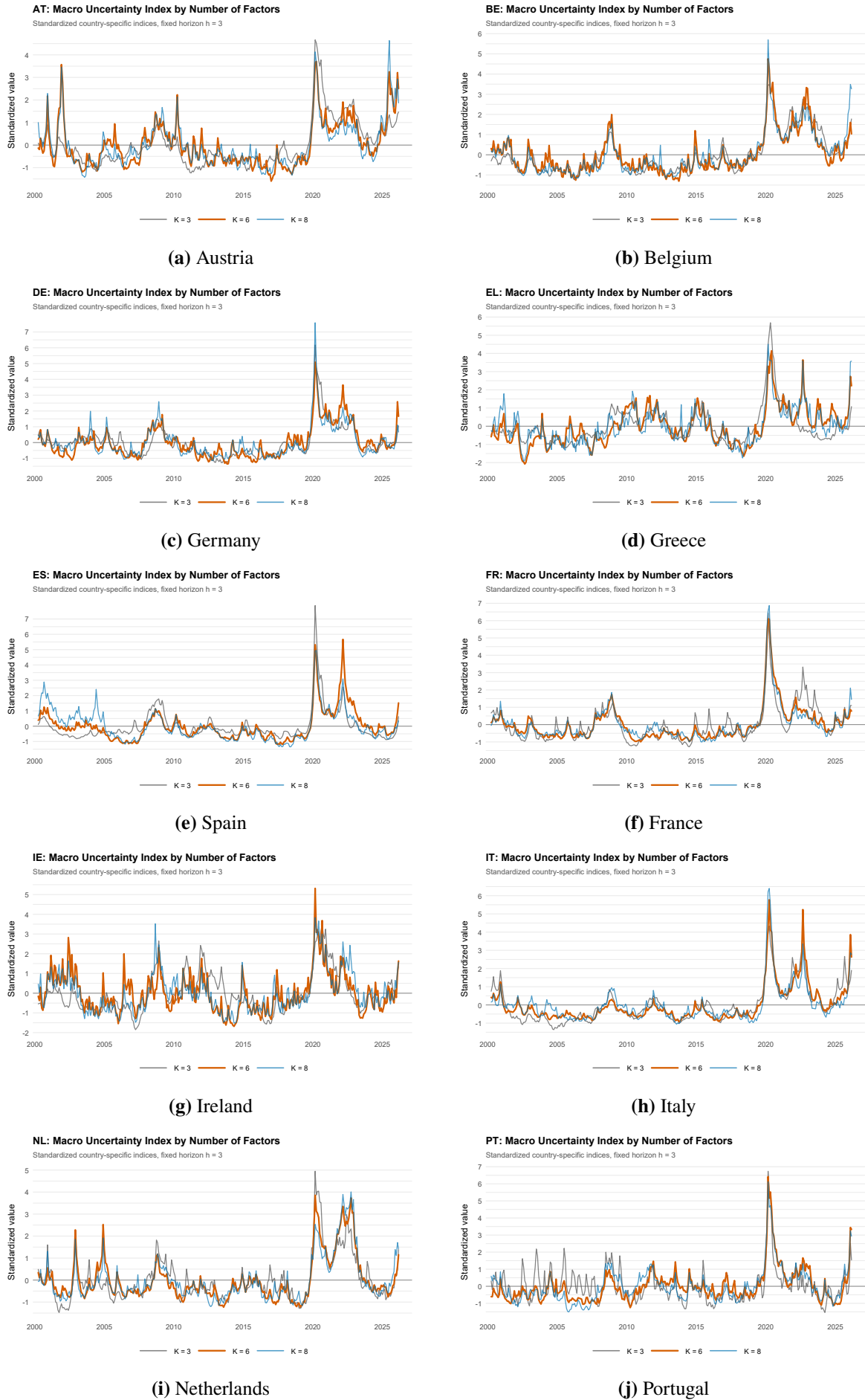


(i) Netherlands



(j) Portugal

**Figure 8:** MUI by country with the first PCA factor as base for index (PC1) and equal weighting

Figure 9: MUI by country for  $K = 3, 6, 8$

## B Forecasting results for all countries

As only the results for Germany and the whole panel were discussed in the main text, I also report country-level results here. Overall, the general trend persists with the [MUI](#) being more significant for inflation forecasts.

### B.1 In-sample Forecast

This section reports the country-specific in-sample quantile regression results underlying the main analysis. While the main text focuses on Germany and on the pooled panel estimates, Tables 16-25 provide the corresponding evidence for all individual countries. All specifications jointly include [CISS](#), [CLIFS](#), and the proposed [MUI](#), together with autoregressive controls. The reported coefficients therefore measure the conditional association of each risk indicator with the respective quantile of the predictive distribution, holding the other included indicators fixed.

Overall, the country-level results confirm the main patterns discussed in the text. The [MUI](#) is most consistently significant for upper-tail inflation forecasts. In most countries, higher values of the [MUI](#) are associated with higher conditional inflation quantiles, especially at  $\tau = 0.90$  and  $\tau = 0.95$ . This suggests that the proposed uncertainty measure captures information about upside inflation risks that is not fully absorbed by standard financial-stress indicators such as [CISS](#) and [CLIFS](#).

For GDP growth, the [MUI](#) frequently enters with a negative sign at the lower quantiles. This is particularly visible for countries such as Belgium, Germany, France, Italy, the Netherlands, and Portugal, where higher macroeconomic uncertainty is associated with weaker downside growth outcomes. The pattern is less uniform than for inflation, but it is broadly consistent with the interpretation that macroeconomic uncertainty is informative about lower-tail real activity risks.

The results for unemployment are more heterogeneous across countries. In several cases, the [MUI](#) is positively associated with upper unemployment quantiles, indicating higher unemployment risk when macroeconomic uncertainty rises. However, the strength and statistical significance of this relationship vary more across countries than for inflation. This may reflect the more persistent and institutionally mediated adjustment of unemployment compared with inflation or GDP growth.

Taken together, the in-sample country results support the interpretation that the [MUI](#) contains additional information beyond financial-stress indicators. The evidence is strongest for upside inflation risks, followed by lower-tail GDP growth risks, while unemployment responses are more country-specific.

**Table 16:** Quantile regression results for Austria

| Outcome $\tau$                              | CISS                  | CLIFS                  | MUI                    |
|---------------------------------------------|-----------------------|------------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                       |                        |                        |
| 0.05                                        | -0.819**<br>(p=0.011) | -2.549***<br>(p=0.008) | -0.927***<br>(p=0.009) |
| 0.10                                        | -0.114<br>(p=0.822)   | -0.413<br>(p=0.669)    | -0.605<br>(p=0.164)    |
| 0.25                                        | -0.293*<br>(p=0.095)  | -0.465**<br>(p=0.041)  | -0.309*<br>(p=0.059)   |
| <i>HICP inflation, three-month-ahead</i>    |                       |                        |                        |
| 0.75                                        | -0.048<br>(p=0.367)   | -0.023<br>(p=0.662)    | 0.138***<br>(p=0.000)  |
| 0.90                                        | -0.045<br>(p=0.469)   | -0.058<br>(p=0.208)    | 0.080<br>(p=0.190)     |
| 0.95                                        | -0.012<br>(p=0.862)   | -0.084<br>(p=0.124)    | 0.103<br>(p=0.289)     |
| <i>Unemployment rate, three-month-ahead</i> |                       |                        |                        |
| 0.75                                        | 0.017<br>(p=0.605)    | 0.069*<br>(p=0.074)    | -0.003<br>(p=0.915)    |
| 0.90                                        | -0.034<br>(p=0.387)   | 0.028<br>(p=0.329)     | 0.060<br>(p=0.274)     |
| 0.95                                        | -0.016<br>(p=0.800)   | -0.025<br>(p=0.720)    | 0.106*<br>(p=0.087)    |

**Table 17:** Quantile regression results for Belgium

| Outcome $\tau$                              | CISS                   | CLIFS                 | MUI                    |
|---------------------------------------------|------------------------|-----------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                        |                       |                        |
| 0.05                                        | -0.375**<br>(p=0.017)  | -0.544<br>(p=0.138)   | -1.364***<br>(p=0.000) |
| 0.10                                        | -0.165<br>(p=0.215)    | -0.054<br>(p=0.859)   | -0.797*<br>(p=0.071)   |
| 0.25                                        | -0.065<br>(p=0.752)    | -0.122<br>(p=0.632)   | -0.132<br>(p=0.533)    |
| <i>HICP inflation, three-month-ahead</i>    |                        |                       |                        |
| 0.75                                        | -0.205**<br>(p=0.046)  | -0.119<br>(p=0.226)   | 0.196***<br>(p=0.003)  |
| 0.90                                        | -0.218***<br>(p=0.008) | -0.147*<br>(p=0.068)  | 0.282***<br>(p=0.000)  |
| 0.95                                        | -0.192<br>(p=0.128)    | -0.176<br>(p=0.127)   | 0.351***<br>(p=0.000)  |
| <i>Unemployment rate, three-month-ahead</i> |                        |                       |                        |
| 0.75                                        | 0.020<br>(p=0.133)     | 0.034***<br>(p=0.008) | 0.029*<br>(p=0.092)    |
| 0.90                                        | 0.017<br>(p=0.532)     | 0.078**<br>(p=0.028)  | 0.014<br>(p=0.653)     |
| 0.95                                        | 0.020<br>(p=0.495)     | 0.053<br>(p=0.122)    | 0.049<br>(p=0.391)     |

**Table 18:** Quantile regression results for Germany

| Outcome $\tau$                              | CISS                | CLIFS                  | MUI                    |
|---------------------------------------------|---------------------|------------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                     |                        |                        |
| 0.05                                        | 0.225<br>(p=0.394)  | -0.720***<br>(p=0.000) | -1.163***<br>(p=0.000) |
| 0.10                                        | 0.165<br>(p=0.352)  | -0.771***<br>(p=0.006) | -1.000***<br>(p=0.006) |
| 0.25                                        | -0.001<br>(p=0.995) | -0.160<br>(p=0.588)    | -0.318<br>(p=0.135)    |
| <i>HICP inflation, three-month-ahead</i>    |                     |                        |                        |
| 0.75                                        | -0.033<br>(p=0.737) | -0.020<br>(p=0.843)    | 0.172**<br>(p=0.030)   |
| 0.90                                        | 0.043<br>(p=0.523)  | 0.032<br>(p=0.690)     | 0.289***<br>(p=0.000)  |
| 0.95                                        | 0.010<br>(p=0.874)  | 0.071<br>(p=0.360)     | 0.431***<br>(p=0.000)  |
| <i>Unemployment rate, three-month-ahead</i> |                     |                        |                        |
| 0.75                                        | 0.000<br>(p=1.000)  | 0.000<br>(p=1.000)     | 0.000<br>(p=1.000)     |
| 0.90                                        | -0.002<br>(p=0.837) | 0.002<br>(p=0.887)     | 0.017*<br>(p=0.055)    |
| 0.95                                        | -0.004<br>(p=0.601) | -0.001<br>(p=0.902)    | 0.005<br>(p=0.483)     |

**Table 19:** Quantile regression results for Greece

| Outcome $\tau$                              | CISS                   | CLIFS                  | MUI                   |
|---------------------------------------------|------------------------|------------------------|-----------------------|
| <i>GDP growth, next quarter</i>             |                        |                        |                       |
| 0.05                                        | -0.507<br>(p=0.513)    | -0.717<br>(p=0.679)    | -1.050<br>(p=0.232)   |
| 0.10                                        | -0.869<br>(p=0.204)    | -0.145<br>(p=0.920)    | -0.410<br>(p=0.580)   |
| 0.25                                        | -0.789***<br>(p=0.009) | -0.208<br>(p=0.230)    | 0.060<br>(p=0.697)    |
| <i>HICP inflation, three-month-ahead</i>    |                        |                        |                       |
| 0.75                                        | 0.112<br>(p=0.174)     | -0.200***<br>(p=0.000) | 0.022<br>(p=0.783)    |
| 0.90                                        | 0.179<br>(p=0.175)     | -0.235<br>(p=0.256)    | 0.041<br>(p=0.762)    |
| 0.95                                        | 0.114<br>(p=0.439)     | -0.146<br>(p=0.528)    | 0.161**<br>(p=0.037)  |
| <i>Unemployment rate, three-month-ahead</i> |                        |                        |                       |
| 0.75                                        | 0.038<br>(p=0.452)     | 0.181***<br>(p=0.001)  | 0.075*<br>(p=0.052)   |
| 0.90                                        | 0.062<br>(p=0.272)     | 0.136**<br>(p=0.041)   | 0.203***<br>(p=0.002) |
| 0.95                                        | 0.091<br>(p=0.187)     | 0.018<br>(p=0.796)     | 0.305***<br>(p=0.001) |

**Table 20:** Quantile regression results for Spain

| Outcome $\tau$                              | CISS                   | CLIFS               | MUI                   |
|---------------------------------------------|------------------------|---------------------|-----------------------|
| <i>GDP growth, next quarter</i>             |                        |                     |                       |
| 0.05                                        | -0.682<br>(p=0.386)    | 0.527<br>(p=0.751)  | -2.576<br>(p=0.180)   |
| 0.10                                        | -0.048<br>(p=0.912)    | 0.267<br>(p=0.747)  | -1.294<br>(p=0.217)   |
| 0.25                                        | 0.162<br>(p=0.425)     | -0.162<br>(p=0.325) | -0.032<br>(p=0.946)   |
| <i>HICP inflation, three-month-ahead</i>    |                        |                     |                       |
| 0.75                                        | 0.115<br>(p=0.144)     | 0.021<br>(p=0.828)  | 0.306***<br>(p=0.000) |
| 0.90                                        | 0.175**<br>(p=0.047)   | 0.085<br>(p=0.288)  | 0.371***<br>(p=0.000) |
| 0.95                                        | 0.114<br>(p=0.139)     | -0.033<br>(p=0.682) | 0.360***<br>(p=0.000) |
| <i>Unemployment rate, three-month-ahead</i> |                        |                     |                       |
| 0.75                                        | -0.026<br>(p=0.137)    | 0.021<br>(p=0.279)  | 0.017<br>(p=0.322)    |
| 0.90                                        | -0.047***<br>(p=0.010) | 0.006<br>(p=0.500)  | 0.017<br>(p=0.202)    |
| 0.95                                        | -0.052*<br>(p=0.070)   | -0.003<br>(p=0.928) | 0.022<br>(p=0.560)    |

**Table 21:** Quantile regression results for France

| Outcome $\tau$                              | CISS                | CLIFS                 | MUI                    |
|---------------------------------------------|---------------------|-----------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                     |                       |                        |
| 0.05                                        | -0.101<br>(p=0.432) | 0.143<br>(p=0.476)    | -1.346**<br>(p=0.010)  |
| 0.10                                        | 0.057<br>(p=0.675)  | 0.215<br>(p=0.193)    | -1.467***<br>(p=0.001) |
| 0.25                                        | 0.044<br>(p=0.745)  | -0.021<br>(p=0.893)   | -0.604<br>(p=0.135)    |
| <i>HICP inflation, three-month-ahead</i>    |                     |                       |                        |
| 0.75                                        | 0.024<br>(p=0.575)  | 0.032<br>(p=0.419)    | 0.045<br>(p=0.461)     |
| 0.90                                        | -0.002<br>(p=0.960) | 0.068<br>(p=0.339)    | 0.075<br>(p=0.304)     |
| 0.95                                        | 0.031<br>(p=0.498)  | 0.093<br>(p=0.133)    | 0.179*<br>(p=0.058)    |
| <i>Unemployment rate, three-month-ahead</i> |                     |                       |                        |
| 0.75                                        | 0.003<br>(p=0.809)  | 0.040***<br>(p=0.006) | -0.004<br>(p=0.839)    |
| 0.90                                        | -0.008<br>(p=0.457) | 0.025***<br>(p=0.008) | 0.058*<br>(p=0.053)    |
| 0.95                                        | -0.010<br>(p=0.505) | 0.014<br>(p=0.473)    | 0.078**<br>(p=0.031)   |

**Table 22:** Quantile regression results for Ireland

| Outcome $\tau$                              | CISS                 | CLIFS                 | MUI                   |
|---------------------------------------------|----------------------|-----------------------|-----------------------|
| <i>GDP growth, next quarter</i>             |                      |                       |                       |
| 0.05                                        | 1.052**<br>(p=0.046) | 0.508<br>(p=0.314)    | -0.068<br>(p=0.818)   |
| 0.10                                        | 0.023<br>(p=0.969)   | -0.193<br>(p=0.696)   | -0.271<br>(p=0.454)   |
| 0.25                                        | 0.163<br>(p=0.705)   | -0.438<br>(p=0.251)   | 0.023<br>(p=0.945)    |
| <i>HICP inflation, three-month-ahead</i>    |                      |                       |                       |
| 0.75                                        | 0.043<br>(p=0.614)   | -0.093<br>(p=0.306)   | 0.125**<br>(p=0.026)  |
| 0.90                                        | -0.056<br>(p=0.356)  | -0.006<br>(p=0.917)   | 0.113*<br>(p=0.094)   |
| 0.95                                        | -0.132<br>(p=0.147)  | -0.166*<br>(p=0.088)  | 0.199**<br>(p=0.049)  |
| <i>Unemployment rate, three-month-ahead</i> |                      |                       |                       |
| 0.75                                        | -0.012<br>(p=0.521)  | 0.074***<br>(p=0.000) | 0.022*<br>(p=0.069)   |
| 0.90                                        | 0.023<br>(p=0.628)   | 0.096**<br>(p=0.017)  | 0.070***<br>(p=0.001) |
| 0.95                                        | -0.096<br>(p=0.217)  | 0.070<br>(p=0.206)    | 0.060<br>(p=0.145)    |

**Table 23:** Quantile regression results for Italy

| Outcome $\tau$                              | CISS                  | CLIFS                | MUI                    |
|---------------------------------------------|-----------------------|----------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                       |                      |                        |
| 0.05                                        | -0.084<br>(p=0.716)   | -0.125<br>(p=0.509)  | -1.990***<br>(p=0.000) |
| 0.10                                        | -0.211<br>(p=0.181)   | -0.056<br>(p=0.546)  | -1.734**<br>(p=0.013)  |
| 0.25                                        | 0.152<br>(p=0.603)    | -0.190<br>(p=0.732)  | -0.073<br>(p=0.919)    |
| <i>HICP inflation, three-month-ahead</i>    |                       |                      |                        |
| 0.75                                        | -0.078*<br>(p=0.056)  | 0.045*<br>(p=0.073)  | 0.269***<br>(p=0.002)  |
| 0.90                                        | -0.100<br>(p=0.224)   | -0.022<br>(p=0.688)  | 0.444***<br>(p=0.003)  |
| 0.95                                        | -0.211**<br>(p=0.034) | -0.093<br>(p=0.542)  | 0.704***<br>(p=0.000)  |
| <i>Unemployment rate, three-month-ahead</i> |                       |                      |                        |
| 0.75                                        | -0.050**<br>(p=0.039) | 0.038**<br>(p=0.012) | -0.020<br>(p=0.584)    |
| 0.90                                        | -0.028<br>(p=0.514)   | 0.019<br>(p=0.738)   | 0.082<br>(p=0.169)     |
| 0.95                                        | -0.005<br>(p=0.871)   | 0.067<br>(p=0.222)   | 0.115***<br>(p=0.000)  |

**Table 24:** Quantile regression results for Netherlands

| Outcome $\tau$                              | CISS                 | CLIFS                  | MUI                    |
|---------------------------------------------|----------------------|------------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                      |                        |                        |
| 0.05                                        | -0.214<br>(p=0.197)  | -1.134***<br>(p=0.005) | -0.860***<br>(p=0.000) |
| 0.10                                        | -0.084<br>(p=0.538)  | -0.501<br>(p=0.220)    | -0.541<br>(p=0.132)    |
| 0.25                                        | 0.136**<br>(p=0.022) | -0.086<br>(p=0.639)    | -0.066<br>(p=0.613)    |
| <i>HICP inflation, three-month-ahead</i>    |                      |                        |                        |
| 0.75                                        | -0.063<br>(p=0.406)  | -0.099**<br>(p=0.016)  | 0.368***<br>(p=0.002)  |
| 0.90                                        | -0.122<br>(p=0.123)  | -0.202**<br>(p=0.046)  | 0.575***<br>(p=0.000)  |
| 0.95                                        | 0.083<br>(p=0.392)   | -0.099<br>(p=0.257)    | 0.787***<br>(p=0.002)  |
| <i>Unemployment rate, three-month-ahead</i> |                      |                        |                        |
| 0.75                                        | 0.000<br>(p=0.999)   | -0.001<br>(p=0.801)    | 0.017<br>(p=0.186)     |
| 0.90                                        | 0.005<br>(p=0.590)   | 0.026<br>(p=0.495)     | 0.020<br>(p=0.250)     |
| 0.95                                        | 0.018**<br>(p=0.030) | 0.093**<br>(p=0.012)   | 0.050***<br>(p=0.000)  |

**Table 25:** Quantile regression results for Portugal

| Outcome $\tau$                              | CISS                  | CLIFS                  | MUI                    |
|---------------------------------------------|-----------------------|------------------------|------------------------|
| <i>GDP growth, next quarter</i>             |                       |                        |                        |
| 0.05                                        | -0.241<br>(p=0.509)   | -0.248<br>(p=0.485)    | -2.367***<br>(p=0.000) |
| 0.10                                        | -0.063<br>(p=0.745)   | -0.054<br>(p=0.724)    | -2.230***<br>(p=0.000) |
| 0.25                                        | -0.103<br>(p=0.472)   | -0.324<br>(p=0.129)    | -0.778<br>(p=0.136)    |
| <i>HICP inflation, three-month-ahead</i>    |                       |                        |                        |
| 0.75                                        | 0.062<br>(p=0.242)    | -0.126***<br>(p=0.007) | 0.164**<br>(p=0.020)   |
| 0.90                                        | 0.040<br>(p=0.427)    | -0.094<br>(p=0.301)    | 0.172**<br>(p=0.020)   |
| 0.95                                        | 0.163<br>(p=0.110)    | 0.031<br>(p=0.683)     | 0.177***<br>(p=0.001)  |
| <i>Unemployment rate, three-month-ahead</i> |                       |                        |                        |
| 0.75                                        | -0.003<br>(p=0.846)   | 0.034***<br>(p=0.003)  | 0.037*<br>(p=0.097)    |
| 0.90                                        | -0.030<br>(p=0.388)   | 0.006<br>(p=0.787)     | 0.106***<br>(p=0.004)  |
| 0.95                                        | -0.043**<br>(p=0.036) | -0.010<br>(p=0.769)    | 0.143***<br>(p=0.000)  |

Notes: Entries are coefficient estimates from country-specific quantile regressions. Parentheses report p-values. All specifications include autoregressive controls and jointly include CISS, CLIFS, and the proposed MUI. Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Increasingly dark shading denotes significance at the 10, 5, and 1 percent levels, respectively.

## B.2 Out-of-sample Forecasts

This section reports the country-specific out-of-sample pinball losses underlying the aggregate results discussed in the main text. Tables 26-28 compare the baseline specification, specifications augmented with individual risk indicators, and the full model including CISS, CLIFS, and the proposed MUI. Lower values indicate better quantile forecast performance.

Overall, the country-level results are broadly consistent with the evidence from Germany and from the pooled panel. In most countries, specifications that include the MUI improve forecast performance relative to the baseline model and relative to models that only include financial-stress indicators. The gains are particularly visible for upper-tail inflation forecasts, where either the MUI-only specification  $\mathcal{M}_1$  or the full specification  $\mathcal{M}_5$  frequently delivers the lowest pinball loss. This suggests that the proposed macroeconomic uncertainty measure contains information about inflation risks that is not fully captured by CISS or CLIFS.

For GDP growth, the full model  $\mathcal{M}_5$  also performs well in most countries, especially at the lower quantiles. This is consistent with the interpretation that combining macroeconomic uncertainty with financial-stress indicators is useful for forecasting downside risks to real activity. The results for unemployment are somewhat more heterogeneous. In several cases, the full model remains competitive, but the improvements over specifications using CLIFS or CISS are generally smaller than for GDP growth and inflation. This is plausible, since unemployment adjusts more gradually and may be less immediately sensitive to short-run changes in uncertainty or financial stress.

Taken together, the appendix tables support the main conclusion that the **MUI** provides additional predictive content for tail-risk forecasting. At the same time, the results show that the strength of this contribution differs across countries, variables, and quantiles. The most robust improvements appear for inflation risks and lower-tail GDP growth, whereas unemployment forecasts display more country-specific variation.

### B.2.1 **DM-tests for all countries**

This section reports the country-specific **DM**-test results underlying the panel evidence discussed in the main text. Overall, the results are broadly consistent with the aggregate findings, although there is meaningful cross-country heterogeneity. The most systematic improvements from adding the **MUI** arise for upper-tail inflation forecasts, where statistically significant gains are observed for several countries and quantiles. Evidence for downside GDP growth is less uniform and is concentrated primarily in the more adverse lower-tail quantiles. At the same time, some countries show little or no statistically significant improvement, indicating that the incremental predictive content of the **MUI** is not homogeneous across the euro area. Taken together, the country-level results support the panel conclusion that the **MUI** is particularly informative for upside inflation risk, while its contribution to downside GDP forecasting is more country-specific.

### B.2.2 **Forecast robustness to the number of factors**

The baseline **MUI** is constructed using  $K=6$  macroeconomic factors. To assess whether the forecasting conclusions depend on this choice, I repeat the complete recursive forecasting exercise using indices constructed with  $K=3$  and  $K=8$ . Because the specifications that do not contain the **MUI** are unaffected by  $K$ , reproducing the complete set of model comparisons would largely duplicate the baseline tables. Table 32 therefore focuses on the incremental comparison between  $\mathcal{M}_5$ , which includes the **MUI**, **CISS**, and **CLIFS**, and the  $\mathcal{M}_4$  benchmark containing **CISS** and **CLIFS** only.

The results confirm that the substantive conclusions are not sensitive to the number of factors used to construct the **MUI**. Lower-tail GDP forecasts improve for most country–quantile combinations and by similar magnitudes in the pooled panel under all three specifications, although the corresponding  $\mathcal{M}_4$ – $\mathcal{M}_5$  loss differences remain mostly statistically insignificant except for the 0.05 and 0.10 quantile for  $K = 8$ . The inflation results are also robust:  $\mathcal{M}_5$  improves upon  $\mathcal{M}_4$  in 22 of 30 country–quantile combinations for  $K=3$  and in 25 combinations for  $K=6$  and  $K=8$ . Moreover, the gains at the 90 and 95 percent inflation quantiles remain statistically significant for every value of  $K$ . The relatively modest unemployment improvements are likewise consistent across specifications.

**Table 26:** Country-specific out-of-sample pinball losses: Austria, Belgium, Germany, and Greece

| Panel A: Austria |        |                 |                 |                 |                 |                 |                 | Panel B: Belgium |        |                 |                 |                 |                 |                 |                 |
|------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Target           | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | Target           | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| GDP              | 0.05   | 1.013           | 0.549           | 0.679           | 0.716           | 0.783           | <b>0.511</b>    | GDP              | 0.05   | 0.586           | 0.599           | 0.522           | <b>0.488</b>    | 0.508           | 0.573           |
| GDP              | 0.10   | 0.883           | 0.701           | 0.819           | 0.725           | 0.840           | <b>0.606</b>    | GDP              | 0.10   | 0.682           | 0.688           | 0.646           | <b>0.571</b>    | 0.621           | 0.641           |
| GDP              | 0.25   | 1.070           | 1.062           | 1.001           | 0.843           | 0.873           | <b>0.836</b>    | GDP              | 0.25   | 0.808           | 0.943           | 0.833           | <b>0.790</b>    | 0.881           | 0.883           |
| HICP             | 0.75   | 0.709           | 0.644           | 0.710           | 0.704           | 0.699           | <b>0.619</b>    | HICP             | 0.75   | 0.714           | 0.713           | 0.685           | 0.698           | <b>0.685</b>    | 0.689           |
| HICP             | 0.90   | 0.607           | 0.428           | 0.569           | 0.593           | 0.514           | <b>0.410</b>    | HICP             | 0.90   | 0.417           | 0.422           | 0.420           | 0.415           | 0.417           | <b>0.410</b>    |
| HICP             | 0.95   | 0.424           | 0.283           | 0.409           | 0.440           | 0.361           | <b>0.268</b>    | HICP             | 0.95   | 0.257           | 0.273           | <b>0.245</b>    | 0.255           | 0.260           | 0.252           |
| UNE              | 0.75   | 0.181           | 0.183           | 0.182           | <b>0.177</b>    | 0.180           | 0.181           | UNE              | 0.75   | 0.156           | 0.154           | 0.158           | <b>0.153</b>    | 0.160           | 0.159           |
| UNE              | 0.90   | 0.123           | <b>0.115</b>    | 0.130           | 0.119           | 0.135           | 0.129           | UNE              | 0.90   | 0.097           | 0.095           | 0.095           | <b>0.090</b>    | 0.093           | 0.094           |
| UNE              | 0.95   | 0.096           | <b>0.086</b>    | 0.110           | 0.104           | 0.121           | 0.098           | UNE              | 0.95   | 0.060           | 0.059           | 0.062           | <b>0.058</b>    | 0.062           | 0.061           |

| Panel C: Germany |        |                 |                 |                 |                 |                 |                 | Panel D: Greece |        |                 |                 |                 |                 |                 |                 |
|------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Target           | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | Target          | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| GDP              | 0.05   | 0.809           | <b>0.447</b>    | 0.770           | 0.676           | 0.802           | 0.537           | GDP             | 0.05   | 1.625           | 1.489           | <b>1.230</b>    | 1.298           | 1.511           | 1.343           |
| GDP              | 0.10   | 0.943           | <b>0.605</b>    | 0.882           | 0.709           | 0.868           | 0.617           | GDP             | 0.10   | 1.698           | 1.634           | 1.415           | 1.422           | 1.548           | <b>1.333</b>    |
| GDP              | 0.25   | 1.063           | 0.822           | 1.054           | 0.881           | 0.961           | <b>0.801</b>    | GDP             | 0.25   | 2.353           | 2.134           | 1.806           | 1.890           | 1.883           | <b>1.699</b>    |
| HICP             | 0.75   | 0.681           | <b>0.567</b>    | 0.693           | 0.692           | 0.696           | 0.577           | HICP            | 0.75   | 0.688           | 0.612           | 0.624           | 0.629           | 0.625           | <b>0.603</b>    |
| HICP             | 0.90   | 0.491           | <b>0.329</b>    | 0.511           | 0.469           | 0.473           | 0.347           | HICP            | 0.90   | 0.467           | <b>0.398</b>    | 0.438           | 0.459           | 0.448           | 0.401           |
| HICP             | 0.95   | 0.311           | <b>0.235</b>    | 0.330           | 0.269           | 0.295           | 0.252           | HICP            | 0.95   | 0.318           | 0.286           | 0.349           | 0.381           | 0.365           | <b>0.284</b>    |
| UNE              | 0.75   | 0.070           | 0.070           | 0.072           | 0.070           | 0.069           | <b>0.069</b>    | UNE             | 0.75   | 0.423           | 0.401           | 0.350           | <b>0.283</b>    | 0.288           | 0.291           |
| UNE              | 0.90   | 0.040           | 0.043           | 0.041           | 0.043           | <b>0.039</b>    | 0.039           | UNE             | 0.90   | 0.271           | 0.236           | 0.221           | <b>0.179</b>    | 0.187           | 0.194           |
| UNE              | 0.95   | <b>0.026</b>    | 0.027           | 0.028           | 0.028           | 0.031           | 0.029           | UNE             | 0.95   | 0.196           | 0.156           | 0.148           | <b>0.126</b>    | 0.134           | 0.129           |

Notes: Lower values indicate better quantile forecast performance. Bold entries denote the best-performing specification within each target–quantile combination. Shaded columns denote specifications containing the proposed MUI. For all countries shown,  $N = 76$  for GDP and  $N = 215$  for HICP and unemployment.  $\mathcal{M}_0$  = baseline;  $\mathcal{M}_1$  = baseline + MUI;  $\mathcal{M}_2$  = baseline + CISS;  $\mathcal{M}_3$  = baseline + CLIFS;  $\mathcal{M}_4$  = baseline + CISS + CLIFS;  $\mathcal{M}_5$  = baseline + CISS + CLIFS + MUI.

**Table 27:** Country-specific out-of-sample pinball losses: Spain, France, Ireland, and Italy

| Panel A: Spain |        |                 |                 |                 |                 |                 |                 | Panel B: France |        |                 |                 |                 |                 |                 |                 |
|----------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Target         | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | Target          | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| GDP            | 0.05   | 1.476           | <b>0.806</b>    | 1.334           | 1.454           | 1.398           | 0.920           | GDP             | 0.05   | 1.032           | 0.699           | 1.354           | 0.827           | 0.727           | <b>0.600</b>    |
| GDP            | 0.10   | 1.356           | <b>0.964</b>    | 1.207           | 1.316           | 1.360           | 1.014           | GDP             | 0.10   | 1.019           | <b>0.743</b>    | 0.953           | 0.816           | 0.775           | 0.765           |
| GDP            | 0.25   | 1.385           | 1.293           | 1.201           | 1.269           | <b>1.182</b>    | 1.214           | GDP             | 0.25   | 1.023           | 0.871           | 0.954           | 0.860           | 0.845           | <b>0.784</b>    |
| HICP           | 0.75   | 0.694           | 0.640           | 0.615           | 0.659           | 0.619           | <b>0.579</b>    | HICP            | 0.75   | 0.391           | 0.406           | 0.371           | <b>0.358</b>    | 0.362           | 0.372           |
| HICP           | 0.90   | 0.473           | 0.359           | 0.454           | 0.456           | 0.458           | <b>0.347</b>    | HICP            | 0.90   | 0.215           | 0.224           | 0.204           | <b>0.191</b>    | 0.199           | 0.212           |
| HICP           | 0.95   | 0.377           | <b>0.240</b>    | 0.369           | 0.352           | 0.370           | 0.244           | HICP            | 0.95   | 0.126           | 0.130           | 0.130           | <b>0.115</b>    | 0.130           | 0.141           |
| UNE            | 0.75   | 0.234           | 0.234           | <b>0.203</b>    | 0.221           | 0.204           | 0.210           | UNE             | 0.75   | 0.117           | <b>0.107</b>    | 0.113           | 0.109           | 0.110           | 0.107           |
| UNE            | 0.90   | 0.152           | 0.155           | 0.148           | <b>0.146</b>    | 0.151           | 0.161           | UNE             | 0.90   | 0.091           | <b>0.066</b>    | 0.086           | 0.071           | 0.073           | 0.069           |
| UNE            | 0.95   | 0.120           | 0.119           | 0.118           | <b>0.110</b>    | 0.115           | 0.122           | UNE             | 0.95   | 0.073           | <b>0.045</b>    | 0.063           | 0.053           | 0.054           | 0.051           |

| Panel C: Ireland |        |                 |                 |                 |                 |                 |                 | Panel D: Italy |        |                 |                 |                 |                 |                 |                 |
|------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Target           | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | Target         | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| GDP              | 0.05   | <b>0.904</b>    | 1.182           | 1.150           | 0.968           | 1.199           | 1.391           | GDP            | 0.05   | 1.303           | 0.841           | 0.960           | 0.856           | 0.901           | <b>0.735</b>    |
| GDP              | 0.10   | 1.293           | 1.598           | 1.367           | <b>1.272</b>    | 1.454           | 1.676           | GDP            | 0.10   | 1.527           | 1.118           | 1.044           | <b>0.858</b>    | 0.926           | 0.902           |
| GDP              | 0.25   | 2.103           | 2.024           | 1.921           | <b>1.765</b>    | 2.023           | 2.148           | GDP            | 0.25   | 1.475           | 1.419           | 1.157           | <b>1.014</b>    | 1.073           | 1.220           |
| HICP             | 0.75   | 0.706           | 0.678           | 0.683           | <b>0.677</b>    | 0.685           | 0.683           | HICP           | 0.75   | 0.708           | 0.588           | 0.664           | 0.660           | 0.664           | <b>0.578</b>    |
| HICP             | 0.90   | 0.419           | 0.407           | 0.427           | 0.423           | 0.429           | <b>0.391</b>    | HICP           | 0.90   | 0.539           | 0.340           | 0.529           | 0.483           | 0.481           | <b>0.326</b>    |
| HICP             | 0.95   | 0.288           | 0.289           | 0.306           | 0.304           | 0.313           | <b>0.282</b>    | HICP           | 0.95   | 0.381           | <b>0.236</b>    | 0.371           | 0.377           | 0.371           | 0.238           |
| UNE              | 0.75   | 0.280           | 0.254           | 0.223           | 0.227           | 0.215           | <b>0.214</b>    | UNE            | 0.75   | 0.188           | 0.187           | <b>0.163</b>    | 0.171           | 0.164           | 0.165           |
| UNE              | 0.90   | 0.206           | 0.148           | 0.148           | 0.163           | 0.144           | <b>0.136</b>    | UNE            | 0.90   | 0.129           | 0.117           | 0.109           | 0.111           | 0.111           | <b>0.108</b>    |
| UNE              | 0.95   | 0.146           | 0.099           | 0.110           | 0.114           | 0.110           | <b>0.094</b>    | UNE            | 0.95   | 0.107           | <b>0.079</b>    | 0.090           | 0.087           | 0.091           | 0.082           |

Notes: Lower values indicate better quantile forecast performance. Bold entries denote the best-performing specification within each target–quantile combination. Shaded columns denote specifications containing the proposed **MUI**. For all countries shown,  $N = 76$  for GDP and  $N = 215$  for HICP and unemployment. Model definitions are given in Table 26.

**Table 28:** Country-specific out-of-sample pinball losses: the Netherlands and Portugal

| Panel A: Netherlands |        |                 |                 |                 |                 |                 |                 | Panel B: Portugal |        |                 |                 |                 |                 |                 |                 |
|----------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-------------------|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Target               | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ | Target            | $\tau$ | $\mathcal{M}_0$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ | $\mathcal{M}_5$ |
| GDP                  | 0.05   | 0.636           | 0.672           | <b>0.550</b>    | 0.641           | 0.627           | 0.642           | GDP               | 0.05   | 0.765           | 0.786           | <b>0.663</b>    | 0.758           | 0.700           | 0.678           |
| GDP                  | 0.10   | 0.768           | 0.831           | <b>0.659</b>    | 0.774           | 0.758           | 0.705           | GDP               | 0.10   | 0.960           | 0.909           | <b>0.844</b>    | 0.911           | 0.915           | 0.845           |
| GDP                  | 0.25   | 1.092           | 1.151           | <b>1.010</b>    | 1.067           | 1.103           | 1.103           | GDP               | 0.25   | 1.353           | 1.115           | 1.159           | 1.117           | 1.096           | <b>1.044</b>    |
| HICP                 | 0.75   | 0.726           | <b>0.631</b>    | 0.718           | 0.729           | 0.714           | 0.635           | HICP              | 0.75   | 0.716           | 0.722           | 0.709           | 0.708           | <b>0.707</b>    | 0.718           |
| HICP                 | 0.90   | 0.573           | 0.447           | 0.578           | 0.580           | 0.568           | <b>0.443</b>    | HICP              | 0.90   | 0.482           | 0.432           | 0.462           | 0.456           | 0.466           | <b>0.426</b>    |
| HICP                 | 0.95   | 0.390           | <b>0.338</b>    | 0.389           | 0.398           | 0.395           | 0.344           | HICP              | 0.95   | 0.334           | 0.300           | 0.321           | 0.328           | 0.320           | <b>0.292</b>    |
| UNE                  | 0.75   | 0.131           | <b>0.127</b>    | 0.130           | 0.128           | 0.128           | 0.128           | UNE               | 0.75   | 0.240           | 0.230           | 0.222           | 0.224           | 0.218           | <b>0.209</b>    |
| UNE                  | 0.90   | 0.093           | 0.087           | 0.094           | <b>0.086</b>    | 0.089           | 0.086           | UNE               | 0.90   | 0.148           | 0.138           | 0.128           | 0.134           | 0.131           | <b>0.126</b>    |
| UNE                  | 0.95   | 0.068           | 0.066           | 0.072           | 0.064           | 0.067           | <b>0.063</b>    | UNE               | 0.95   | 0.111           | 0.093           | <b>0.085</b>    | 0.099           | 0.091           | 0.092           |

Notes: Lower values indicate better quantile forecast performance. Bold entries denote the best-performing specification within each target–quantile combination. Shaded columns denote specifications containing the proposed **MUI**. For all countries shown,  $N = 76$  for GDP and  $N = 215$  for HICP and unemployment. Model definitions are given in Table 26.

**Table 29:** Country-specific Diebold–Mariano tests: Austria, Belgium, Germany, and Greece

| Panel A: Austria |        |     |           |          |       |          | Panel B: Belgium |        |     |           |          |        |       |
|------------------|--------|-----|-----------|----------|-------|----------|------------------|--------|-----|-----------|----------|--------|-------|
| Target           | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM    | $p$      | Target           | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$   |
| GDP              | 0.05   | 76  | 0.273     | 0.146    | 1.868 | 0.033**  | GDP              | 0.05   | 76  | -0.065    | 0.068    | -0.951 | 0.828 |
| GDP              | 0.10   | 76  | 0.234     | 0.149    | 1.575 | 0.060*   | GDP              | 0.10   | 76  | -0.020    | 0.070    | -0.292 | 0.615 |
| GDP              | 0.25   | 76  | 0.037     | 0.072    | 0.512 | 0.304    | GDP              | 0.25   | 76  | -0.002    | 0.064    | -0.032 | 0.513 |
| HICP             | 0.75   | 215 | 0.080     | 0.031    | 2.590 | 0.005*** | HICP             | 0.75   | 215 | -0.004    | 0.020    | -0.203 | 0.580 |
| HICP             | 0.90   | 215 | 0.104     | 0.051    | 2.013 | 0.023**  | HICP             | 0.90   | 215 | 0.007     | 0.019    | 0.365  | 0.358 |
| HICP             | 0.95   | 215 | 0.092     | 0.039    | 2.367 | 0.009*** | HICP             | 0.95   | 215 | 0.008     | 0.010    | 0.835  | 0.202 |

| Panel C: Germany |        |     |           |          |       |         | Panel D: Greece |        |     |           |          |       |          |
|------------------|--------|-----|-----------|----------|-------|---------|-----------------|--------|-----|-----------|----------|-------|----------|
| Target           | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM    | $p$     | Target          | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM    | $p$      |
| GDP              | 0.05   | 76  | 0.264     | 0.135    | 1.957 | 0.027** | GDP             | 0.05   | 76  | 0.168     | 0.168    | 0.996 | 0.161    |
| GDP              | 0.10   | 76  | 0.252     | 0.130    | 1.935 | 0.028** | GDP             | 0.10   | 76  | 0.215     | 0.182    | 1.182 | 0.120    |
| GDP              | 0.25   | 76  | 0.160     | 0.098    | 1.640 | 0.053*  | GDP             | 0.25   | 76  | 0.184     | 0.227    | 0.808 | 0.211    |
| HICP             | 0.75   | 215 | 0.119     | 0.053    | 2.252 | 0.013** | HICP            | 0.75   | 215 | 0.022     | 0.018    | 1.222 | 0.112    |
| HICP             | 0.90   | 215 | 0.126     | 0.071    | 1.785 | 0.038** | HICP            | 0.90   | 215 | 0.047     | 0.020    | 2.393 | 0.009*** |
| HICP             | 0.95   | 215 | 0.043     | 0.047    | 0.913 | 0.181   | HICP            | 0.95   | 215 | 0.082     | 0.037    | 2.230 | 0.013**  |

Notes: The loss differential is defined as  $d_t = L_{\mathcal{M}_{4,t}} - L_{\mathcal{M}_{5,t}}$ , so that positive values of  $\bar{d}$  indicate lower average pinball loss for  $\mathcal{M}_5$ . Reported  $p$ -values correspond to the one-sided alternative that  $\mathcal{M}_5$  has lower expected pinball loss than  $\mathcal{M}_4$ . HAC standard errors use the Newey–West estimator. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 30:** Country-specific Diebold–Mariano tests: Spain, France, Ireland, and Italy

| Panel A: Spain |        |     |           |          |        |          | Panel B: France |        |     |           |          |        |       |
|----------------|--------|-----|-----------|----------|--------|----------|-----------------|--------|-----|-----------|----------|--------|-------|
| Target         | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$      | Target          | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$   |
| GDP            | 0.05   | 76  | 0.478     | 0.272    | 1.760  | 0.041**  | GDP             | 0.05   | 76  | 0.127     | 0.211    | 0.605  | 0.274 |
| GDP            | 0.10   | 76  | 0.346     | 0.245    | 1.412  | 0.081*   | GDP             | 0.10   | 76  | 0.010     | 0.108    | 0.092  | 0.464 |
| GDP            | 0.25   | 76  | -0.032    | 0.092    | -0.348 | 0.636    | GDP             | 0.25   | 76  | 0.061     | 0.103    | 0.594  | 0.277 |
| HICP           | 0.75   | 215 | 0.040     | 0.028    | 1.422  | 0.078*   | HICP            | 0.75   | 215 | -0.010    | 0.020    | -0.489 | 0.687 |
| HICP           | 0.90   | 215 | 0.111     | 0.051    | 2.195  | 0.015**  | HICP            | 0.90   | 215 | -0.013    | 0.012    | -1.085 | 0.860 |
| HICP           | 0.95   | 215 | 0.125     | 0.052    | 2.391  | 0.009*** | HICP            | 0.95   | 215 | -0.011    | 0.009    | -1.188 | 0.882 |

| Panel C: Ireland |        |     |           |          |        |         | Panel D: Italy |        |     |           |          |        |          |
|------------------|--------|-----|-----------|----------|--------|---------|----------------|--------|-----|-----------|----------|--------|----------|
| Target           | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$     | Target         | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$      |
| GDP              | 0.05   | 76  | -0.191    | 0.187    | -1.024 | 0.846   | GDP            | 0.05   | 76  | 0.166     | 0.134    | 1.244  | 0.109    |
| GDP              | 0.10   | 76  | -0.222    | 0.185    | -1.200 | 0.883   | GDP            | 0.10   | 76  | 0.024     | 0.173    | 0.141  | 0.444    |
| GDP              | 0.25   | 76  | -0.125    | 0.079    | -1.584 | 0.941   | GDP            | 0.25   | 76  | -0.147    | 0.153    | -0.961 | 0.830    |
| HICP             | 0.75   | 215 | 0.002     | 0.012    | 0.135  | 0.446   | HICP           | 0.75   | 215 | 0.086     | 0.053    | 1.634  | 0.052*   |
| HICP             | 0.90   | 215 | 0.038     | 0.018    | 2.120  | 0.018** | HICP           | 0.90   | 215 | 0.155     | 0.062    | 2.504  | 0.007*** |
| HICP             | 0.95   | 215 | 0.031     | 0.017    | 1.834  | 0.034** | HICP           | 0.95   | 215 | 0.133     | 0.069    | 1.923  | 0.028**  |

Notes: The loss differential is defined as  $d_t = L_{\mathcal{M}_{4,t}} - L_{\mathcal{M}_{5,t}}$ , so that positive values of  $\bar{d}$  indicate lower average pinball loss for  $\mathcal{M}_5$ . Reported  $p$ -values correspond to the one-sided alternative that  $\mathcal{M}_5$  has lower expected pinball loss than  $\mathcal{M}_4$ . HAC standard errors use the Newey–West estimator. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 31:** Country-specific Diebold–Mariano tests: Netherlands and Portugal

| Panel A: Netherlands |        |     |           |          |        |          | Panel B: Portugal |        |     |           |          |        |         |
|----------------------|--------|-----|-----------|----------|--------|----------|-------------------|--------|-----|-----------|----------|--------|---------|
| Target               | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$      | Target            | $\tau$ | $N$ | $\bar{d}$ | HAC s.e. | DM     | $p$     |
| GDP                  | 0.05   | 76  | -0.016    | 0.092    | -0.173 | 0.568    | GDP               | 0.05   | 76  | 0.021     | 0.052    | 0.415  | 0.340   |
| GDP                  | 0.10   | 76  | 0.053     | 0.085    | 0.622  | 0.268    | GDP               | 0.10   | 76  | 0.070     | 0.087    | 0.808  | 0.211   |
| GDP                  | 0.25   | 76  | 0.000     | 0.108    | 0.003  | 0.499    | GDP               | 0.25   | 76  | 0.053     | 0.155    | 0.340  | 0.367   |
| HICP                 | 0.75   | 215 | 0.079     | 0.045    | 1.765  | 0.039**  | HICP              | 0.75   | 215 | -0.011    | 0.016    | -0.678 | 0.751   |
| HICP                 | 0.90   | 215 | 0.125     | 0.042    | 2.965  | 0.002*** | HICP              | 0.90   | 215 | 0.040     | 0.021    | 1.887  | 0.030** |
| HICP                 | 0.95   | 215 | 0.050     | 0.028    | 1.809  | 0.036**  | HICP              | 0.95   | 215 | 0.028     | 0.022    | 1.262  | 0.104   |

Notes: The loss differential is defined as  $d_t = L_{M_4,t} - L_{M_5,t}$ , so that positive values of  $\bar{d}$  indicate lower average pinball loss for  $M_5$ . Reported  $p$ -values correspond to the one-sided alternative that  $M_5$  has lower expected pinball loss than  $M_4$ . HAC standard errors use the Newey–West estimator. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 32:** Robustness of forecasting performance to the number of factors

| Outcome                                                                                              | Quantile $\tau$ | $K = 3$         | $K = 6$         | $K = 8$         |
|------------------------------------------------------------------------------------------------------|-----------------|-----------------|-----------------|-----------------|
| <i>Panel A: Panel pinball loss of <math>M_5</math> (percentage gain over <math>M_4</math>)</i>       |                 |                 |                 |                 |
| GDP growth                                                                                           | 0.05            | 0.789 (13.9**)  | 0.794 (13.3**)  | 0.737 (19.6***) |
|                                                                                                      | 0.10            | 0.923 (8.4)     | 0.911 (9.5)     | 0.868 (13.8*)   |
|                                                                                                      | 0.25            | 1.198 (−0.4)    | 1.174 (1.6)     | 1.118 (6.3)     |
| HICP inflation                                                                                       | 0.75            | 0.616 (4.6**)   | 0.605 (6.2***)  | 0.608 (5.9***)  |
|                                                                                                      | 0.90            | 0.374 (16.0***) | 0.371 (16.6***) | 0.379 (14.9***) |
|                                                                                                      | 0.95            | 0.264 (16.9***) | 0.260 (18.3***) | 0.268 (15.8***) |
| Unemployment                                                                                         | 0.75            | 0.175 (−0.9)    | 0.173 (0.4)     | 0.174 (0.1)     |
|                                                                                                      | 0.90            | 0.111 (3.5)     | 0.114 (0.9)     | 0.113 (2.0)     |
|                                                                                                      | 0.95            | 0.080 (8.1)     | 0.082 (6.2)     | 0.082 (6.7)     |
| <i>Panel B: Country–quantile combinations in which <math>M_5</math> outperforms <math>M_4</math></i> |                 |                 |                 |                 |
| GDP growth                                                                                           |                 | 20/30           | 21/30           | 23/30           |
| HICP inflation                                                                                       |                 | 22/30           | 25/30           | 25/30           |
| Unemployment                                                                                         |                 | 16/30           | 20/30           | 16/30           |

Notes: Panel A reports the pooled-panel pinball loss of  $M_5$ . Values in parentheses are percentage reductions in pinball loss relative to  $M_4$ ; positive values indicate that adding the MUI improves forecast performance.  $M_4$  contains the baseline macroeconomic controls, CISS, and CLIFS, while  $M_5$  additionally contains the MUI. Significance stars refer to one-sided DM-tests of equal predictive accuracy between  $M_4$  and  $M_5$ . No DM-tests are reported for unemployment. Panel B reports the number of country–quantile combinations for which  $M_5$  has a lower pinball loss than  $M_4$ , out of 30 combinations for each outcome. Significance levels are denoted by \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ .

## **C Statutory Declaration**

I have written the present thesis myself and have used exclusively the sources and aides mentioned. This thesis has not yet been submitted as an examination in another degree programme. All passages taken word-by-word or the meaning of which are quoted from published or unpublished texts, as well as all indications based on oral accounts, have been marked as such.

Place, Date: ..... Signature: .....