



# ENERGY RISK FACTORS AND MACRO-FINANCIAL VULNERABILITY

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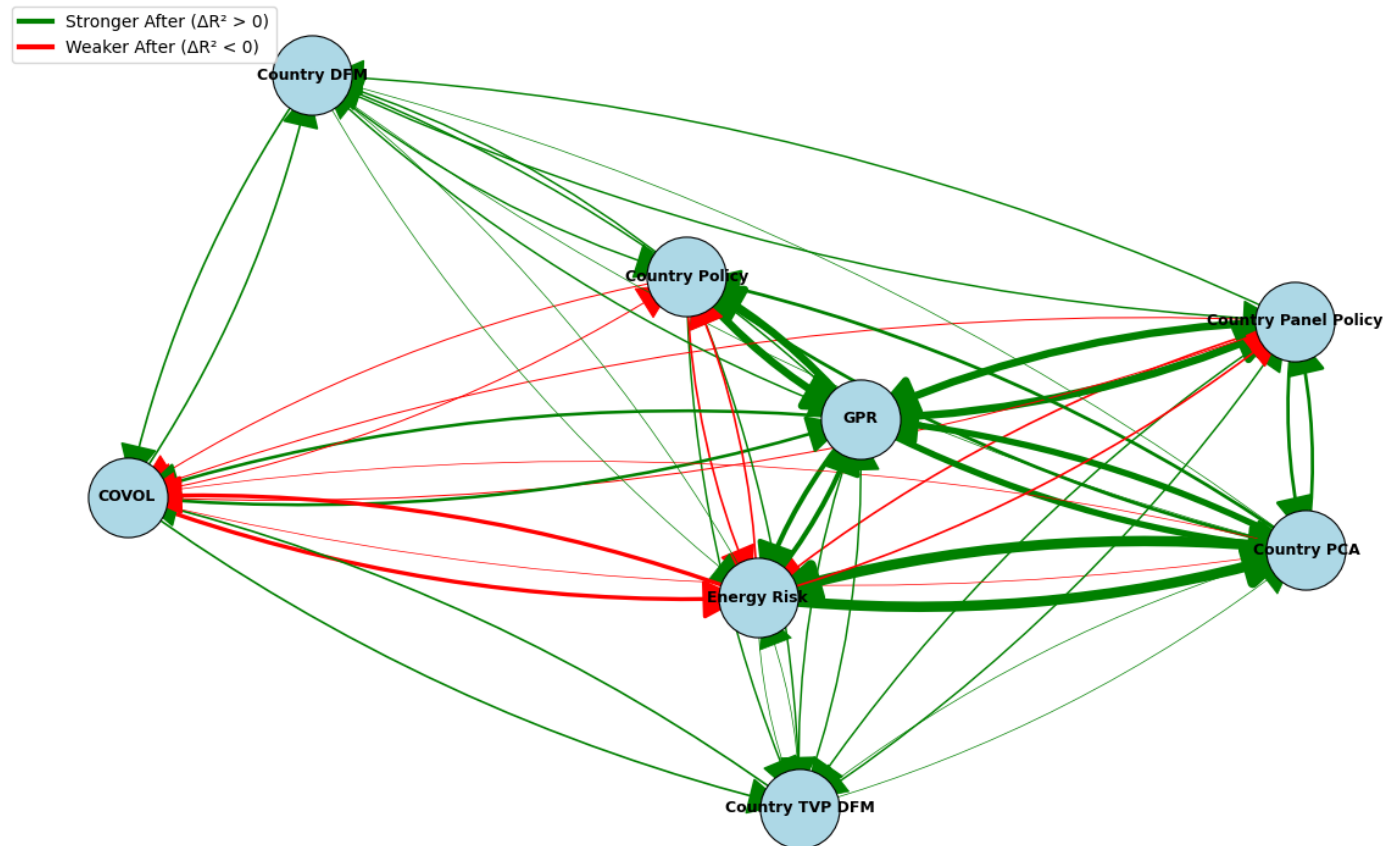


- There is a potential to fit many different FSI's even if we just restrict ourselves to one methodology.
- There are further stress indices which are portfolio based: SovCISS, and CLIFS.
- Geopolitical risk is a multi-faceted phenomenon, given recent events (Russo-Ukraine War, Closure of Strait of Hormuz) we will focus on georisk stemming from energy markets.
- Energy risk is captured by price volatility and extreme price movements, which are related to two major risk measures: variance and value-at-risk.
- **Which stress indices are ideal for policy makers?**
  - Best practice in literature is method of [Kaminsky and Reinhart, 1999], which determines the signalling potential of a variable.
  - Problem: Method requires knowledge of crises timings. The purpose of an FSI is to identify stress events for high frequency data (catch-22 problem).

# CAUSALITY LINKS BETWEEN GEOPOLITICAL RISK AND FINANCIAL STRESS



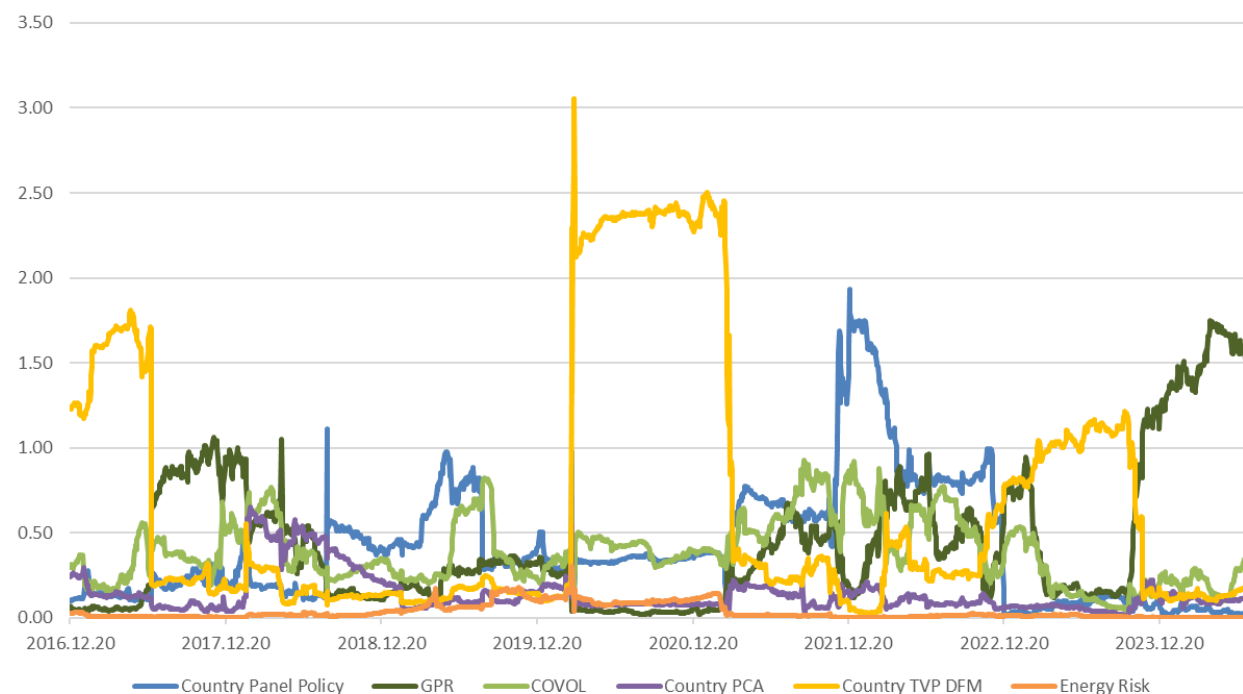
Case-Aligned  $\Delta R^2$  Causality Network (JP Test)  
Green = Stronger After, Red = Weaker After



## PEARL-TYPE CAUSALITY NETWORK OF GEOPOLITICAL RISK, ENERGY RISK AND FINANCIAL STRESS

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation. The colours of the arrows indicate the direction of the change in dominance before and after the start of the Russian invasion of Ukraine.

- The predictive causality test, based on Judea Pearl's  $\Delta R^2$  diagnostic reveals the changing architecture of geopolitical volatility. Based on the results of the test, causal channels of prediction may be identified between the financial stress variables and the geopolitical and energy risk indicators.
- The set of indicators used in the analysis includes the geopolitical risk indicators (the GPR Index and COVOL Index), as well as metrics from financial markets themselves, such as those for country exchange-traded funds (ETFs), foreign exchange rates and energy markets.
- Following the Russian invasion of Ukraine, a clear structural transition can be observed, the GPR Index and the Energy Risk Index increase their predictive impact. This suggests that risks arising from the energy market and those related to the GPR Index became dominant in transmitting shocks to other market-based indicators, such as the equity and foreign exchange markets.



- The variance decomposition reveals individual spillover channels with shifts in the relative importance of the transmission channels over time.
- Financial markets are interconnected during periods of geopolitical stress, potentially giving rise to spillovers across markets, asset classes and countries.
- Diebold-Yilmaz variance decomposition enables us to capture how stress linked to geopolitical, and energy linked factors spreads within the financial system, allows to identify the evolving systemic importance of different financial markets over time.
- As a consequence, there is no index with superior performance. Index performance highly depends on the time period and the focus of the index.

## DIEBOLD-YILMAZ SPILLOVERS BETWEEN RISK INDICES

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation. Notes: This figure shows the dynamics of the Total Volatility Spillover Index estimated using the Diebold-Yilmaz method.

Notes: DFM stands for dynamic factor model, GPR for Standard Geopolitical Risk Index, COVOL for Common Volatility Index, PCA for principal component analysis and TVP DFM for time-varying parameter dynamic factor model.

## Dynamic Factor model

$$X_{t \times m} = f_{t \times m} L_{r \times m} + \epsilon_{t \times m}$$

$$\Phi(L)f_t = d + \theta(L)u_t$$

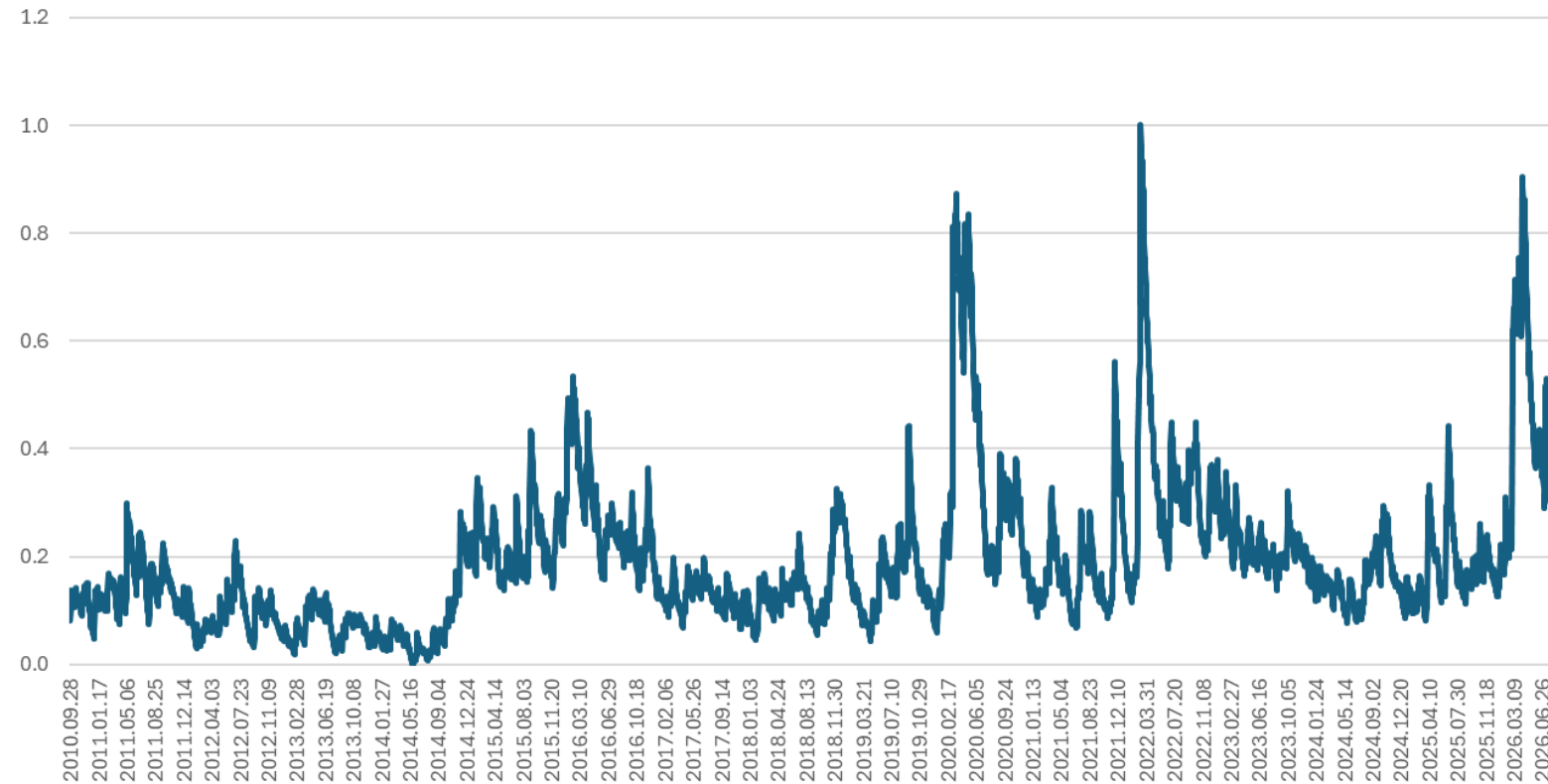
where  $r$  is the number of variables,  $m$  is the number of factors,  $f$  is the latent factor, and  $X$  is the design matrix

- Differencing variables changes information content.
- Differencing variables makes it difficult to capture gradual build-up of stress.
- We apply non-stationary dynamic factor model for this reason (Varga, K., & Szendrei, T. 2025).

# ENERGY STRESS INDEX- COMBINING FACTORS



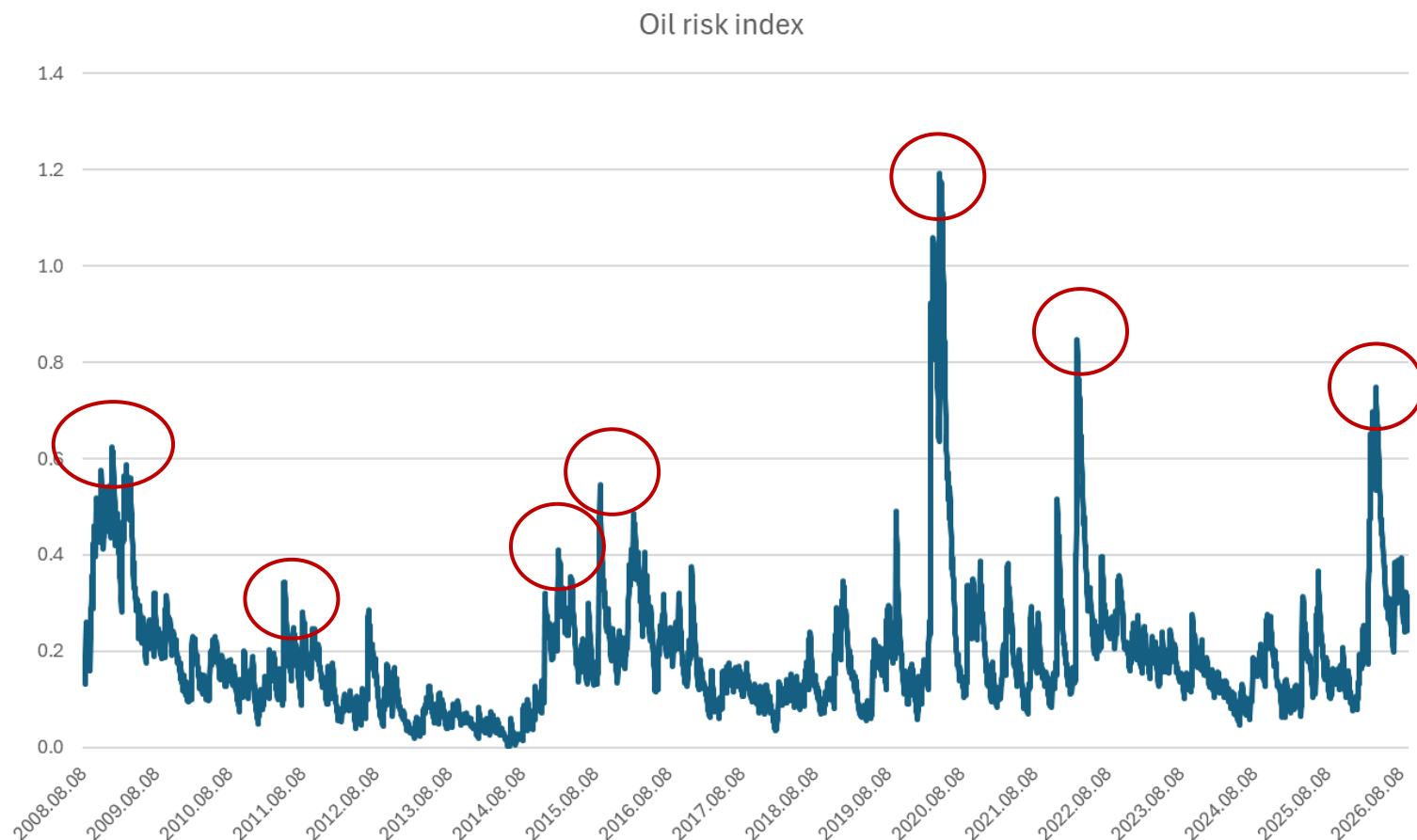
Energy risk index



ENERGY STRESS INDEX (OIL AND GAS)

- Data: 18 global oil and gas spot price index return series transformed to EWMA volatilities and CMAX measures.
- The energy stress index peaks at the COVID breakout, at certain points during the Russo-Ukraine War and the second historical highest peak is now, in midst of the US-Iran war.

# OIL STRESS INDEX- COMBINING OIL RELATED FACTORS



## OIL STRESS INDEX

Source: own calculations, MNB

### Events:

- In January 2009, the oil market was in the midst of a severe collapse, as the global financial crisis caused a dramatic contraction in demand.
- May 5–6, 2011 (The Crash): After peaking near for Brent in late April/early May, prices plummeted on May 5 and 6, falling roughly 9% to 10% in a single day due to fears of slowing global demand.
- On February 2, 2015, the global oil market was experiencing intense volatility, characterized by a significant rebound in prices after a severe, month-long price crash to start the year.
- On September 9, 2015, the oil market saw a brief stabilization and upward rally, with Brent crude trading around per barrel, up 9 cents from the previous close. This followed a 4% jump in the previous session and was largely driven by a stock market rally and speculation regarding potential OPEC production cuts.
- Russo-Ukraine war break out.
- Beginning of US-Iran war and following volatile events.

- [Adrian et al., 2019] popularised the Growth-at-Risk (GaR) framework: modelling GDP growth with a value-at-risk framework.
  - Downside risk of GDP can be captured by the lower quantiles of the GDP growth density.
  - [Adrian et al., 2019] show that downside risk of GDP growth evolves with the state of the financial market.
  - Policy makers can glean how vulnerable the economy is to shocks with the help of the following.
- The key insight, is that the proposed risk indices fit nicely into this GaR framework.
  - Can use Quantile Regression of [Koenker and Bassett, 1978] to fit GaR.

**Construct GaR models with the different risk indices and evaluate their performance**

$$\Delta GDP_{t+h}^{\tau} = const + \Delta GDP_t * \beta_{GDP} + FISS_t * \beta_{FISS} + ERI_t * \beta_{ERI}$$

Where

- $\Delta GDP_{t+h}^{\tau}$  is the average monthly GDP growth from t to t+h, h=1-6.
- $\Delta GDP_t$  is the monthly GDP growth at t.
- $FISS_t$  is the Factor Based Index of Systemic Stress, the Hungarian financial stress index.
- $ERI_t$  is the Energy Risk Index.

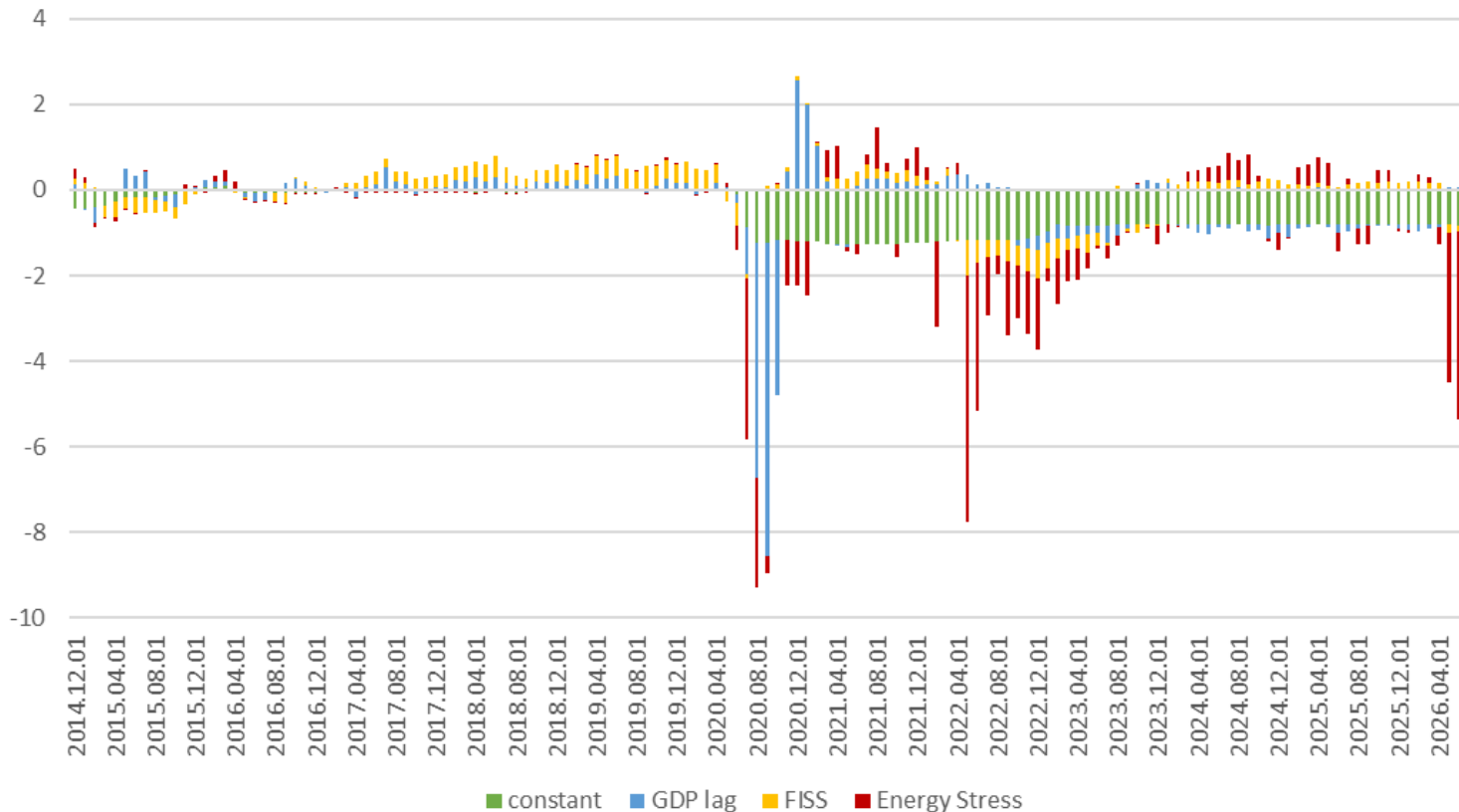
Important to note: the coefficient of the lag of GDP is not involved in the Lasso variable selection. Monthly GDP is model based, see: [Schorfheide and Song, 2015] and [Koop et al., 2023].

The quantiles are estimated jointly with adaptive LASSO on the levels (Szendrei, Varga, 2023).

# GDP-AT-RISK RESULTS



Forecast contribution, H=3 months, Q=0.1



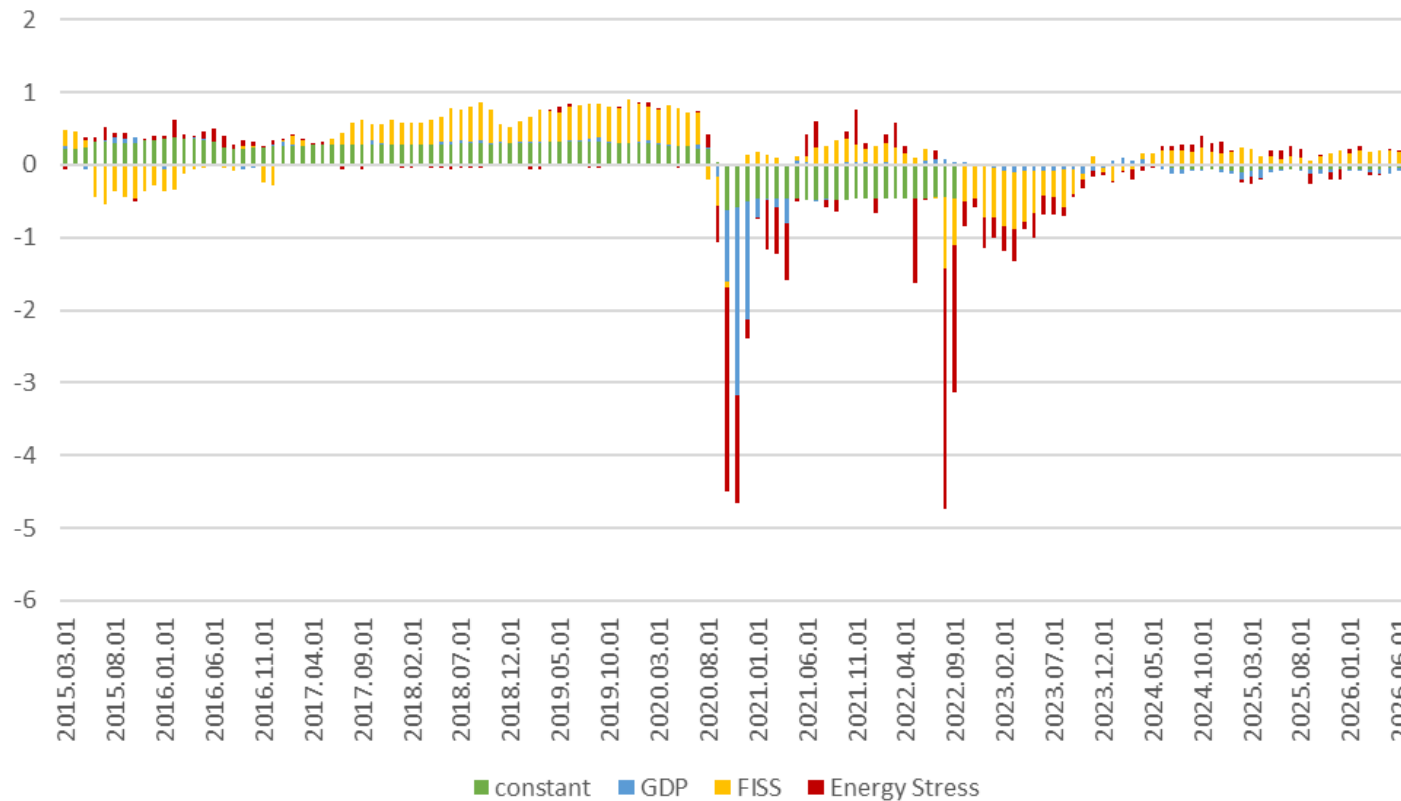
## GDP-AT-RISK FORECAST CONTRIBUTIONS

- During the COVID period financial stress has minor impact on GDP vulnerability (0.1 quantile of GDP growth distribution).
- Energy risk has major role during the COVID pandemic, the beginning of the Russo-Ukraine war and also recently as a consequence of the US-Iran war.
- GDP vulnerability has increased significantly recently.

# GDP-AT-RISK RESULTS



Forecast contribution, H=6 months, Q=0.1



## GDP-AT-RISK FORECAST CONTRIBUTIONS

- In the longer run during the COVID period financial stress still has minor impact on GDP vulnerability (0.1 quantile of GDP growth distribution).
- Energy risk is still playing has major role after the COVID pandemic, the beginning of the Russo-Ukraine war and also recently as a consequence of the US-Iran war.
- As compared to the short run financial stress has increasing importance, which may be a result of spillovers from energy risks.

$$\Delta CPI_{t+h}^{\tau} = const + \Delta CPI_t * \beta_{GDP} + FISS_t * \beta_{FISS} + ERI_t * \beta_{ERI} + X_t^T * B_X$$

Where

- $\Delta CPI_{t+h}^{\tau}$  is the average monthly CPI inflation from t to t+h, h=1-6.
- $\Delta CPI_t$  is the monthly CPI growth at t.
- $FISS_t$  is the Factor Based Index of Systemic Stress, the Hungarian financial stress index.
- $ERI_t$  is the Energy Risk Index.
- $X_t^T$  is the vector of additional regressors: Brent oil price return and GDP quarterly growth.

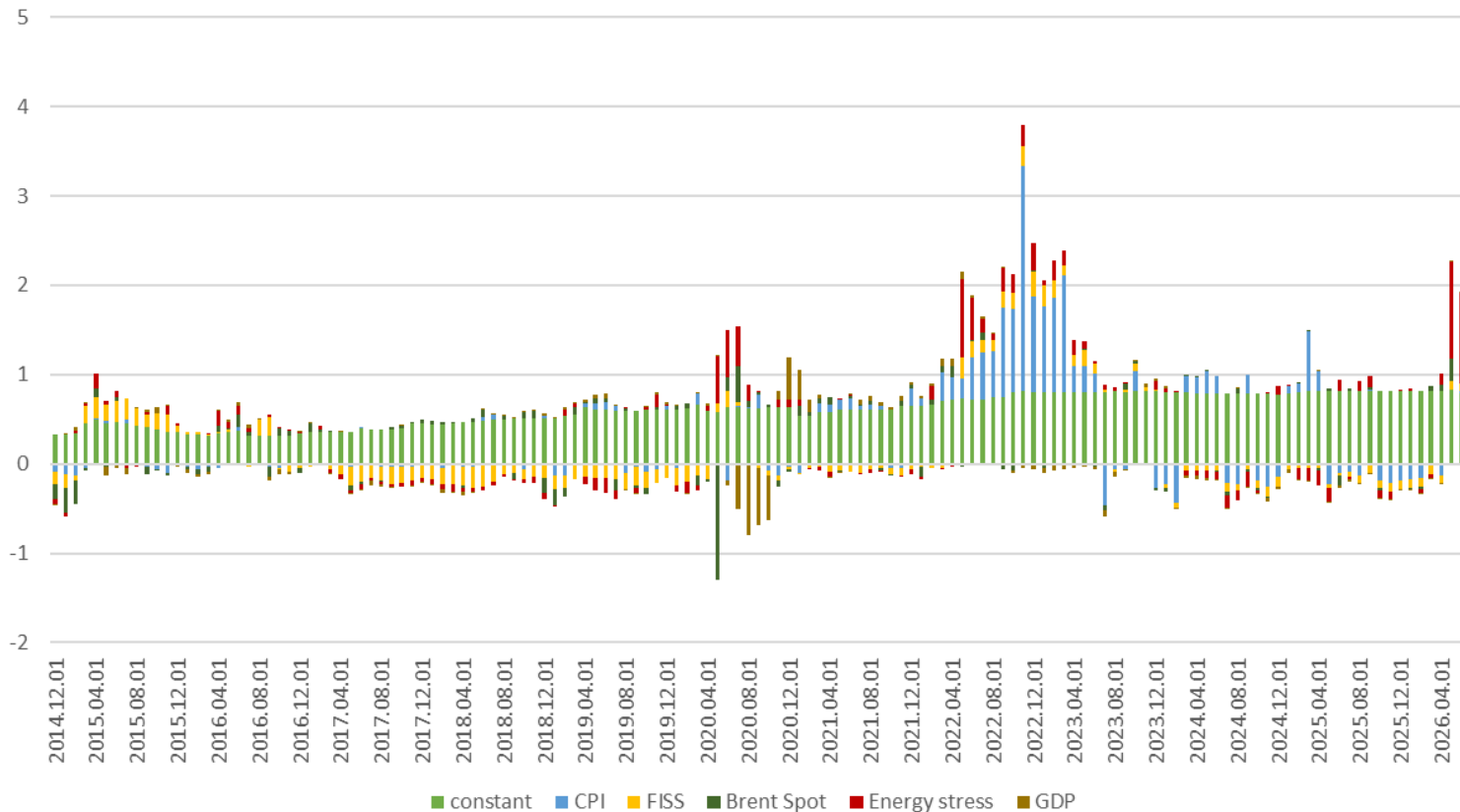
Important to note: the coefficient of the lag of CPI is not involved in the Lasso variable selection.

The quantiles are estimated jointly with adaptive LASSO on the levels (Szendrei, Varga, 2023).

# INFLATION-AT-RISK RESULTS



Forecast contribution, H=3 months, Q=0.9



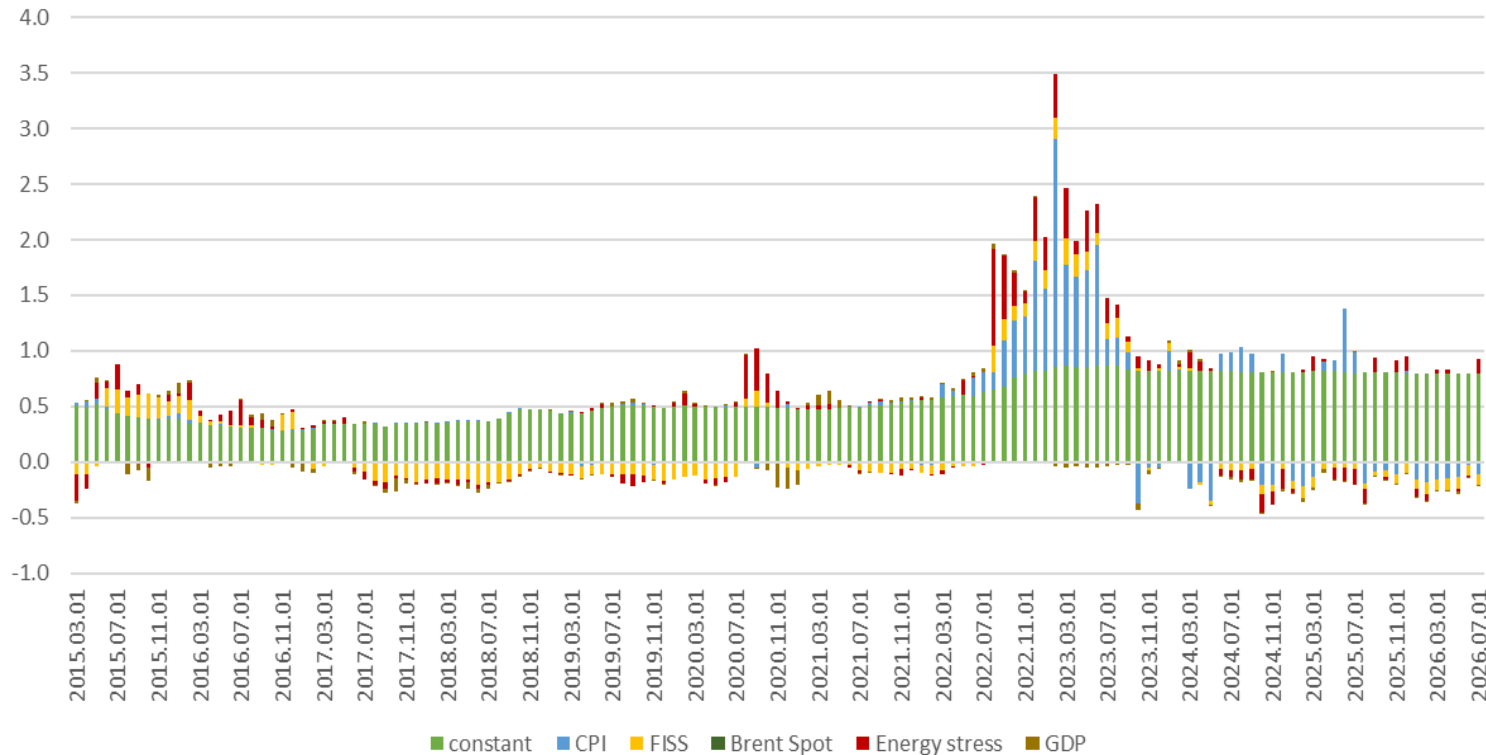
## INFLATION-AT-RISK FORECAST CONTRIBUTIONS

- Energy price impact on inflation risk (0.9 quantile of CPI inflation distribution) is more prominent in the short run (1-3 months).
- Energy risk impact is significant for all horizons (1-6 months).
- This effect is positive and highly significant during and after crisis events.
- Recently inflation risk has emerged mostly due to risks stemming from energy.
- GDP is playing an important role during and post pandemic.

# INFLATION-AT-RISK RESULTS



Forecast contribution, H=6 months, Q=0.9



- In the longer run energy price impact is fading.
- Energy risk impact is still significant but financial stress is becoming more prominent.
- At longer horizons one possible explanation of decreasing explanatory power of energy risk and at the same time increasing significance of financial stress could be the existing spillovers.
- During COVID times GDP still remains important.

## INFLATION-AT-RISK FORECAST CONTRIBUTIONS

- Increasing energy risk as well as increasing energy prices put a double toll on the macro-financial system.
- Energy risk has major impact on inflation- and GDP vulnerability especially during crises events.
- In „at-Risk” models for GDP (and inflation) the lower (and upper) tail portrays emerging vulnerabilities.
- The positive neutral stance together with increasing capital buffers of the banks may support increasing resilience in the financial system.



# APPENDIX

# VARIABLES AND NON-STATIONARITY



Table 1: Variables for the Factor model and the P-values for the ADF test

| Market   | Variable                                                                                                   | ADF test | Market 2 | Variable 2                                                                                      | ADF test 2 |
|----------|------------------------------------------------------------------------------------------------------------|----------|----------|-------------------------------------------------------------------------------------------------|------------|
| Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Crude Oil Spot, EWMA volatility, w=20               | 0.057    | Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Crude Oil Spot, CMAX, w=20               | 0.001      |
| Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Heating Oil Spot, EWMA volatility, w=20             | 0.012    | Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Heating Oil Spot, CMAX, w=20             | 0.001      |
| Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Gas Oil Spot, EWMA volatility, w=20                 | 0.008    | Oil spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Gas Oil Spot, CMAX, w=20                 | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) - Gas Oil Spot Index, EWMA volatility, w=20                           | 0.034    | Oil spot | Merrill Lynch Commodity Index (MLCX) - Gas Oil Spot Index, CMAX, w=20                           | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) Heating Oil Spot Index, EWMA volatility, w=20                         | 0.051    | Oil spot | Merrill Lynch Commodity Index (MLCX) Heating Oil Spot Index, CMAX, w=20                         | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) Unseasonal Heating Oil Spot, EWMA volatility, w=20                    | 0.003    | Oil spot | Merrill Lynch Commodity Index (MLCX) Unseasonal Heating Oil Spot, CMAX, w=20                    | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) ME Heat Oil Spot Index, EWMA volatility, w=20                         | 0.012    | Oil spot | Merrill Lynch Commodity Index (MLCX) ME Heat Oil Spot Index, CMAX, w=20                         | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) XCL Crude Oil Spot Index, EWMA volatility, w=20                       | 0.004    | Oil spot | Merrill Lynch Commodity Index (MLCX) XCL Crude Oil Spot Index, CMAX, w=20                       | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) Crude Oil (West Texas Intermediate) Spot Index, EWMA volatility, w=20 | 0.045    | Oil spot | Merrill Lynch Commodity Index (MLCX) Crude Oil (West Texas Intermediate) Spot Index, CMAX, w=20 | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) Semiannual Roll Heating Oil Spot, EWMA volatility, w=20               | 0.007    | Oil spot | Merrill Lynch Commodity Index (MLCX) Semiannual Roll Heating Oil Spot, CMAX, w=20               | 0.001      |
| Oil spot | Merrill Lynch Commodity Index (MLCX) Armored Wolf Heating Oil Spot Index, EWMA volatility, w=20            | 0.051    | Oil spot | Merrill Lynch Commodity Index (MLCX) Armored Wolf Heating Oil Spot Index, CMAX, w=20            | 0.001      |
| Oil spot | Europe Brent Spot Price Free on Board (Dollars Per Barrel) Daily, EWMA volatility, w=20                    | 0.023    | Oil spot | Europe Brent Spot Price Free on Board (Dollars Per Barrel) Daily, CMAX, w=20                    | 0.001      |
| Gas spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Natural Gas Spot, EWMA volatility, w=20             | 0.052    | Gas spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Natural Gas Spot, CMAX, w=20             | 0.001      |
| Gas spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Gas Oil Spot, EWMA volatility, w=20                 | 0.002    | Gas spot | Standard and Poors Goldman Sachs Commodity Index(GSCI) Gas Oil Spot, CMAX, w=20                 | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) - Gas Oil Spot Index, EWMA volatility, w=20                           | 0.031    | Gas spot | Merrill Lynch Commodity Index (MLCX) - Gas Oil Spot Index, CMAX, w=20                           | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) Natural Gas Spot Index, EWMA volatility, w=20                         | 0.031    | Gas spot | Merrill Lynch Commodity Index (MLCX) Natural Gas Spot Index, CMAX, w=20                         | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) Unseasonal Natural Gas Spot Index, EWMA volatility, w=20              | 0.041    | Gas spot | Merrill Lynch Commodity Index (MLCX) Unseasonal Natural Gas Spot Index, CMAX, w=20              | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) ME NAT Gas Spot Index, EWMA volatility, w=20                          | 0.003    | Gas spot | Merrill Lynch Commodity Index (MLCX) ME NAT Gas Spot Index, CMAX, w=20                          | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) XNG Natural Gas Spot Index, EWMA volatility, w=20                     | 0.002    | Gas spot | Merrill Lynch Commodity Index (MLCX) XNG Natural Gas Spot Index, CMAX, w=20                     | 0.001      |
| Gas spot | Merrill Lynch Commodity Index (MLCX) LD - Natural Gas Spot Index, EWMA volatility, w=20                    | 0.054    | Gas spot | Merrill Lynch Commodity Index (MLCX) LD - Natural Gas Spot Index, CMAX, w=20                    | 0.001      |

Table 2: Factor number test: Notice similarity to cointegration test of Johansen!

| $r$ | Crit. Values |            | $S_{m-r}$ test given $k$ |          |          |
|-----|--------------|------------|--------------------------|----------|----------|
|     | $q_{0.05}$   | $q_{0.95}$ | $k = 1$                  | $k = 2$  | $k = 3$  |
| 0   | 61.261       | 103.010    | 345.182*                 | 324.672* | 306.423* |
| 1   | 46.595       | 83.675     | 278.449*                 | 259.980* | 243.718* |
| 2   | 33.930       | 66.339     | 213.897*                 | 198.607* | 185.526* |
| 3   | 23.269       | 50.998     | 149.414*                 | 137.643* | 128.074* |
| 4   | 14.611       | 37.652     | 86.546*                  | 79.304*  | 73.986*  |
| 5   | 7.962        | 26.296     | 24.593                   | 22.257   | 21.464   |
| 6   | 3.325        | 16.919     | 2.983                    | 2.971    | 2.964    |
| 7   | 0.711        | 9.488      | 1.985                    | 1.975    | 1.971    |
| 8   | 0.004        | 3.841      | 0.988                    | 0.981    | 0.979    |

- The factor equations describes a general dynamic factor model.
- Just like with PCA, most common advice is to make data stationary before proceeding
- **Differencing variables changes information content**
  - For example: Term spread is often non-stationary
  - Common measure of financial stress pertaining to govt. bond market
  - What does it's (time) difference capture?
- Financial risks are described as elevated levels of variables, **NOT** elevated differences of variables
- Differencing variables makes it difficult to capture gradual build-up of financial stress

- A key step to make the factor equation apply to non-stationary data is to generalise the estimation of the covariance matrix.
- Follow [Peña and Poncela, 2006], and take the generalized covariance matrix of  $X$  (integrated of order  $d$ ):

$$C_X(k) = \frac{1}{T^{2d+D}} \sum_{t=k+1}^T (X_{t-k} - \bar{X})(X_t - \bar{X})'$$

- $\bar{X}$  is the sample average and  $D = \{0,1\}$  depending on the existence of a drift in  $X_t$ , and  $k$  is the lag order.
- Just like the empirical covariance matrix is important for stationary data, this matrix will play a key role in non-stationary factor analysis.

## 1. Identify the number of factors

- Calculate the canonical correlations for  $X_t$  and  $X_{t-k}$
- Apply  $\chi^2$  test to determine number of factors

## 2. Calculate Generalised covariance matrix $C_X(k)$

- Estimate eigenvectors and eigenvalues
- The initial estimate of factor loadings is the first  $r$  eigenvectors, see [Varga, K., & Szendrei, T. (2025). Non-stationary financial risk factors and macroeconomic vulnerability for the UK. International Review of Financial Analysis, 97, 103866.]

## 3. Analyse the univariate time series properties of the initial factors to determine order of integration

## 4. Write the model in state-space form and estimate using maximum likelihood

- We use a Bayesian state space model for estimation.
- See [Koop et al., 2010] for more details

- GaR is conceptually simple, but:
- How do we estimate the  $\beta(\tau)$ ?

## Quantile Regressions "Pinball" Loss Function

Quantile regression aims to fit the following model:  $y_t = x_t' \beta(\tau) + \varepsilon_t$

Here  $\tau \in (0,1)$  is the quantile of interest.

[Koenker and Bassett, 1978] show that one can obtain estimates of  $\beta(\tau)$  by optimising the following function:

$$\hat{\beta}(\tau) = \underset{\beta(\tau)}{\operatorname{argmax}} \sum_{t=1}^{T-h} [I(y_{t+h} \geq x_t' \beta(\tau)) |y_{t+h} - x_t' \beta(\tau)| \tau + I(y_{t+h} < x_t' \beta(\tau)) |y_{t+h} - x_t' \beta(\tau)| (1 - \tau)]$$

The Lasso minimization, (see: Szendrei, Varga, 2023):

$$\hat{\beta}(\tau) = \underset{\beta, \alpha}{\operatorname{argmin}} \sum_{q=1}^Q \sum_{i=1}^n \rho_{\tau_q} (y_i - \alpha_{\tau_q} - x_i^T \beta_{\tau_q})$$

Subject to  $\alpha_{\tau_q} + x^T \beta_{\tau_q} \geq \alpha_{\tau_{q-1}} + x^T \beta_{\tau_{q-1}}, x \in D, D \subset R^p, j = 2, \dots q.$

$$\sum_{q=1}^Q \sum_{k=1}^K w_{k,\tau_q} |\beta_{k,\tau_q}| \leq t^*$$

Where  $w_{k,\tau_q} = |\theta_{k,\tau_q}|^{-1}$  are the estimated coefficients of a regular QR with full design matrix.

$t^*$  is a global variation parameter, which non quantile specific.

To choose the optimal  $t^*$  a grid search is employed. The model with the lowest AIC and BIC will be chosen as optimal model.

- Start from quarterly GDP values based on expenditure and production approach
  - Consider these as noisy measures of true GDP

$$\begin{bmatrix} GDP_{P,t} \\ GDP_{E,t} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} GDP_t + \begin{bmatrix} \varepsilon_{P,t} \\ \varepsilon_{E,t} \end{bmatrix}$$

$$GDP_t = \rho GDP_{t-1} + \varepsilon_{G,t}$$

- [Koop et al., 2023] use noise restriction: assumption that the variance of true GDP is less than the variance some of its noisy observation

$$\xi_i = \frac{\text{var}(GDP)}{\text{var}(GDP_i)}$$

- We assume that  $0.35 < \xi_P, \xi_E < 1.15$  based on the empirical variance of production- and expenditure-based GDP

- The mixed frequency model can be summarised as:

$$y_t = (X'_t, U_t, GDP_t, GDP_{P,t}, GDP_{E,t})$$

$$y_t^Q = \Delta_3 \ln(Y_t)$$

- $Y_t^Q$  is the quarterly variable observed every third month
- $U_t$  is the unemployment rate
  - depends on  $GDP_t$  but not on  $GDP_{P,t}$  or  $GDP_{E,t}$
- $X'_t$  is a set of monthly explanatory variables
  - variables of [Schorfheide and Song, 2015] and [Koop et al., 2023]
  - retail sales, inflation, industrial production, base rate, short-term interest rates, long-term interest rates, and stock prices
- We use  $GDP_P$ , since it does not contain taxes.

- We fit densities for different forecast horizons
- We can use density evaluation metrics commonly used in the forecasting literature
  - [Gneiting and Ranjan, 2011] a good choice as it outlines how to utilise weighted combination of quantiles to evaluate fits of the density:

$$qwCRPS_{(t+h)} = \int_0^1 w_i QS_{(t+h,\tau)} d\tau$$

- We are interested in the out-of-sample performance of fitting the left tail: place more weight on lower quantiles' forecast performance
- Since FSI's are fast moving, we construct monthly GDP estimates for the UK using the method of [Koop et al., 2023], [Varga, K., & Szendrei, T. (2025). Non-stationary financial risk factors and macroeconomic vulnerability for the UK. International Review of Financial Analysis, 97, 103866.]