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Introduction

Over the past four years, the global economy has been hit by a series of exceptionally destabilising shocks. Uncertainty has surged and economic forecasting has become extremely challenging. In June 2020, Christine Lagarde, President of the European Central Bank (ECB), described the economic situation as one "characterised by profound uncertainty" and stated that "looking into the future has rarely been harder." [1] Uncertainty continues to affect policymaking, as central banks contend with inflation persisting above target. [2]

In this article, we exploit academic advances that quantify uncertainty and apply these methods to develop a measure of euro area (EA) macroeconomic uncertainty. Our measure allows us to trace past episodes of uncertainty and make sense of the exceptional challenges that have been faced by forecasters during recent periods of crisis. Furthermore, a comprehensive decomposition of our measure enables us to delineate the various components of uncertainty linked to commodity prices, interest rates and spreads, economic activity, and consumer and producer prices.

Our study applies a methodology proposed by Jurado, Ludvigson, and Ng (2015), (henceforth "JLN"), to a large dataset of 159 economic indicators. To capture EA uncertainty, our data rely heavily on EA economies, but also contain variables that are important for the global economy, such as commodity prices. In a nutshell, the JLN methodology posits that uncertainty is inversely related to the degree to which something can be forecast with accuracy. Thus, according to their framework, the more difficult it is to forecast economic indicators, the greater the uncertainty.

Figure 1 previews our EA macroeconomic uncertainty measure and compares it with the updated measure by JLN, which tracks macroeconomic uncertainty for the US up to the end of 2023. As is the case for the original JLN measure, our EA measure peaks during the global financial crisis (GFC) of 2007-2008. Unlike US uncertainty, which drops gradually following the GFC, EA uncertainty remains high in the post-crisis years, peaking in 2011 in the midst of the European sovereign debt crisis. EA and US uncertainty then spike again during the COVID-19 pandemic. In the wake of Russia's invasion of Ukraine, the two measures diverge, with the EA

1 Remarks by Christine Lagarde, President of the ECB, at the inaugural session of the Italian National Consultation, 13 June 2020.
2 See speech by Christine Lagarde, President of the ECB, at the "ECB and its Watchers" XXIV Conference, 20 March 2024.

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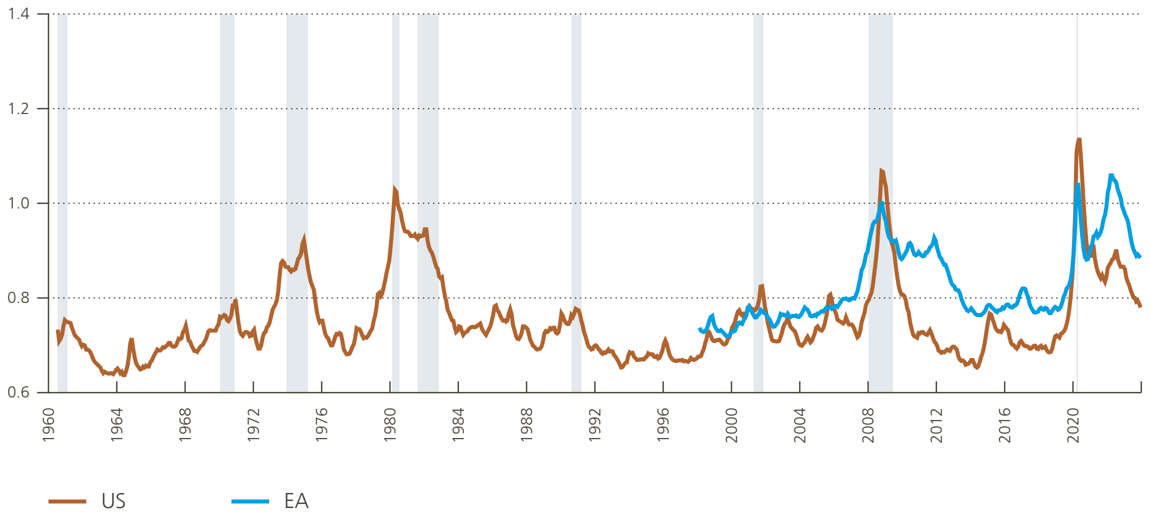
Figure 1

Macroeconomic uncertainty in the US and EA



Source: updated JLN results for the US and authors' own computations for the EA.
Note: Figure 1 shows EA and US macroeconomic uncertainty averaged across forecast horizons. The US macroeconomic uncertainty measure is an update of the original uncertainty measure by JLN, made available on the personal webpage of one of the co-authors, Sydney Ludvigson. We compute the EA uncertainty measure following the JLN methodology, as described in Section 2. Shaded areas represent NBER US recession dates.

measure of uncertainty reaching all-time highs. This is in line with how the energy crisis played out, which had a greater impact on Europe than on the US.

We can summarise the main findings of this article as follows. Firstly, as mentioned above, EA macroeconomic uncertainty increased substantially following the COVID-19 pandemic, Russia's invasion of Ukraine, and the ensuing energy crisis. Uncertainty has since retreated but still remains well-above its historical average, serving as evidence of the difficulty in making confident forecasts about economic variables.

Secondly, the decomposition of our uncertainty measure allows us to pinpoint some of the elements behind the current high levels of uncertainty. We find that the latest increase in EA macroeconomic uncertainty is associated with higher levels of commodity price uncertainty, as well as higher levels of uncertainty over consumer and producer prices. This is related to the findings of Chahad et al. (2024), who associate recent inflation forecasting errors in Eurosystem/ECB staff projections to the rise in unpredictability over commodity prices. Furthermore, we confirm the results of Comunale et al. (2023), who also find a large recent increase in consumer and producer price uncertainty. However, in contrast to Comunale et al. (2023), we explicitly account for commodity prices in our measure of EA macroeconomic uncertainty, allowing us to uncover an important relationship between the uncertainty of commodity prices and that of producer and consumer prices.

Thirdly, an in-depth analysis of the uncertainty of individual economic series reveals that, in most cases, our EA macroeconomic uncertainty measure can explain most of the variation in the uncertainty of individual economic variables. That is, the uncertainty of some variables, such as those associated with economic activity or consumer prices, is largely explained by a single factor, linked to EA macroeconomic uncertainty. However, the uncertainty of other variables, particularly interest rates and spreads and some commodity prices, cannot be explained by our EA macroeconomic uncertainty measure. We posit that uncertainty in these variables might either have a large idiosyncratic component or have a common factor only weakly linked to our EA macroeconomic uncertainty measure. For example, in the case of commodity price uncertainty, the idiosyncratic component might be a market-specific shock, such as a weather event impacting food markets. Meanwhile, the common component could be thought of as some other disruption which results in uncertainty across several commodities, without spreading to EA-wide macroeconomic uncertainty.

Fourthly, we develop a price uncertainty index for Belgium to track the unpredictability of Belgian consumer and producer prices. We find that Belgian price uncertainty is closely related to EA price uncertainty. Further, the tendency for Belgian and EA price uncertainty to move in a correlated manner has increased over the recent crisis-filled years. As of December 2023, price uncertainty in Belgium and in the EA continues to remain high, underscoring the current challenge of predicting inflation dynamics.

The article is structured as follows. Section 1 provides a brief literature review tracing the academic developments surrounding uncertainty and measures of uncertainty. Section 2 and 3 present our methodology and data, respectively. Section 4 analyses our EA macroeconomic uncertainty measure, while Section 5 looks at its decomposition by variable groupings. Section 6 presents our conclusions.

1. Measures of uncertainty: a state of play

Uncertainty has been a central theme in economics at least since the work of Knight (1921), in which he defines the concept and distinguishes it from the notion of risk. According to Knight, uncertainty is characterised by alternative outcomes whose probabilities are unmeasurable, whereas risk has known outcomes with measurable probabilities. For example, by this definition, a die with six sides represents risk, whereas launching a new business is associated with uncertainty, because this endeavour may have many outcomes with unknown probabilities. Uncertainty is also a central theme of "The General Theory of Employment, Interest and Money" by Keynes (1936).[3] Although Keynes did not develop an explicit theory of uncertainty, he recognised the importance of expectations and uncertainty in shaping investment decisions and economic outcomes. For instance, uncertainty is central to the Keynesian concept of "liquidity preference" — the idea that economic agents prefer to hold wealth in liquid forms.

While the recognition of the importance of uncertainty to economic activity dates back at least a century, it is only in recent decades that economists have begun to develop empirical methods to measure and understand its impact. In particular, Nicholas Bloom provided key contributions to quantify the impact of uncertainty shocks on macroeconomic variables, such as output, employment, investment, and consumption. Bloom (2009) found that, following a rise in uncertainty, economic activity first dampens significantly and, successively, recovers and overshoots. This overshooting has been the subject of several studies and debates among economists.

Over the past two decades, several alternative measures of economic uncertainty have been proposed. These can be categorised into five main groups. First, with the advent of large panel datasets, researchers have developed micro-based indicators using the dispersion of industry, firm, or plant data. For example, Bloom et al. (2018) measure the dispersion of earnings and total factor productivity at the establishment-level. They conclude that, similarly to macro-based measures of uncertainty, these micro-based indicators are highly countercyclical i.e. they increase during recessions and fall during expansions.

Secondly, studies have relied on financial market data, such as the volatility of stock returns, bond yields, or exchange rates, to serve as a proxy for economic uncertainty (e.g. Bloom, 2009). This is convenient because measures of market volatility are, frequently, readily available from financial data providers and generally do not require sophisticated computations. Moreover, indices based on implied volatility measures, such as the VIX or

3 For an extensive discussion of the treatises of Knight and Keynes on uncertainty, see Packard et al. (2021).

VXO indices, offer the advantages of being forward-looking, in the sense that they capture market expectations of near-term volatility.[4] Generally, these indices peak during episodes of market turbulence, such as the GFC of 2007-2008.[5]

A third strand of the literature has developed text-based uncertainty measures using newspaper articles and material from other media channels. In their paper, Baker et al. (2016) introduce the Economic Policy Uncertainty Index (EPU), which tracks the number of newspaper articles mentioning certain key words. The authors find that the EPU peaks during crucial events (e.g. the 9/11 attacks) and that it is associated with reductions in investment, output, and employment.

Fourthly, several measures of uncertainty have been constructed from surveys of professional forecasters, which can be used in different ways. For instance, uncertainty can be measured by forecast disagreement i.e. the dispersion of survey forecasts around the mean forecast. It is important to note that forecast disagreement may also capture divergences of opinion among forecasters and is thus considered an imperfect measure of uncertainty (Istrefi and Mouabbi, 2018). Alternatively, forecasters can sometimes attach subjective probabilities to indicate how certain they are about their forecasts. Uncertainty measured in this way is sometimes termed subjective uncertainty (Bloom, 2014).

Lastly, measures of uncertainty can be built using forecast errors — the difference between expectations and the realisation of certain variables. For example, Bachmann et al. (2013) use business survey data, which capture the outlook of firm managers, to construct a measure of uncertainty based on the difference between expected and realised firm production growth. Scotti (2016) compares pre-release estimates of economic aggregates, such as of the quarterly GDP, with actual releases. The author uses a weighted average of the square of the deviation between the estimates and actual figures to build an uncertainty index. Unlike financial-based indicators, Scotti's index is entirely tied to real economic activity, and is therefore not influenced by noise from the financial markets.

The uncertainty measure developed by JLN falls within this last category of measures which are based on forecast errors. A novelty of the JLN approach is the formalisation of the idea that macroeconomic uncertainty is closely related to the (un)predictability of macroeconomic indicators. Instead of using forecasts from professionals or pre-release estimates of economic aggregates, JLN build their own forecasts based on a high-performance econometric model (more details are provided in the next section).

Since the publication of their paper, JLN have made frequent updates to their uncertainty measure.[6] Whereas most of the studies discussed above identify many episodes of high uncertainty, according to the JLN measure, after 1960, peaks in uncertainty only coincide with five key events: the OPEC I crisis (1973-1974), the US recessions of the early 1980s, the GFC (2007-2008), the COVID-19 pandemic, and the outbreak of the war in Ukraine (see Figure 1). In an analysis of the impact of uncertainty, JLN show that their measure does not produce the activity overshoot featured in other papers.

Most of the literature on uncertainty measures has not dedicated much attention to the role of commodity prices. However, commodity prices are particularly relevant when studying the uncertainty surrounding the European economy, which recently experienced an unforeseen rise in consumer and producer prices amidst an energy (and food) price crisis. Commodity prices tend to be driven by a combination of global demand, supply, and financial factors and have important repercussions on economic activity and households around the world.[7]

4 The VIX and VXO indices are compiled by the Chicago Board Options Exchange (CBOE) and are based on options on the S&P 500 and S&P 100, respectively.

5 For an index tracking uncertainty in fixed-income markets, see the Merrill Lynch Option Volatility Estimate (known as the "MOVE") index, which is linked to the volatility of US Treasury bills.

6 Available from https://www.sydneyludvigson.com.

7 For factors driving commodity prices, see Kilian (2009); Buyuksahin and Robe (2014); Kilian and Murphy (2014); Singleton (2014); Alquist et al. (2019); Baumeister and Hamilton (2019); Caldara et al. (2019). For studies on the impact of commodity prices on economic activity and households, see Peersman and Van Robays (2012); Herrera and Rangaraju (2020); De Winne and Peersman (2021); Mohimont (2022); Houssa et al. (2023).

Although the literature on the sources and consequences of commodity price fluctuations is extremely rich, only a limited number of studies has dealt with commodity price uncertainty, focusing primarily on oil price uncertainty. Uncertainty about future scarcity of oil can affect its price (Alquist and Kilian, 2010), and uncertainty surrounding the price itself can have important repercussions on firms investment decisions (Bernanke, 1983).

Studies have analysed the relationship between economic uncertainty and the price of selected commodities. For example, Van Robays (2016) finds that economic uncertainty, measured by the volatility of global industrial production, increases the sensitivity of the price of oil to demand and supply shocks. Joëts et al. (2017) study the impact of the JLN economic uncertainty index on seventeen commodities. They find that agricultural and energy commodity prices are more sensitive to economic uncertainty than precious metals, due to the safe-haven properties of the latter. Bakas and Triantafyllou (2018) focus on the relationship between measures of economic uncertainty and commodity price volatility, uncovering a stronger positive relation for so-called "latent" measures *à la* JLN than observable measures of economic uncertainty, such as the VXO or EPU indices. [8]

2. Methodology

To measure EA macroeconomic uncertainty, we adopt the econometric framework developed by JLN. [9] The central idea behind their framework is that a good macroeconomic uncertainty measure should help us understand whether the economy is becoming more or less predictable. In this sense, JLN measure macroeconomic uncertainty according to our ability — or inability — to produce accurate forecasts for a large set of macroeconomic variables. JLN also insist on two aspects. Firstly, they emphasise the fact that uncertainty and volatility are two distinct concepts. For example, a large but anticipated rise in a variable contributes to increasing volatility, but it should not influence the level of uncertainty. Thus, we should distinguish between the predictable and unpredictable components of the fluctuations of a variable to correctly measure its level of uncertainty. Secondly, macroeconomic uncertainty is computed based on a broad dataset to capture the common variations in uncertainty across many series. The JLN macroeconomic uncertainty measure is thus an aggregation over the uncertainty of many variables.

JLN start by formalising the notion of uncertainty in a particular variable y (e.g. the consumer price index, henceforth CPI). Uncertainty is measured at a given date t and concerns a forecast horizon h : for example, today we are forecasting the future evolution of the CPI over the next 12 months, and we would like to know how much uncertainty there is around this forecast. More formally, the uncertainty associated with forecasting variable y over the h-month period ahead is given by:

$$\mathcal{U}_t^y(h) = \sqrt{\mathbb{E}[(y_{t+h} - \mathbb{E}[y_{t+h} \mid I_t])^2 \mid I_t]}. \quad (1)$$

The term $\mathbb{E}[y_{t+h} \mid I_t]$ represents a forecast: it is the most likely value that the variable y may take h periods ahead (at time $t+h$), given the information I_t available at time t. It follows that the element under the square root in Equation 1, $\mathbb{E}[(y_{t+h} - \mathbb{E}[y_{t+h} \mid I_t])^2 \mid I_t]$, is the expected squared error made when attempting to forecast y at future horizon h. [10] Intuitively, if the precision of a forecast is expected to decrease, one can expect to make potentially larger prediction errors that may take positive or negative values. The expected squared error thus provides a measure of the expected imprecision in the forecast. Thus, this measure of uncertainty $\mathcal{U}_t^y(h)$ rises when the precision of a forecast is expected to decline.

8 It is important to stress here the difference between commodity price volatility and uncertainty. Unlike uncertainty, volatility may be attributable to predictable price fluctuations. This distinction is made clear in Joëts et al. (2017).

9 This framework has become a workhorse model among economists for measuring economic uncertainty, see Bloom (2014), Joëts et al. (2017), and other references mentioned in Section 1 of this article.

10 By construction, the expectation of the forecast error is zero, reflecting that the forecasting model will be right on average.

The framework of JLN can be implemented in three steps. Firstly, we build a forecast model to distinguish the predictable component of y from the unpredictable forecast error. Ideally, this model should combine all relevant information available today to produce an optimal forecast. However, it should be noted that, in their study, JLN estimate their model on the full sample of data. Similarly to JLN, we use final, revised data to estimate the forecast model. This means that forecasts are not made in "real-time". According to JLN, restricting information to real-time data would be impractical and would likely underestimate the amount of information agents have when making their forecast. We follow JLN and use a factor model, which has the compelling property of summarising large amounts of data into a compact and tractable framework. Our factor model summarises the information contained in 159 macroeconomic time series into 14 factors that, together, explain half of the variance contained in the original time series.

Second, once the factor model has been fine-tuned to the dataset, we produce forecasts for our variables of interest (one at a time). JLN focus on a series of macroeconomic variables that capture the US economy (industrial production, nonfarm payrolls, average hours worked, etc.). In our case, we exploit 159 macroeconomic time series that largely represent the EA economy, its main trade partners, and commodity markets. [11] Each of our time series are forecasted with a regression model that includes 12 lags of the dependent variable and one lag of the 14 factors identified in the previous step. [12]

In the third step, we compute the time-varying volatility of the forecast errors, which we recover from the differences between the forecast and realised values. [13] In this way, we obtain a time-varying uncertainty measure for each individual variable of interest. We then compute different aggregate measures of uncertainty based on these individual series. Firstly, we compute four group-specific measures capturing the uncertainty in (1) commodity prices, (2) interest rates and spreads, (3) real economic activity, and (4) consumer and producer prices. Uncertainty for variable group g, at horizon h, is given by

$$\mathcal{U}_t^g(h) = \sum_{j=1}^{N_g} \frac{1}{N_g} \mathcal{U}_t^j(h),$$

where N_g is the number of variables of interest belonging to group g. Secondly, we define the overall macroeconomic uncertainty indicator as the weighted average of the group-specific uncertainty measures:

$$\mathcal{U}_t(h) = \sum_{g=1}^{4} w_g \, \mathcal{U}_t^g(h),$$

where w_g represents the weight assigned to the uncertainty of variable group g. We assume that the real economic activity and the consumer and producer price groups each receive a weight of 1/3, while the two remaining variable groups each receive a weight of 1/6. We put lower weights on the commodity price and interest rate and spread groups because they contain more foreign information than EA information. [14]

11 See Section 3 for a detailed description of the data.

12 We also follow JLN by adding one lag of the first two factors of the squared data to capture potential non-linearities.

13 JLN assume that variables and factors have so-called stochastic volatility, which is a flexible model to capture time-varying volatility. It follows that the conditional volatility of forecast errors (the JLN measure of uncertainty) will vary over time and over the forecast horizon. The interested reader should refer to their paper.

14 In JLN, all individual variables have the same weight (1/N). So, groups with more variables have a larger weight. In our study, the "real economic activity" and "consumer and producer price" groups have more variables, so following the strategy of JLN would bring similar results.

3. Data

We compile a large dataset of 159 macroeconomic time series that are relevant to the EA. The data rely heavily on EA economies (focusing on Germany, France, Italy, Spain, as well as Belgium, which allows us to develop a Belgian price uncertainty index, discussed in Box 2). However, considering that the EA is an open economy, it is important to include international macroeconomic variables in our analysis. Thus, we include variables from key partners (the US and the UK) as well as measures of global economic activity (e.g. a world industrial production index) and commodity prices on international financial markets. The data represent the four aforementioned groups of macroeconomic indicators: (1) commodity prices, (2) interest rates and spreads, (3) measures of real economic activity, and (4) consumer and producer prices. The period we study ranges from January 1997 (when data on consumer prices became available) to December 2023 (the most recent data available at the time of our analysis).

The first group of indicators comprises 28 commodity prices, including for agricultural raw materials, energy, fertilisers, food and beverages, and industrial metals. We selected commodities based on their importance to international trade and on data availability. We use real commodity prices, by deflating nominal prices (in USD) by the US CPI.

The second group — the interest rate and spreads category — comprises the Federal Funds Rate (FFR), the yields on US government bonds (with maturities ranging from three months to ten years), the ten-year German bund yield, ten-year sovereign spreads in the EA, and average corporate spreads. [15]

The third group collects measures of real economic activity — in EA economies, the US, and the UK — such as industrial production, retail sales, the unemployment rate, hours worked, and wages. We take the year-on-year growth rate of these variables, except for unemployment rates. We complement these measures with a few indicators of global economic activity (i.e. the Baltic Dry Index, the Index of Global Real Economic Activity (IGREA) by Kilian (2009), the Global Economic Conditions Indicator (GECI) by Baumeister et al. (2022), and a measure of industrial production at the world level). We also include consumer, construction sector, and manufacturing sector confidence indicators in this group of variables.

The fourth group includes the year-on-year growth rates of consumer and producer prices. For the five aforementioned EA economies, we use the headline CPI and the decomposition of their respective harmonised index of consumer prices (HICP) into six consumption expenditure categories (food; housing and energy; furniture; transport; recreation; and restaurants and hotels). [16] For the US and the UK, we use the decomposition of the headline CPI into its five components (core; energy; food; services; and housing). Lastly, for each of these economies (where available), we use the producer price index (PPI) decomposed by product category: intermediate goods; capital goods; consumer durables and non-durables; energy products; and manufactured products.

Although some of these time series are, in theory, stationary, they often display a strong degree of persistence. We follow JLN and apply the methodology described in Section 2 to the first difference of the data.

15 Sovereign spreads of EA countries are with respect to the German bund, whereas corporate spreads are with respect to the corresponding sovereign yield. See appendix for further details.

16 We exclude some categories such as health, education, and communication, such that the overall CPI brings extra information not included in the HICP sub-indices.

4. EA macroeconomic uncertainty

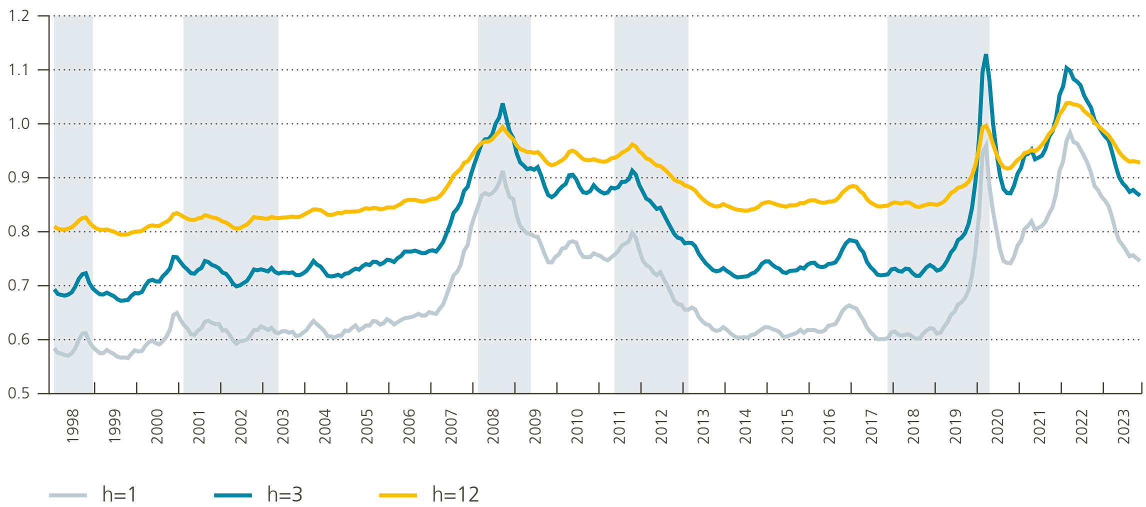
Figure 2 presents our EA macroeconomic uncertainty measure, computed for three different forecast horizons: one month ahead (h=1), three months ahead (h=3), and one year ahead (h=12). It shows that EA macroeconomic uncertainty peaks during four crucial events: the GFC, the European debt crisis, the COVID-19 pandemic, and Russia's invasion of Ukraine. It is well known that macroeconomic uncertainty rises during recessions (e.g. Bloom, 2014), and our measure also captures this pattern. Indeed, the EA fell into recession during the GFC, the European debt crisis, and the COVID-19 pandemic, according to the Euro Area Business Cycle Network. While the energy crisis caused by Russia's invasion of Ukraine did not push the EA economy into recession, the shock significantly contributed to two successive quarters of negative growth in the EA.

The four events identified are characterised as periods of high global uncertainty. The GFC of 2007-2008 sent shockwaves through interconnected financial institutions, triggering a credit crunch, and threatening the stability of economies worldwide. Uncertainty loomed over the depth of the subprime crisis and the extent of its spillover effects on the real economy. Similarly, the EA debt crisis cast a shadow of uncertainty over the future of the euro currency and the risk of sovereign defaults, posing significant challenges to the stability of the European Union. The COVID-19 outbreak unleashed a wave of uncertainty regarding the severity and spread of the virus, the race to develop vaccines and treatments, and the efficacy of containment measures, profoundly impacting global health and economies. More recently, the war in Ukraine has fueled concerns about the rationing of gas, threats to global food security, and the ominous spectre of an escalation into a broader conflict, heightening uncertainty and geopolitical tensions on a global scale.

Figure 2 also highlights how uncertainty can increase rapidly and, at times, linger at an elevated level. Note, for example, how uncertainty did not return to pre-2007 levels after the GFC. Rather, it continued to remain high and then spiked again during the European sovereign debt crisis. Thanks to the flexible specification of the JLN model, our EA macroeconomic uncertainty measure can increase rapidly, as was the case during

Figure 2

EA macroeconomic uncertainty by forecast horizon



Source: Authors' own calculations.

Note: Figure 2 shows the EA macroeconomic uncertainty measure computed for three different forecast horizons: one month ahead (h=1), three months ahead (h=3), and one year ahead (h=12). The shaded areas represent the OECD Recession Indicator for the EA (from the period following the peak through the trough).

the COVID-19 crisis, when uncertainty surged. During the post-pandemic recovery, uncertainty only partially declined, as successive infection waves rendered the economic outlook highly unpredictable. At the time, economists were unsure about the shape of the recovery — primarily whether it would be V-shaped or U-shaped (e.g. see IMF, 2021). Uncertainty spiked again following Russia's invasion of Ukraine in February 2022, which led to an energy crisis in Europe.

The high levels of uncertainty observed during the COVID-19 and energy crises provide an explanation for the underperformance of econometric and model-based forecasting tools over the past three years. In fact, during this period, economic predictions diverged significantly from realised values, particularly for inflation. The most recent observation (December 2023) shows that uncertainty has receded from its previous highs. However, the measure remains above its historical average, at levels comparable to those reached during crucial past events, such as the European sovereign debt crisis. This underlines the continuous challenge of producing forecasts in the current environment.

A pattern observed in Figure 2 is that, generally, uncertainty tends to increase with longer forecast horizons. This is consistent with the idea that making predictions far away in the future is, in most cases, more difficult than predicting the near-term. However, it is noteworthy that during some specific events, such as the GFC, the COVID-19 pandemic, or the energy crisis, mid-term (h=3) uncertainty may actually be higher than long-term (h=12) uncertainty. Although these events triggered periods of heightened uncertainty, in the long run, some return to normality was foreseeable. This made long-run predictions relatively more precise than medium-term predictions, although forecasts deteriorated across all horizons.

The JLN methodology not only allows us to recover an economy-wide measure of uncertainty, but it also allows us to analyse the uncertainty of individual variables or even groups of variables. In Section 5, we exploit this feature and trace uncertainty in four variable groups: commodity prices, interest rates and spreads, measures of economic activity, and consumer and producer prices. In Box 1, below, we link the uncertainty of individual variables with EA macroeconomic uncertainty.

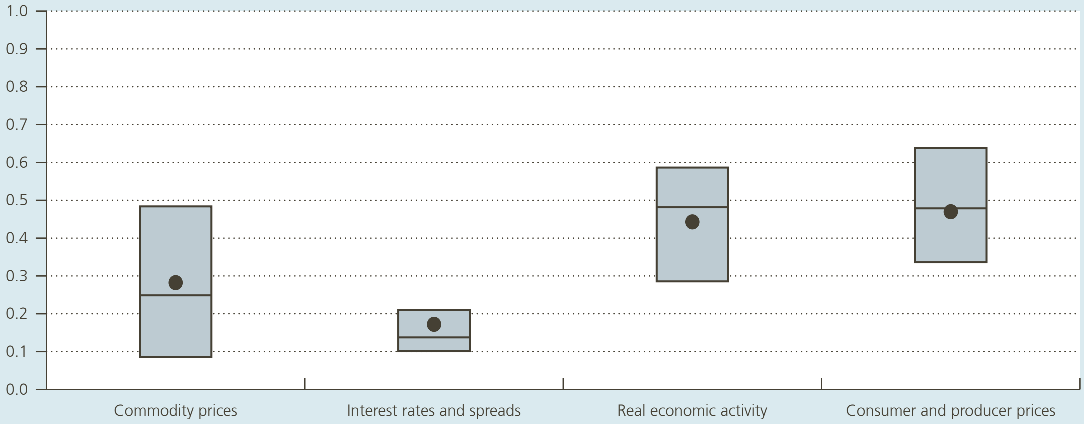
BOX 1

Does our macroeconomic uncertainty measure explain uncertainty of individual variables?

Our measure of macroeconomic uncertainty is a weighted average of the uncertainty in 159 macroeconomic time series. But how well does our measure of macroeconomic uncertainty summarise the information contained in the individual uncertainty series? To answer this question, we regress, sequentially, every individual uncertainty measure on our macroeconomic uncertainty index (and a constant). For each regression, we extract the R-squared, which measures the fraction of the uncertainty of a variable that is explained by the level of macroeconomic uncertainty. We collect the R-squared values and summarise them in Figure A.

Figure A shows the distribution of R-squared values by variable groups and shows that there is substantial heterogeneity in the ability of EA macroeconomic uncertainty to explain the uncertainty in individual series.

Figure A: Contribution of macroeconomic uncertainty to the uncertainty of individual variables, categorised in four groups



Source: Authors' own calculations.
Note: the shaded boxes show the inter-quartile range of the R-squared values from 159 regressions of the uncertainty of individual economic variables on EA macroeconomic uncertainty. R-squared values are categorised according to the four groupings of economic variables, as described in Section 3. The lower and upper edges of the boxes represent the first and third quartiles, respectively. Horizontal lines within boxes represent the median, and dots show the mean R-squared values.

On the one hand, EA macroeconomic uncertainty explains almost half of the uncertainty of variables belonging to the real economic activity and the consumer and producer prices groups. This indicates that uncertainty in these series is closely related to fluctuations in EA macroeconomic uncertainty. It should also be noted that this result is not driven by the higher weight assigned to the real economic activity and to the consumer and producer price groups in the computation of the EA macroeconomic uncertainty index. Indeed, we obtained similar results using identical weights of ¼ applied to the four groups.

On the other hand, EA macroeconomic uncertainty seems to be a poor predictor of the uncertainty of the interest rate and spread variables. As a reminder, our dataset mostly includes EA economic variables, as well as some global variables such as commodity prices and other series capturing the US and UK economy. Since most of these variables reflect real economic conditions, our EA macroeconomic uncertainty measure will not be able to capture the uncertainty of variables tied to financial markets, such as the variables in the interest rates and spreads group. Furthermore, as shown by JLN, the uncertainty of macroeconomic variables diverges from the uncertainty of financial variables during certain financial market events. This is also evident for our EA macroeconomic uncertainty measure, which decouples from the uncertainty of interest rates and spreads during events such as the emerging market crisis of the late 1990s and the 2000 dotcom bubble (cf. Figure 3).

In addition, we note that there is much heterogeneity in the R-squared values of the commodity price group, indicating that macroeconomic uncertainty is a good predictor of the uncertainty of some commodities, while it fails to predict the uncertainty of others. The boxplot in Figure A shows that, for almost a quarter of the commodities in our data, macroeconomic uncertainty can explain more than half of the associated price uncertainty. However, for some 25 % of our commodities, macroeconomic uncertainty explains less than 10 % of their price uncertainty.

It is likely that uncertainty in commodity prices has a large, unpredictable component not captured by our methodology. For example, commodity prices are influenced by demand shocks originating from large emerging markets — such as China — which we do not account for in our data. Furthermore, commodity price uncertainty can be associated with supply shocks that arise, for example, from the escalation of geopolitical tensions or from extreme weather events. To the extent that these supply shocks are large and general enough in scale, they will be picked up by our EA macroeconomic uncertainty measure. However, some shocks may be confined to specific commodity markets and, therefore, are unlikely to be fully captured by our measure.

5. Decomposing EA uncertainty

One of the benefits of the JLN methodology is that it allows the decomposition of uncertainty into sub-indices based on the initial dataset of economic variables. Figure 3 shows uncertainty for commodity prices (group 1), interest rates and spreads (group 2), real economic activity (group 3), and consumer and producer prices (group 4).

Figure 3 helps us discern the various sources behind the large fluctuations in EA macroeconomic uncertainty observed during the last three years (cf. Figure 2). In March 2020, concomitant with the outbreak of the COVID-19 pandemic in Europe, we report a large spike of uncertainty related to economic activity, as well as interest rate uncertainty. At the same time, several European countries, including Belgium, France, Germany, Italy, Spain, had imposed national lockdowns. [17] Apart from stringent mobility restrictions, these also involved the closure of several non-essential businesses. This had an immediate impact on consumption, investment, and employment, which are reflected in the real economic activity group of variables.

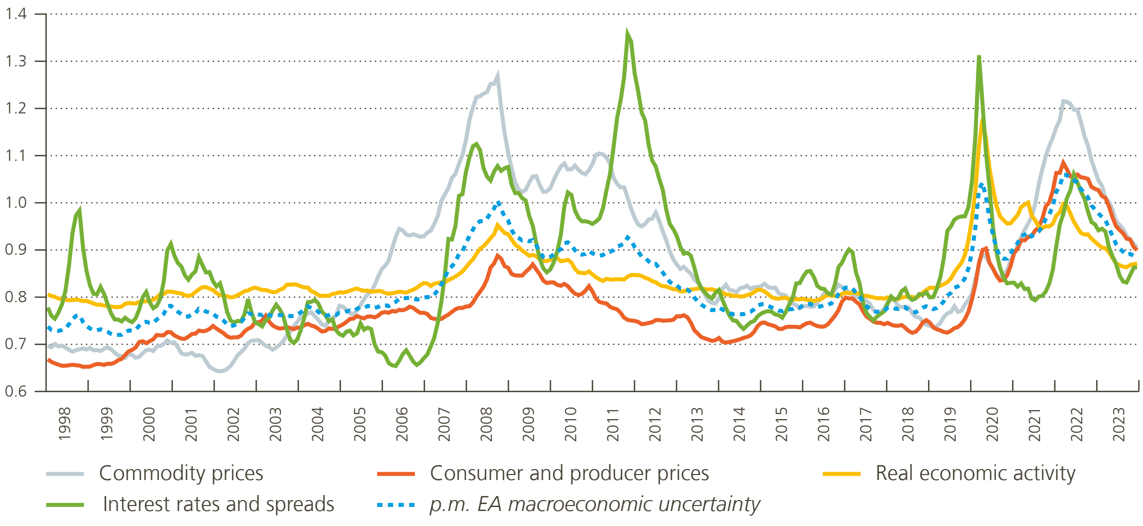
Following the COVID-19 outbreak, the reaction of fixed-income markets was immediate. Investors flocked to assets that are typically considered to be safe havens, such as US Treasury bills. The yield on 10-year US Treasury bonds almost halved during the month of March 2024, falling under the level of 1 % for the first time in history. [18] At the same, in Europe, spreads on sovereign bonds, particularly those of Italy and Spain, increased tremendously, as did spreads on European corporate bonds. The large uncertainty in financial markets is reflected in our sub-index of uncertainty related to interest rates. The prompt intervention of the ECB — as well as that of the Federal Reserve (Fed) — stabilised financial markets. On 12 March 2020, the ECB immediately reacted to the COVID-19 outbreak with a series of measures to support bank liquidity conditions and money market activity, as well as expanding its Asset Purchase Programme with an additional envelope of €120bn. [19] Subsequently, on 18 March 2020, it established the Pandemic Emergency Purchase Programme (PEPP), with an initial envelope of €750bn. [20]

Our interest rate uncertainty sub-index quickly retreated after its initial spike in March 2020. This seems to suggest that heightened uncertainty surrounding fixed income markets was alleviated thanks to the quick

17 Italy was the first European country to impose a national lockdown on 9 March 2020. Belgium enforced a lockdown on 18 March 2020.
18 Yields are inversely related to bond prices, increasing when bond prices decline and decreasing when bond prices rise.
19 For additional details, see https://www.ecb.europa.eu/press/accounts/2020/html/ecb.mg200409~0026941ce4.en.html.
20 The PEPP was further expanded with an additional €600bn on 4 June 2020 and with an additional €500bn on 10 December 2020.

Figure 3

A decomposition of EA macroeconomic uncertainty



Source: Authors' own calculations.
Note: Figure 3 presents the decomposition of EA macroeconomic uncertainty into four variable groups. Here, uncertainty is averaged over all forecast horizons ranging between one month and one year.

action taken by the ECB and the Fed. On the other hand, after peaking in March 2020, uncertainty surrounding economic activity declined but remained above pre-pandemic levels, indicating persistently high uncertainty during the post-pandemic recovery. At the time, regional resurgences in COVID-19 infections amplified uncertainty around the economic outlook and made the global recovery vulnerable to setbacks.

The decomposition of our uncertainty indicator allows us to look more closely at the two most recent years of our sample, which are characterised by Russia's invasion of Ukraine and the ensuing energy crisis. During this period, all four sub-indices of uncertainty peak. However, it is uncertainty in commodity prices that shows the largest increase. This is in line with the unfolding of the energy crisis. Following the outbreak of the war in Ukraine, there was a surge in the volatility of prices for several energy commodities, including oil and natural gas, and agricultural commodities, such as wheat, corn, and barley. Fertilizers and metal commodities, such as iron ore, were also impacted.

These input-price pressures, combined with still persistent supply-side disruptions inherited from the COVID-19 pandemic, were gradually passed through to higher producer and consumer prices (see Arce et al., 2024). Note, in Figure 3, that the uncertainty of consumer and producer prices rises in 2021 — amid a worsening of supply side bottlenecks — and reaches an all-time high in March 2022 — right after Russia's invasion of Ukraine. Uncertainty only partially declines in 2023, underscoring the challenges of accurately forecasting consumer and producer inflation in the aftermath of the European energy crisis. This concurs with the analysis of Chahad et al. (2024), which ascribes most of the errors in Eurosystem/ECB staff projections for HICP inflation to the unpredictability of energy prices.

Using a similar methodology as ours, Comunale et al. (2023) also find a strong increase in EA price uncertainty during the energy crisis, although not as high as the uncertainty they observe at the onset of the pandemic. On the contrary, we find a higher peak in price uncertainty during the aftermath of the war in Ukraine, than during the COVID-19 crisis. Our consumer and producer price uncertainty measure also indicates that forming accurate price forecasts with econometric models remains challenging at the current juncture.

Indeed, the CPI and PPI uncertainty sub-index declines very slowly and remains above its historical average at the end of the sample period.

The decomposition of the EA macroeconomic uncertainty measure reveals intriguing dynamics throughout the entirety of the sample period, not just during the last years of our sample. During the European sovereign debt crisis, for example, we observe a strong surge in our sub-index of interest rate uncertainty, reflecting the widening of spreads of distressed European government bonds. Earlier during the GFC of 2007-2008, we observe an increase across all four sub-indices of uncertainty, and note that the escalation of the uncertainty of commodity prices and interest rates and spreads could be due to the important role of financial markets during the GFC. As mentioned in the previous section, macroeconomic uncertainty remained high in the post-GFC years. From Figure 3, we can discern that commodity price uncertainty had an important role in supporting the high levels of EA macroeconomic uncertainty during this period.

5.1 Uncertainty during three major crises

In this subsection, we explore whether the increase in EA macroeconomic uncertainty observed during crisis times coincides with a broad-based rise in uncertainty across many individual time series. Figure 4 displays the share of variables belonging to the economic activity group and to the consumer and producer prices group that were found to be "highly uncertain" during the three major crises in our sample — the GFC, the COVID-19 pandemic, and the energy crisis. In this subsection, we choose to focus our analysis on economic activity and consumer and producer prices because these are the largest variable groups and, therefore, have the highest weight for our EA macroeconomic uncertainty measure.

We consider a variable, y, as highly uncertain if its uncertainty measure $\mathcal{U}_t^y(h)$ exceeds 1.65 standard deviations above its historical mean. [21] This threshold is selected to capture the few occurrences when variables become very difficult to predict. In this instance, we used uncertainty measured at the three-month forecast horizon, $\mathcal{U}_t^y(h = 3)$, because, as can be noted from Figure 2, the macroeconomic uncertainty measure for the three-month horizon peaked above its one and twelve-month counterparts during the three extreme events we consider here.

Figure 4 shows that, over the course of our sample period, the average share of highly uncertain variables in the real economic activity group and the consumer and producer prices group reached, respectively, 6 % and 8 %. During the GFC of 2007-2008, the share of highly uncertain variables increased above one third in both categories. The share was even larger during the pandemic and the energy crisis. Thus, the three crisis episodes analysed were characterised by high uncertainty across an extensive number of individual variables, in addition to high aggregate EA macroeconomic uncertainty.

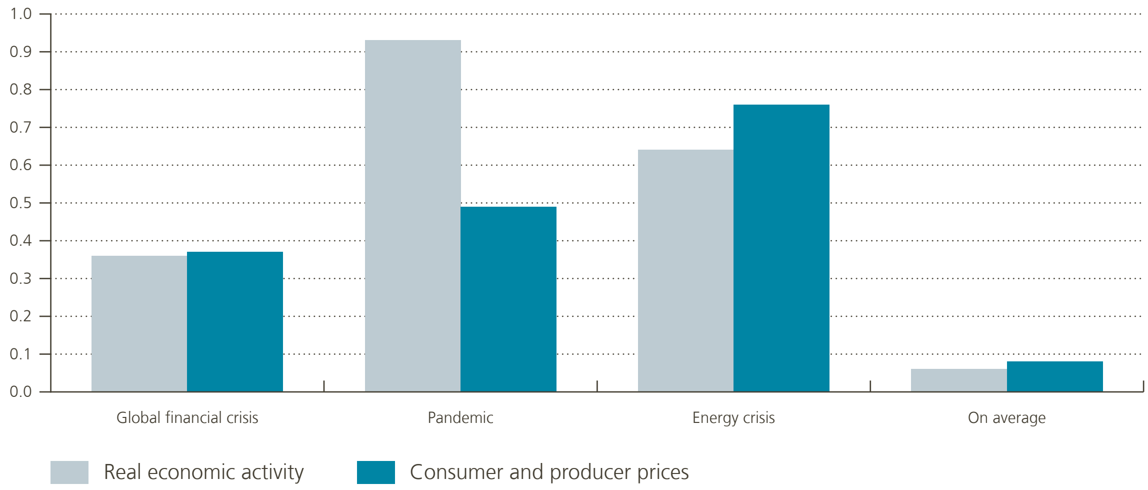
During the COVID-19 pandemic, the share of highly uncertain variables belonging to the real economic activity group reached 93 %. Mobility restrictions and the uneven post-pandemic recovery had a widespread impact on the predictability of these economic variables. In addition, the COVID-19 crisis had repercussions on the predictability of price variables. About half of the variables in the consumer and producer prices group could be considered highly uncertain during the pandemic.

Whereas the COVID-19 pandemic had a large influence on the unpredictability of variables related to real economic activity, the energy crisis triggered by Russia's invasion of Ukraine had a relatively broader impact on the unpredictability of price-related variables. In fact, Figure 4 shows that the share of highly uncertain consumer and producer price variables increased to 76 %, compared to 64 % for real economic activity variables.

21 If uncertainty were following a standard normal distribution, it would breach this threshold 5 % of the time.

Figure 4

Share of highly uncertain variables



Source: Authors' own calculations.
Note: the figure shows the share of variables with high uncertainty during three events: the GFC, the COVID-19 pandemic, and the energy crisis. We consider a variable y as highly uncertain if its uncertainty measure $\mathcal{U}_t^y(h = 3)$ exceeds 1.65 standard deviations above its historical mean.

Once again, results underscore the distinctiveness of the European energy crisis and the increased difficulty of predicting consumer and producer prices during this time.

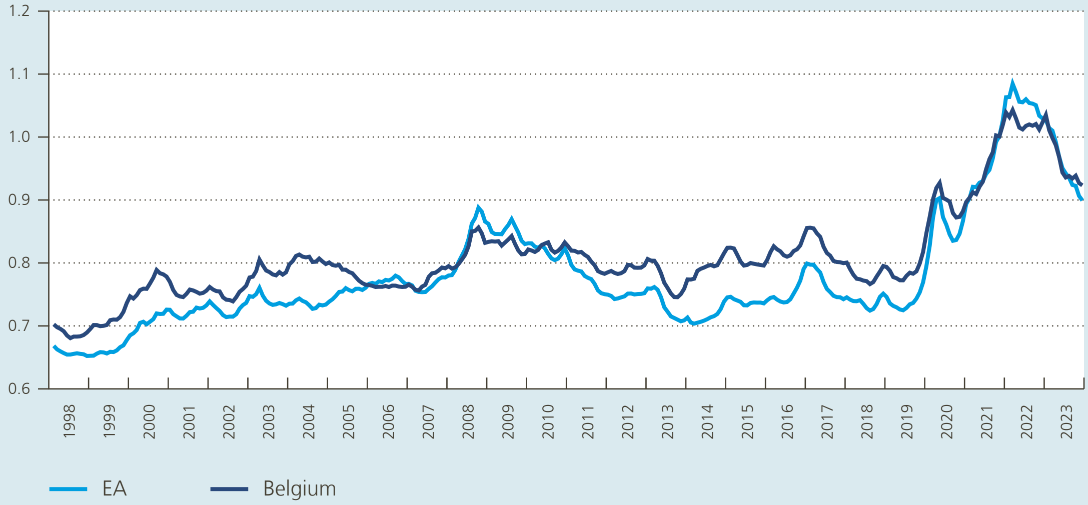
BOX 2

Uncertainty in Belgian consumer and producer prices

How does Belgian price uncertainty compare with our EA measure? To answer this question, we compute a Belgian consumer and producer price uncertainty index averaging the uncertainty of Belgian prices. In Figure B, we compare the Belgian index with that of the EA.

Figure B shows a very strong contemporaneous correlation between consumer and producer price uncertainty in Belgium and in the EA. The degree with which Belgian and EA price uncertainty move in tandem is particularly strong during the pandemic and during the EA energy crisis, when both measures increased drastically. The high level of uncertainty illustrates the challenges that were faced in predicting the evolution of prices during the two past crises. Moreover, our latest observation, which dates to December 2023, shows that price uncertainty remains high in Belgium, as in the EA. This suggests that producing accurate forecasts from econometric models is likely to remain challenging.

Figure B : Consumer and producer price uncertainty in Belgium and in the EA



Source : Authors' own calculations.

6. Conclusion

The EA macroeconomic uncertainty measure developed in this article represents a valuable resource in the analytical toolkit available to economists and central bankers. It can help us assess and monitor fluctuations in uncertainty in the EA. This is especially important, given recent debates surrounding forecasting during periods of crisis. [22]

This article applies the JLN methodology to a large dataset of 159 economic variables to extract a measure of EA macroeconomic uncertainty. The measure is based on the ability to forecast economic variables at different future horizons. EA macroeconomic uncertainty increases during times when economic predictions are less precise and declines when economic predictions improve.

We find that EA macroeconomic uncertainty peaks during crisis events, such as the GFC, the recent COVID-19 pandemic and the energy crisis provoked by Russia's invasion of Ukraine. By December 2023, EA macroeconomic uncertainty had declined from its peak in 2022. However, it remains substantially higher than its long-term average. This serves as evidence of the persistently challenging environment for economic forecasting.

22 See for example, the Bernanke (2024) review of the BoE and some of the responses it gathered (Aikman and Barwell, 2024).

By decomposing our measure, we show that a large part of the recent surge in EA uncertainty is linked to increases in the uncertainty in commodity, consumer, and producer prices. The high uncertainty over commodity prices is a distinguishing feature of the recent energy crisis. On the contrary, however, during the COVID-19 pandemic, EA macroeconomic uncertainty was primarily associated with the uncertainty of variables linked to real economic activity, such as consumption, production, and employment.

Annex

List of variables included in our macroeconomic uncertainty measure

(by variable group)

Group 1. Commodity prices		
Variable type	**Product**	**Source**
Energy products	Crude oil, coal, gas (Europe and US)	WB
Beverages	Cocoa, coffee (Robusta & Arabica), tea (Colombo & Mombasa)	WB
Food	Soybeans, maize, rice, wheat, palm oil, banana, orange, beef, chicken, sugar	WB
Agricultural raw materials	Cotton, rubber, timber (logs & sawn wood)	WB
Fertilisers	Index	WB
Metals and minerals	Aluminium, iron ore, copper, lead, tin, nickel, zinc	WB

Group 2. Interest rates and spreads		
Variable type	**Country and maturity**	**Source**
FFR	US Federal funds rate	Fed
Sovereign bonds rates	3-6 months (US), 1-3-5 years (US), 10 years (US, DE)	Fed (US), OECD (DE)
Sovereign spreads (vs German Bund)	BE, FR, IT, ES (10-year yields)	OECD, Eurostat
Corporate spreads (vs sovereign)	US (residual maturities >1 year, investment grade), DE (all maturities, all ratings)	BoA (US), DBB (DE)

Group 3. Measures of real economic activity		
Variable type	**Country /index**	**Source**
Global economic activity indicators	Baltic Dry Index, IGREA, GECI, OECD+6NME industrial production	Baltic Exchange, FRED (based on Kilian, 2009), Baumeister *et al.* (2022)
Unemployment rates	US, UK, BE, DE, FR, IT, ES	OECD, Bundesagentur für Arbeit, NBB
Wages	US, UK	OECD, Refinitiv
Hours worked	US, UK	BLS (US), ONS (UK)
Retail sales	US, UK, DE, FR, BE	OECD
Industrial production	US, UK, BE, DE, FR, IT, ES	OECD
Consumer confidence	US, UK, BE, DE, FR, IT	OECD
Construction confidence	UK, BE, DE, FR, IT	OECD
Manufacturing confidence	US, UK, BE, DE, FR, IT, ES	OECD

Group 4. Consumer and producer prices		
Variable type	**Country**	**Source**
Core-CPI	US, UK	OECD (UK), BLS (US)
Food-CPI	US, UK	OECD (UK), BLS (US)
Energy-CPI	US, UK	OECD (UK), BLS (US)
Housing-CPI	US (incl. rents), UK (retail price)	BLS (US), ONS (UK)
Services-CPI	US (excl. housing), UK (retail price)	BLS (US), ONS (UK)
Headline-CPI	BE, DE, FR, IT, ES	StatBel, Federal Statistical Office (DE), INSEE (FR), Istat (IT), INE (ES)
HICP by consumption expenditures, including COICOP 01, 04, 05, 07, 09, 11	BE, DE, FR, IT, ES	Eurostat
Intermediate goods-PPI	US, BE, DE, FR, IT, ES	Eurostat, OECD, Istat (IT), The Conference Board (US)
Capital goods-PPI	US, BE, IT, ES	Eurostat, OECD, StatBel, The Conference Board (US)
Consumer durables-PPI	US, BE, DE, FR, ES	Eurostat, OECD, BLS (US)
Consumer non-durables-PPI	US, BE, DE, IT, ES	Eurostat, OECD, BLS (US)
Energy products-PPI	US, BE, DE, FR, IT, ES	Eurostat, OECD, StatBel, INSEE (FR), BLS (US)
Manufactured products-PPI	UK	ONS

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Conventional signs

%	per cent
etc.	*et cetera*
et al.	*et alia* (and other)
i.e.	*id est* (that is)
e.g.	*exempli gratia* (for example)

List of abbreviations

Countries or regions

BE Belgium
DE Germany
ES Spain
FR France
IT Italy
EU European Union
UK United Kingdom
US United States

Abbreviations

BLS	Bureau of Labor Statistics (of the United States)
BoA	Bank of America
COICOP	Classification of Individual Consumption by Purpose
CPI	Consumer Price Index
DBB	Deutsch Bundesbank
EA	euro area
ECB	European Central Bank
ESCB	European System of Central Banks
Fed	Federal Reserve System (of the United States)
FFR	Federal Funds Rate
FRED	Federal Reserve Economic Data (St. Louis Fed)
GECI	Global Economic Conditions Indicator
GFC	Global financial crisis
HICP	Harmonised Index of Consumer Prices
IGREA	Index of Global Real Economic Activity
INSEE	Institut nationale de statistiques et des études économiques (France)
JLN	Jurado, Ludvigson, and Ng (2015)
LHS	Left-hand side

OECD	Organisation for Economic Co-operation and Development
OECD+6NME	OECD and major six non-member economies
ONS	Office of National Statistics (of the United Kingdom)
PPI	Producer Price Index
RHS	Right-hand side
WB	World Bank

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