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The effects of macro uncertainty shocks in the euro area: A FAVAR approach*

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Abstract

This paper estimates the effects of uncertainty shocks on a large set of economic and financial variables in the euro area. For this purpose, we first build a large monthly macro dataset with euro area-wide data, which we summarize by principal components. Second, we estimate a heteroskedastic factor-augmented vector autoregressive (FAVAR) model using a survey-based measure of macroeconomic uncertainty and a large dataset. Third, we identify five shocks by employing a new identification scheme based on sign restrictions exploiting our large dataset, including uncertainty shocks, financial shocks, standard monetary policy shocks, aggregate demand shocks, and supply shocks. Fourth, we show more than one hundred impulse responses to an uncertainty shock. In this setup, we find that an uncertainty shock has a significantly negative effect on economic activity measures in the euro area, but has no significant effect on savings and inflation. Moreover, uncertainty shocks trigger a contractionary effect on several measures of financial stability. Finally, we discuss the results and possible policy implications.

Keywords: Uncertainty, euro area, FAVAR model, sign restrictions.

JEL Classification: C55, D80, D81, E32.

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1 Introduction

Uncertainty[1] and its impact on the economy has been a subject of heightened interest in recent years. Many authors and institutions have reviewed its role during the Great Recession (Bloom, 2014; Bloom et al., 2018; Caldara et al., 2016; Stock and Watson, 2022; ECB, 2009, 2016; Gieseck and Largent, 2016; Balta et al., 2013; Bundesbank, 2018), its impact on the recovery afterwards (Kose and Terrones, 2012; Haddow et al., 2013), and also during the sovereign debt crisis in the euro area (ECB, 2016) and the recent Covid-19 pandemic (Baker et al., 2024; Carriero et al., 2021; Gieseck and Rujin, 2020)[2]. Despite the solid agreement in the literature on the countercyclical impact of heightened uncertainty on economic activity (Castelnuovo, 2022), some empirical disagreements on the effects of uncertainty persist. Two of such topics are the size of the decline in economic activity after an uncertainty shock hits (Alessandri et al., 2023) and the sign of the effect on prices (Meinen and Roehe, 2018; De Santis and Van der Veken, 2022).

Such disagreements in the uncertainty literature may be related to several empirical challenges that surround the task of estimating the effects of uncertainty shocks. Some of them are related to the use of a small-scale model, which might omit some relevant control variables, the choice of the identification scheme to recover the structural uncertainty shock, using low-frequency models (Castelnuovo and Mori, 2022; Alessandri et al., 2023), and the role of non-linearities (Caggiano et al., 2014; Jackson et al., 2020). Additionally, the use of different measures of uncertainty may make comparability across studies difficult. Regarding identification strategy, recovering an exogenous uncertainty shock from other shocks proves to be a demanding empirical task (Castelnuovo, 2022; Ludvigson et al., 2021; Carriero et al., 2018). Indeed, uncertainty shocks are unlikely to occur independently from others such as global shocks (Berger et al., 2016), a financial shock (Caldara et al., 2016; Ludvigson et al., 2021; Alessandri

[1] Following a *Knightian* sense of uncertainty (Knight, 1921), it arises when economic agents are not able to assess the likelihood of all possible states of nature and in consequence, are not able to characterize their possible effects. Alternatively, risk is a different notion by which agents have the capability of forming views about the probability distributions of all possible future states and calculate the effects of these states in their economic actions.

[2] See Bloom (2014), Castelnuovo et al. (2017), Castelnuovo (2022), Cascaldi-García et al. (2023) and Fernández-Villaverde and Guerrón-Quintana (2020) for comprehensive overviews on measures of uncertainty and its role in the business cycle.

et al., 2023), an aggregate demand shock (Leduc and Liu, 2016) and/or a confidence shock (Haddow et al., 2013). Some particularly contentious assumptions relate to the use of recursive ordering to disentangle the uncertainty shock (Castelnuovo, 2022; Kilian et al., 2022) or sign-restricting prices when using sign restrictions (Meinen and Roehe, 2018).

Focusing on studies using euro area data, the previously described empirical challenges appear to be binding to find estimates of the effects of macro uncertainty shocks that are not affected by relevant identification issues[3]. In these studies, the predominant use of small-scale models, quarterly data, and recursive identification schemes may not be well-suited for the task. Moreover, the prevalent focus on small-scale models also prevents reporting results on the effect of uncertainty shocks on other variables, such as the exchange rate, trade, and measures of systemic risk and financial stability, which are relatively understudied topics. Nevertheless, these studies do not cover recent years characterized by high uncertainty, high inflation, and high geopolitical tensions.

In this study, our main target is to estimate the impact of macro uncertainty shocks on the euro area economy by taking the following steps. First, we construct a monthly database of 132 euro area macroeconomic and financial time series over the sample period 1999:01–2023:06, similar to the popular FRED-MD using US data (see McCracken and Ng, 2016). Second, we estimate a heteroskedastic factor-augmented vector autoregressive (FAVAR) model using our monthly euro area database, while also including a survey-based measure of macro uncertainty as our measure of uncertainty. Using a data-rich monthly FAVAR model presents the following advantages. One, it allows us to mitigate the risk of omitting relevant control variables, which might avoid a potential overestimation of the role of uncertainty shocks in explaining their impact on economic activity (Bundesbank, 2018). Two, a large dataset provides a large set of alternatives to design an identification scheme based on sign restrictions. Three, it allows us to provide more results in terms of impulse responses. Such a model is estimated using data up to June 2023, thus including the recent Covid-19 pandemic with its unprecedented volatility relying on a heteroskedastic treatment along the lines of Lenza and Primiceri (2022).

[3]Table A1 in the Appendix summarizes the main characteristics of euro area studies estimating the effects of macro uncertainty shocks.

Third, we design an identification scheme based on sign restrictions to identify the five underlying shocks: an uncertainty shock, financial shock, standard monetary policy shock, and aggregate demand and supply shocks. To identify our uncertainty shock, we restrict the responses of motor vehicle sales, shares issued by euro area residents, and the credit spread of non-financial corporations (NFC). Additionally, to distinguish the uncertainty shock from a financial shock, we restrict the ratio of the NFC credit spread over our uncertainty measure along the lines of Furlanetto et al. (2019). To identify a standard monetary policy shock, we restrict high-frequency indicators along the lines of Jarocinski and Karadi (2020). Fourth, using such machinery, we estimate more than one hundred impulse responses on the effect of an uncertainty shock on a large set of macroeconomic and financial variables, notably economic activity, inflation, savings, and financial stability in the euro area. In addition, we show the historical decomposition of shocks to real GDP growth. Finally, we discuss the empirical results and derive possible policy implications.

Our empirical analysis reveals several key findings on the effects of uncertainty shocks on the euro area economy. First, uncertainty shocks exert a negative and significant impact on economic activity, with the most pronounced decline observed in industrial production, imports, and both business and housing investments. In contrast, the impact on inflation and savings is muted, indicating limited direct effects on these variables. Moreover, uncertainty shocks contribute to increased systemic and financial stability risks. During the Covid-19 recession, the contribution of uncertainty shocks to real GDP diminished relatively quickly, as a supply shock emerged as the dominant factor driving output contraction. Importantly, the average contribution of uncertainty shocks to output is relatively low, estimated at approximately 2%, which is significantly below the range of 11%-41% reported in benchmark studies. These findings provide nuanced insights into the heterogeneous effects of uncertainty shocks and their significance across different economic dimensions and periods.

The contributions of this study are as follows. First, we deviate from the previous euro area literature using small-scale VAR models by applying a data-rich monthly FAVAR model. To the best of our knowledge, this is the first study employing such model to estimate the effects of uncertainty shocks using euro area data[4], while it is also equipped with an heteroskedasticity treatment *à la* Lenza and Primiceri (2022) to deal with pandemic-induced extreme volatility. Second, our study contributes to the literature on the identification of uncertainty shocks in SVAR models by designing an identification scheme based on sign restrictions that avoids contentious assumptions, particularly concerning the response of prices (see Meinen and Roehe, 2018). While most authors focusing on euro area data employ a recursive approach for that task, following Bloom (2009)[5], or use sign restrictions and restrict the response of prices, in this paper we apply a set of sign restrictions to identify five different shocks, keeping the response of prices to an uncertainty shock unrestricted. In particular, we follow Furlanetto et al. (2019) in sign-restricting the ratio of an excess bond premium proxy to our uncertainty measure while avoiding instead possibly excessive assumptions such as restricting prices (following Meinen and Roehe, 2018) or stock prices. Third, we report more than hundred impulse responses to an uncertainty shock by exploiting our large dataset, allowing us to provide evidence on the transmission of the uncertainty shock to a broad set of variables including inflation, savings, output, productivity, and financial stability, among others. In this way, we contribute to current discussions on the size and sign of the effects of uncertainty (Segal et al., 2015), on the impact of uncertainty on inflation (De Santis and Van der Veken, 2022; Meinen and Roehe, 2018), as well as on savings (Doosche and Zlatanos, 2020), while tackling relatively understudied topics such as the effects of uncertainty on the exchange rate (Akinci et al., 2022), trade (Novy and Taylor, 2020), and financial stability.

Related literature. This paper is related to several strands of the literature. First, it is linked to theoretical studies modeling the channels through which uncertainty affects the macroeconomy. According to this literature, there are three main channels[6]. First, households facing uncertainty may increase savings and/ or decrease consumption to compensate for higher uncertainty on labour income, i.e. precautionary savings (see Carroll, 1997; Eberly, 1994). Sec-

[4]The only study that uses a FAVAR model to estimate the effects of uncertainty shocks we are aware of is Popp and Zhang (2016), which uses US data.

[5]Other studies using Cholesky identification are Bachmann et al. (2013), Jurado et al. (2015), Baker et al. (2016), Leduc, Liu (2016), Scotti (2016), ECB (2016), Gieseck, Largent (2016), Girardi, Reuter (2017) and Gieseck, Rujin (2020).

[6]For an overview see Haddow et al. (2013), Bloom (2014) and ECB (2016).

ond, firms may reduce or postpone investment given uncertainty on future sales and profits, maybe having also negative effects on productivity, which is the so-called *wait and see* effect (see Bernanke, 1983; Dixit and Pindyck, 1994; Bloom, 2009). This effect can also take the form of an *entry and exit* effect, where firms postpone entering new markets (arguably the more productive) and postponing hiring and firing decisions (Bloom, 2009; Bachmann et al., 2013). Third, the impact of uncertainty on investment might be through innovations in credit spreads, given investment irreversibility and fixed investment costs, i.e. a *risk premia* mechanism (see Gilchrist et al., 2014).

Second, our study is also related to empirical papers designing identification schemes to estimate the effects of uncertainty shocks in the economy. While the influential Bloom (2009) and other subsequent studies use recursive identification, other approaches consist in imposing sign restrictions on the obtained impulse responses (e.g. Meinen and Roehe, 2018; Furlanetto et al., 2019; Shin and Zhong, 2020), imposing narrative sign restrictions on the structural shock (De Santis and Van der Veken, 2022; Breitenlechner et al., 2023), using an instrumental variable (Piffer and Podstawski, 2018; Carriero et al., 2015), employing the penalty function approach (Caldara et al., 2016), and also relying on the heteroskedasticity in the shocks across different periods (Brunnermeier et al., 2021). As we explain later in this paper, we use sign restrictions to identify an uncertainty and other shocks, while we also use high frequency indicators to identify a standard monetary policy shock. Using such framework, we contribute to the discussion about good and bad uncertainty (Segal et al., 2015; Uribe and Chulia, 2023; Ludvigson et al., 2021), whether uncertainty shocks are inflationary or deflationary (De Santis and Van der Veken, 2022; Castelnuovo, 2022) and on the effects of uncertainty on trade (Castelnuovo, 2022), exchange rates (Akinci et al., 2022) and on banking and financial stability (Juelsrud and Larsen, 2023).

Third, our approach is related to papers that use relatively big macro datasets. Since the introduction of the factor-augmented VAR model by Bernanke et al. (2005), many researchers use such models both for forecasting and also to estimate the effects of shocks. This is useful for our purposes given that it can contribute to a better identification while it also gives room to provide more results in terms of impulse responses. While the usage of factor models is more widespread to assess the effects of monetary policy shocks (see Corsetti et al., 2022 and Jackson et al., 2018 for euro area data applications), their usage to analyze uncertainty shocks is less common, where a notable exception is Popp and Zhang (2016)[7]. Additionally, we use monthly data to avoid further shock identification issues coming from low frequency data (see Alessandri et al., 2023).

This paper is structured as follows. Section 2 presents our new monthly euro area macroeconomic dataset and our selected uncertainty measure. Section 3 describes the FAVAR model and the identification scheme which we propose to measure the impact of uncertainty shocks on the euro area economy. Section 4 presents the main results and some robustness checks. A discussion of the empirical results is provided in section 5. Finally, section 6 concludes.

2 Data

2.1 Our monthly euro area macro dataset

We construct a monthly database of 132 euro area macroeconomic and financial time series over the sample 1999:01 - 2023:06. The data are organized into several categories: (1) output and income, (2) labour market, (3) orders, turnover and sales, (4) interest rates[8], credit spreads and exchange rates, (5) prices, (6) financial market data, (7) confidence indicators, (8) money, credit and savings and (9) foreign trade and productivity. See Table A2 in the Appendix for a detailed description of each monthly variable in each group, and their transformations to induce stationarity[9].

Our dataset includes monthly and quarterly variables. Regarding the latter, we use a Chow

[7]Popp and Zhang (2016) uses a smooth-transition factor-augmented VAR (ST-FAVAR) model to study the macro effects of uncertainty shocks in the US focusing on the interaction between high uncertainty and credit market conditions when the economy is in recession or expansions.

[8]We backpolate the three interest rates for which we do not have data before 2003 (i.e. IR_LHP, IR_LHC and IR_LNFC according to Table A2 in the Appendix) by using a mixed-frequency VAR of the three series together with the euro area spot rate, 1 month, 3 month and 12 month interest rates, available from 1984.

[9]We assess the stationarity of the time series in levels using ADF tests at 5% significance level. If non-stationary, the series are differenced on year-on-year basis.

and Lin (1971) frequency conversion without indicators to get the monthly estimates of the quarterly variables[10]. Despite these frequency conversions, which affect twenty of the included variables[11], we prefer to use a monthly model to avoid identification issues arising from aggregation in low-frequency models, as shown by Alessandri et al. (2023).

2.2 Informational sufficiency of a small-scale dataset

To investigate whether a small-scale VAR might be enough for studying uncertainty shocks, we perform an informational sufficiency test (see Forni and Gambetti, 2014) on the dataset used by Bloom (2009) with euro area data. Then, we evaluate the ability of the first 15 principal components summarizing a dataset of 124 macroeconomic and financial indicators to Granger-cause the variables in the euro area version of the Bloom (2009) data[12]. The p-values obtained in such test are all close to zero, suggesting that with a 5% significance level, all the 15 estimated factors Granger-cause at least one of the variables used by Bloom (2009). In other words, in the case of the euro area with data up to June 2023, the inclusion of more variables is needed to achieve informational sufficiency, which motivates us in using our large macro dataset to fit a factor-augmented VAR model instead of a small-scale one.

2.3 Selected measures of uncertainty

A large number of proxies or indicators of uncertainty has been developed in the empirical literature which differ along multiple dimensions such as method of calculation, data sources and horizons at which they are calculated (for an overview see Haddow et al., 2013; ECB, 2016, Fernández-Villaverde and Guerrón-Quintana, 2020; and Cascaldi-García et al., 2023, *inter alia*). Their adequacy as a measure of uncertainty depends on the extent to which their fluctuations

[10] Frequency conversion are done using the Matlab library of Quilis (2018).

[11] The quarterly variables converted to monthly frequency are the following: real GDP, private consumption, real disposable income, business investment, housing investment, compensation of employees, compensation per employee, employment, labour force, hours worked, savings, the savings rate, disposable income, housing prices, capacity utilization in manufacturing, government consumption, government investment and the private consumption deflator.

[12] The 124 variables we use for this informational sufficiency test are the 132 variables included in our monthly euro area dataset (see section 2.1) except the eight variables used by Bloom (2009).

can be attributed to changes in uncertainty about economic fundamentals and separated from other related developments. As there is no single best measure of uncertainty available, it appears preferable to measure uncertainty using data from various sources and applying multiple methods.

Our analysis is based on four recently proposed proxies for uncertainty which are derived from diverse sources and identify uncertainty from various angles. First, we consider surveys among households and businesses as a source for the compilation of proxies for uncertainty. Survey-based measures of uncertainty have been used in a number of studies (for example Bachmann et al., 2013; Balta el al., 2013; Popescu and Smets, 2010; Vasicek, 2018) exploiting the availability of positive and negative opinions per question, suggesting that an increase in diversity of opinions reflects an increase in uncertainty. In this paper, we compile a survey-based proxy for uncertainty following Girardi and Reuter (2017) based on the standard deviation of monthly survey balance indicators (SURVEY). We use business and consumer surveys published at monthly frequency by the European Commission as the database. These surveys include both backward-looking and forward-looking questions and are calculated as balance scores of positive and negative answers by respondents. The rationale of this approach as a measure of uncertainty rests on the assumption that uncertainty is related to change. In good times and without uncertainty, households and business would be expected to assess the current situation and the future outlook broadly similar and with only limited changes from one month to the next. Adding uncertainty about the future outlook to this scenario, though, respondents would be expected to view future developments more negatively than the current situation, i.e. causing rising dispersion across questions. As a key advantage of this approach, uncertainty is calculated based on the diversity of opinions across a large sample of households and business across sectors; in addition, European Commission survey data are published very timely (at the end of the month), are available across all euro area countries and often start in 1985. On the downside, the dispersion of answers by businesses and households might also be driven by other factors such as information shocks or simply the heterogeneity of agents that affect their responses.

Second, we apply two forecast-error based measures of uncertainty. Specifically, we follow Jurado et al. (2015) and compile measures of macroeconomic uncertainty (MACRO) and financial uncertainty (FIN) which are based on the difficulty of predicting future economic outcomes, which is a function of the increase in the projection errors for a broad range of business cycle and financial variables. We calculate this econometric-based measure of uncertainty using a large dataset comprising hundreds of macroeconomic and financial indicators for the euro area as well as for the five largest euro area countries and construct estimates of uncertainty for each indicator. The h-period ahead uncertainty in each indicator is defined as the conditional volatility of the unforecastable component of the future value of the indicator, i.e. the difference between the future value of the variable and its expected value based on the information available at time t. The aggregate uncertainty is then calculated as the average of uncertainty measures across all macroeconomic or financial variables. Such measures of macroeconomic or financial uncertainty have been used in a number of recent studies (see *inter alia* Dibiasi and Sarferaz, 2023 for 39 countries; Redl, 2017 for the UK; Ludvigson et al., 2021 for the US; Meinen and Roehe, 2017 for euro area countries as well as Gieseck and Rujin, 2020 for the euro area). While objectivity in measuring uncertainty based on a large dataset is an advantage of this approach, it provides ex post estimates of uncertainty and is available only with some time-lag depending on the length of the forecast horizon, limiting its usefulness for policy-makers.

Third, we turn to the economic policy uncertainty index (henceforth PUI) which has been developed by Baker et al. (2016) and counts the frequency of articles containing the words "uncertain or uncertainty", "economy or economic" and one of a number of policy words (such as "deficit" or "regulation") in leading newspapers. This index is available at monthly frequency for 29 major industrialized and developing countries as well as at the global level based on 21 countries. We calculate a euro area economic policy uncertainty index as a GDP weighted average of available data for 8 euro area countries[13]. The PUI has been applied as proxy for uncertainty in a large number of studies across many countries (e.g. Alexopoulos and Clark, 2015; Baker et al., 2019; 2020), can be adjusted to address particular sources of uncertainty (such

[13] Germany, France, Italy, Spain, the Netherlands, Belgium, Ireland and Greece.

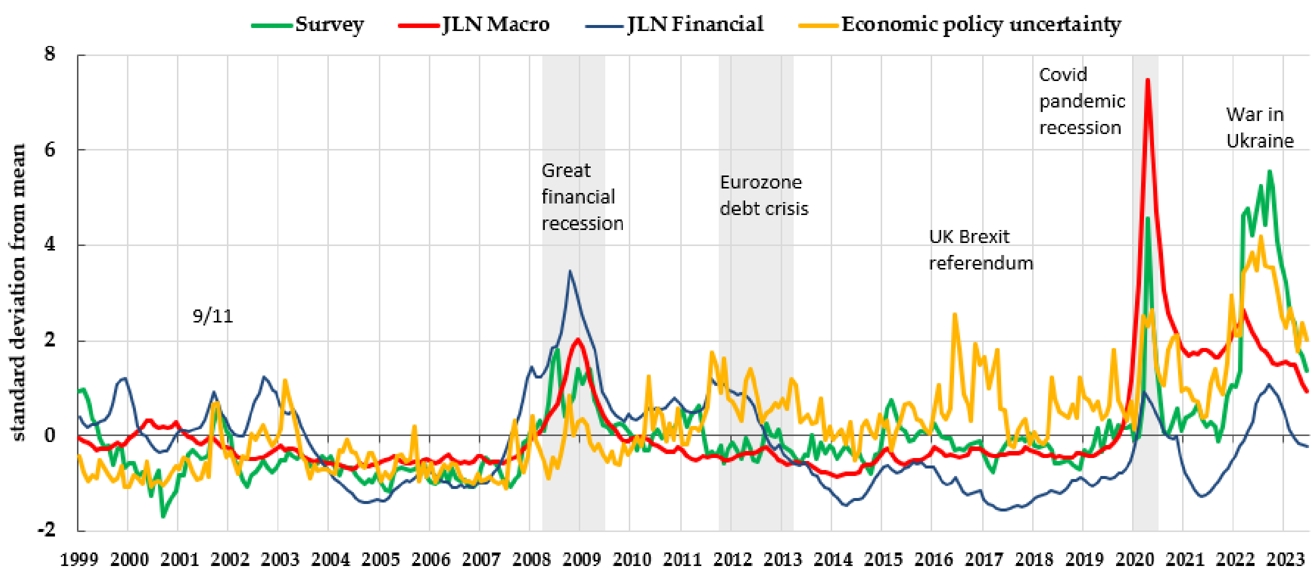
as monetary policy or trade policy), and is attractive due to its early availability. As a caveat of this approach, it reflects the perception of uncertainty of a limited group of journalists (typically from two newspapers per country) and it is assumed that their perception of uncertainty represents that of the economy at large.

The selected uncertainty measures are displayed in Figure 1 below. The overall message from Figure 1 is that a) measures of uncertainty exhibit a negative correlation with business cycle indicators and tend to be elevated during periods of recession, b) the co-movement across the selected uncertainty measures is relatively limited and c) that they tend to increase with different magnitudes across events. For example, while financial uncertainty, survey-based uncertainty and the PUI rose by about 1 standard deviation in the context of the 9/11 attacks in 2001, macroeconomic uncertainty hardly responded. Our uncertainty measures also exhibit notable differences during the Great Recession of 2008/09. Financial uncertainty started to climb already during the course of 2007 in the wake of first signs of financial stress (Northern Rock), surged to almost 3.5 standard deviations in October 2008, and started to decline only during the course of 2009. Macroeconomic uncertainty and survey-based uncertainty increased markedly during the course of 2008, reaching peak levels of around 2 standard deviations, but faded quickly during the first half of 2009. In contrast, economic policy uncertainty spiked only briefly in October 2008, possibly reflecting the strong and immediate response of policy makers early in the Great Recession[14]. The financial and policy related nature of uncertainty during the sovereign debt crisis can be seen in the fact that only financial and economic policy uncertainty spiked in 2011/12, while the other uncertainty proxies remained at subdued levels. Similarly, while economic policy uncertainty increased in 2016 in the context of the UK Brexit referendum, all other uncertainty measures remained subdued. Turning to the pandemic recession in the first half of 2020, all uncertainty measures surged in early 2020 and climbed to around 2 (EPU), 4 (SURVEY) and more than 7 (MACRO) standard deviations in April/May 2020. In contrast, financial uncertainty increased much more moderately. Most uncertainty measures eased

[14] To check that our uncertainty measures are not confounded with global uncertainty, we check that the correlation coefficient between our measures and the WUI (World Uncertainty Index) of Ahir et al. (2022) is low, ranging from -0.30 to +0.39, where the coefficient with respect to our baseline uncertainty measure is -0.23.

quickly during the course of 2020, likely thanks to the policy reaction and swift progress in developing vaccines. In contrast, macroeconomic uncertainty remained rather elevated during the remainder of 2020 and in 2021 as uncertainty about the relaxation of lockdown measures remained high in the context of the new waves of infections. Policy and survey-based uncertainty were pushed up sharply in the wake of the start of the war in Ukraine and started to ease only gradually since. On the other hand, financial uncertainty rose less than in previous episodes; its overall low level since early 2013 could possibly be seen as a success of forward guidance which had reduced the uncertainty about monetary policy in the euro area (see Coenen et al., 2017). Finally, it is noteworthy that one or all uncertainty measures spiked in the context of the three recessionary periods and the period of weakness in the first half of 2022, while the uncertainty measures typically remained at modest levels at other times.

Figure 1: Uncertainty measures in the euro area, 1999 - 2023.



Notes: Own calculations. All data standardized to mean zero and one standard deviation. Shaded areas correspond to recession periods as defined by the CEPR.

The above-mentioned evidence supports the conclusion to assess the current state of uncertainty using different proxies, which may also help in identifying the underlying source of uncertainty and in designing the policy response. In this paper, we consequently use all of the above-mentioned proxies for uncertainty. We apply survey-based uncertainty in our baseline model. It is our preferred measure of uncertainty as it aims to detect uncertainty directly from those agents that consume, save and invest, instead of from journalists or forecasters, while also because of its timeliness. Robustness checks are also performed using the other three uncertainty measures.

3 Modeling approach

To estimate the effects of an uncertainty shock in the euro area we use a FAVAR model, introduced in the literature by Bernanke et al. (2005) building on Stock and Watson (1998)[15]. This modeling framework presents the following advantages over standard parsimonious VAR models. First, it allows the inclusion of a comprehensive set of variables, which helps mitigating the risk of omitting relevant ones in the model. Second, it offers enhanced flexibility in designing the identification scheme. Third, it allows us to estimate the effects of uncertainty shocks to a larger set of economic variables.

3.1 The FAVAR model

The so-called output equation of our heteroskedastic FAVAR model reads as follows:

$$X_t = \Lambda F_t + s_t \varepsilon_t \tag{1}$$

where X_t is the $N \times 1$ information set of N macroeconomic and financial variables, F_t is the $r \times 1$ unobservable latent factor summarizing broad economic developments and Λ is the $N \times r$ matrix containing the factor loadings. ε_t is the vector $N \times 1$ of error terms that is distributed as a white noise with mean zero and covariance matrix Σ_υ. Finally, s_t is a scaling factor which is typically one or larger than one at specific known dates when high volatility clusters occur, along the lines of Lenza and Primiceri (2022). Notably, chosen values of this scaling factor can be calibrated or optimized as additional hyper-parameters. The state equation is such that:

$$F_t = \sum\nolimits_{h=1}^{p} \phi_h \, F_{t-h} + \upsilon_t \tag{2}$$

[15]See Stock and Watson (2016) and Ramey (2016) for surveys.

where the r factors F_t follow a linear vector autoregressive process of order p, ϕ_h is an $r \times r$ matrix including the coefficients of factors at lag h and υ_t is an $r \times 1$ vector of error terms that is distributed as a white noise with mean zero and covariance matrix Σ_υ.

In this framework we can separate the factor F_t in two elements. First, the k unobservable factors that summarize the latent economic developments in the economy under study, i.e. the factors we extract from our euro area dataset. Second, the m observable factors, which in our study is the selected uncertainty measure. Therefore, from equation (1) and assuming that $F_t = [f_t', Y_t']$ and $\Lambda = [\Lambda^f, \Lambda^y]$ we can express the state equation as:

$$X_t = \Lambda^f \ f_t + \Lambda^y Y_t + s_t \varepsilon_t \tag{3}$$

where f_t is the $k \times 1$ vector of latent factors extracted from our dataset, Y_t are the $m \times 1$ observable factors in the system, i.e. our uncertainty measure, while Λ^f is the $N \times M$ matrix of latent factor loadings and Λ^y is an $N \times K$ matrix capturing the effects of the observable factors.

For the estimation of the model, a two-step procedure is used. First, we extract the factors f_t from our euro area monthly dataset by using principal components analysis, notably excluding those observable factors. Second, we estimate the FAVAR model using Bayesian techniques. To that regard, we assume Minnesota priors and optimize its hyper-parameters by maximizing the likelihood over them using unconstrained optimization.

3.2 Identification of the shocks

As previewed earlier, we define an identification scheme based on sign restrictions to identify five shocks, namely an uncertainty shock, a financial shock, a standard monetary policy shock and aggregate demand and supply shocks (see Table 1). Notably, this identification scheme involving a relatively large set of variables would be unfeasible in a small-scale model. In setting those restrictions, we believe that they are rather standard.

Building on the previously documented theoretical literature that is relevant for this paper, in order to identify a positive shock to our survey-based uncertainty measure we restrict the responses of sales of motor vehicles and the response of shares issued by euro area residents (total outstanding) to be negative, while we restrict credit spreads for loans to non-financial corporations to be positive. Additionally, we restrict negatively the ratio of credit spread for loans to non-financial corporations to our uncertainty measure along the lines of Furlanetto et al. (2019)[16]. All these sign restrictions apply one to three months after the uncertainty shock takes place.

Second, we identify a financial shock by assuming it shakes upward the credit spread of non-financial corporations, households in purchasing housing, and governments. Additionally, it positively shocks the VIXX index. In proceeding this way, we depart from the literature in two ways. One, we use the volatility index VIXX to identify a financial shock instead of an uncertainty shock, as done frequently in the literature (Bloom, 2009 among many others afterwards). Two, we leave investment unrestricted to identify a financial shock, given that rigidities in firms' investment plans might make such restriction contentious.

Third, we identify a standard monetary policy shock by shocking our policy rate proxy, that is the Euribor 3 months, while restricting two high frequency indicators such as the 3-month OIS changes and stock price changes (Euro Stoxx 50) around ECB monetary policy events press release window[17]. In particular, a contractionary standard monetary policy shock is assumed to generate a positive effect on the 3-month OIS changes[18], this way signaling a "surprise" in the interest rate shock, while provoking a negative reaction in stock prices, along the lines of Jarocinski and Karadi (2020).

[16]The credit spread for loans to non-financial corporations that we consider (SPR9) is the difference between the average interest rate paid by non-financial corporations for their loans (new business) and the Euro money market rate 12 months. See Table A2 in the Appendix for a complete description of the variables used.

[17]Both high frequency indicators are extracted from the EA-MPD database of Altavilla et al. (2019).

[18]OIS stands for the Overnight Indexed Swaps (OIS) based on the Eonia rate, that is a swap contract in which the parties exchange the variable overnight Eonia rate for the fixed swap rate. In the monetary policy literature, changes in OIS rates around monetary policy events are assumed to reflect market surprises.

Table 1: Sign restrictions.

	Uncertainty	Financial	Monetary	Demand	Supply
Survey (uncertainty measure)	+	NA	NA	NA	NA
Sales of motor vehicles	-	NA	NA	NA	NA
Shares issued by EA residents	-	NA	NA	NA	NA
Credit spread for loans to NFCs	+	+	NA	NA	NA
Credit spread for loans to NFCs / Survey	-	NA	NA	NA	NA
Credit spread of government bond 10 y.	NA	+	NA	NA	NA
Credit spread for loans to HH for HP	NA	+	NA	NA	NA
Credit spread for loans to HH for cons.	NA	+	NA	NA	NA
VIXX	NA	+	NA	NA	NA
Euribor 3 months	NA	NA	+	NA	NA
3 months OIS changes around PRW	NA	NA	+	NA	NA
Stock price changes around PRW	NA	NA	-	NA	NA
Real GDP	NA	NA	NA	+	NA
HICP	NA	NA	NA	+	NA
Private investment / output ratio	NA	NA	NA	-	NA
Industrial production	NA	NA	NA	NA	-
Producer price index	NA	NA	NA	NA	+

Notes: For a complete description of the variables, see Table A2. in the Appendix. NFCs are non-financial corporations, HH are households, HP means house purchase, cons. means consumption. PRW means press release window, from the EA-MPD dataset (see Altavilla et al., 2019). All these sign restrictions apply one to three months after each shock takes place, except in the case of the standard monetary policy shock in which the restrictions apply only after one month.

Finally, we identify an aggregate demand shock following the conventional approach of restricting output and prices in the same direction (see Canova and De Nicolò, 2002). Additionally, we also restrict a private investment to output ratio along the lines of Furlanetto et al. (2019). Fourth, similarly we identify an aggregate supply shock by restricting an output and price measure in different directions along the lines of Canova and De Nicolò (2002). In particular, for this shock we restrict negatively industrial production while producer price index is shocked positively.

4 Results

This section presents the impulse responses from an uncertainty shock obtained from our FAVAR model and identification scheme as described in the previous section. We also show a historical decomposition, the forecast error variance decomposition, as well as a robustness analysis using either alternative uncertainty measures or model specifications.

4.1 Empirical specification

We estimate our factor-augmented VAR model from 2001:01 to 2023:06 with $p = 12$ lags[19], and identify the considered five shocks using sign restrictions as described in the previous section. We consider five variables as our observable factors (i.e. $m = 5$), which are four macroeconomic variables (i.e. real GDP, Euribor 3 months, government bond yield spread SPR9 and producer price index PPIT) and our survey-based uncertainty measure, in that order. Alternatively, we summarize the rest of the variables in our macro dataset (128 variables) by extracting five static principal components (i.e. $k = 5$). Therefore, the FAVAR model we employ is actually a parsimonious VAR model that still allows us to identify five shocks while also lets us report a large number of impulse responses to those shocks.

To extract the five static factors by principal components analysis we use the EM algorithm of Stock and Watson (2002), as McCracken and Ng (2016)[20], which are plotted in Figure A1 in the Appendix. The estimation of factors is useful for us in terms of dimensionality reduction, which allows us to later estimate a rather parsimonious factor-augmented VAR model, still summarizing a rich dataset. The estimated five factors explain 0.68 of the total variation, while the marginal increase in explanatory power after including our five factors is rather small, as we can see in Figure A2 in the Appendix. These factors itself do not have an economic

[19]Optimal lag length selection using information criteria recommends using 12 lags, with agreement between AIC, BIC and HQIC.

[20]We find that five factors explain 0.68 of the variability of all the dataset, which is a larger proportion than the analogous US case analyzed by McCracken and Ng (2016), which explain 0.39 of the total variation. Therefore, we set the maximum factors at five, also to keep our FAVAR rather parsimonious. In this setup, the Bai and Ng (2002) test suggests using five factors.

interpretation, however Table A3 in the Appendix shows the top ten variables per each factor in terms of marginal explanatory power.

Regarding the heteroskedasticity treatment that we apply to our FAVAR model, we set the scaling factor s_t equal to one for all our sample, except in two events in which we allow that parameter to be optimized. These two events correspond with the outbreak of the Covid-19 pandemic in 2020 and the posterior rebound in 2021. The reason for that choice is that during these two events, which spanned several months, we observed large volatility in some economic variables, notably real GDP, which in annual log-differences varied beyond three standard deviations in both events. In particular, we optimize our scaling factor during March 2020 to August 2020 and between May 2021 and June 2021[21]. Later in this section we provide robustness exercises using alternative or no heteroskedasticity treatments in our FAVAR model.

Regarding the Bayesian estimation of the FAVAR model, we generate 3,000 draws from the posterior distribution of the parameters using a Gibbs sampler algorithm[22,23]. The hyper-parameter optimization procedure yields parameter modes close to standard coefficients in the literature[24].

4.2 Impulse responses to an uncertainty shock

Given the data-rich nature of our FAVAR model, we can now report on the impact of an uncertainty shock on a large number of indicators for activity, inflation, the labour market and financial markets. Figure 2 plots the impulse responses of some key macro variables to a positive one month uncertainty shock of one standard deviation[25]. Notice that the figures

[21]The optimized scaling factor s_t ranges between 2.27 and 8.61 during March-August 2020, while it ranges between 2.16 and 2.20 during May-June 2021.

[22]See Canova (2007) and Zellner (1971) for the technical details of the algorithm. We generate candidate draws by using the procedure discussed in Rubio-Ramírez et al. (2010).

[23]This FAVAR model is estimated using the toolbox of Ferroni and Canova (2021).

[24]The posterior mode of the Minnesota priors we obtain are as follows: an overall tightness coefficient of 5.16, a tightness of the lags greater than one of 0.57, a sum-of-coefficient prior of 2.95, a co-persistence prior of 3.84 and a prior on the covariance matrix of 2.00.

[25]Recall from Figure 1 that a positive uncertainty shock of one standard deviation can be considered as a relatively mild shock, given that our baseline measure of survey-based uncertainty during the Great Recession, during the the Covid-19 pandemic and the Russian invasion of Ukraine witnessed increases of roughly 2, 4, and 5 standard deviations uncertainty.

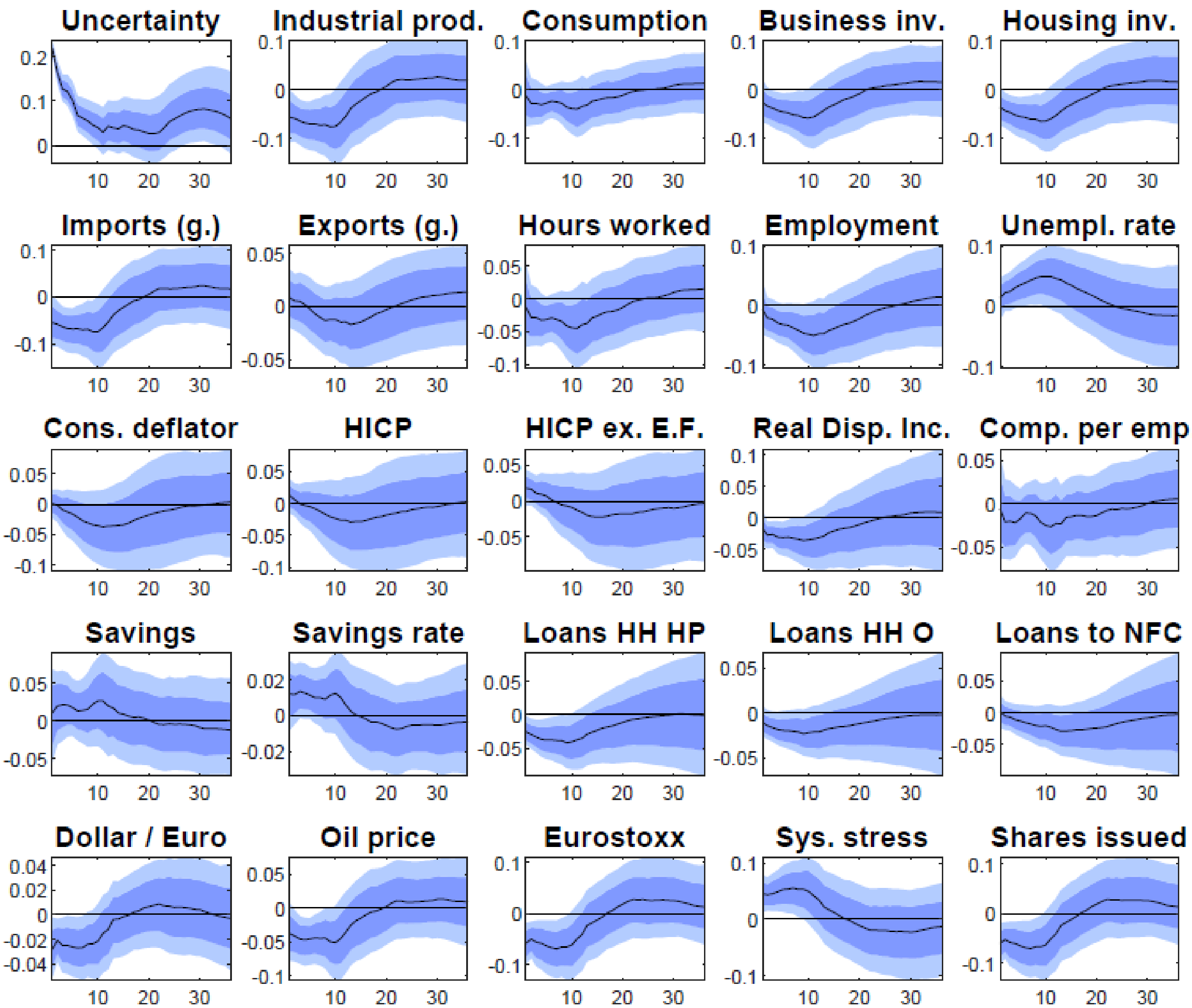
report impulse responses in standard deviation units of year-on-year growth rates (for non-stationary variables in levels). Table 2 below reports the impact in year-on-year growth rates for some key variables.

From Panel A we can extract the following conclusions with regard to key macroeconomic variables. First, macroeconomic activity tends to decline immediately and significantly after the uncertainty shock, in line with theoretical expectations, with industrial production year-on-year growth declining by a peak of 0.43% nine months after the uncertainty shock. Subsequently, industrial production recovers and exhibits some, albeit insignificant overshooting starting about 18 months after the uncertainty shock. In terms of components of demand, private consumption declines only marginally and weakly significant in the wake of an uncertainty shock, while both business and housing investment take significant hits, with year-on-year growth falling by a maximum of 0.37% and 0.3% after about 9-10 months, respectively. Subsequently, both business and housing investment recover and exhibit some, albeit insignificant overshooting, supporting the wait-and-see theory of uncertainty. Imports decline significantly on impact reflecting the hit on investment, while exports do not move. The stickiness of exports seems to be an explanation for the relatively small impact on overall activity and suggests that we are not confounding the exogenous domestic shock to uncertainty with a different shock coming from outside the euro area.

Second, employers tend to reduce employment in persons rather than hours worked per employee, pushing down compensation of employees and leading to a small increase in the unemployment rate. Third, prices do not exhibit any significant impact of the uncertainty shock, suggesting that uncertainty impacts similarly on demand and supply, thus hardly affecting sticky prices. Both consumer prices such as the private consumption deflator, the HICP and its main components as well as producer prices exhibit only insignificant downward impact of the uncertainty shock, perhaps also partly explained by the insignificant impact on wage growth and the small decline in oil prices. As a major exception, house prices tend to fall significantly, as households and construction firms tend to postpone housing investment in times of elevated uncertainty as reflected in the impact on building permits. In this context, loans by private households for house purchases tend to decline as do interest rates paid by households on housing credits.

Figure 2: IRFs to an uncertainty shock (+ 1 std. dev.), baseline FAVAR model.

Panel A



Notes: Median (line), percentiles 32-68 (darker band), percentiles 10-90 (lighter band). See Table A2 for a complete description of the variables included. "prod." means production, "inv." stands for investment, "imports (g.)" and "exports (g.)" refers to imports and exports of goods, "HICP exc. E.F." is the HICP excluding energy and food, "Real Disp. Inc." is real disposable income, "Comp. per emp." is compensation per employee, "Loans HH HP" are loans to households for house purchase, "Loans HH O" are loans to households for other purposes, "NFCs" are non-financial corporations, and "Syst. stress" means systemic stress.

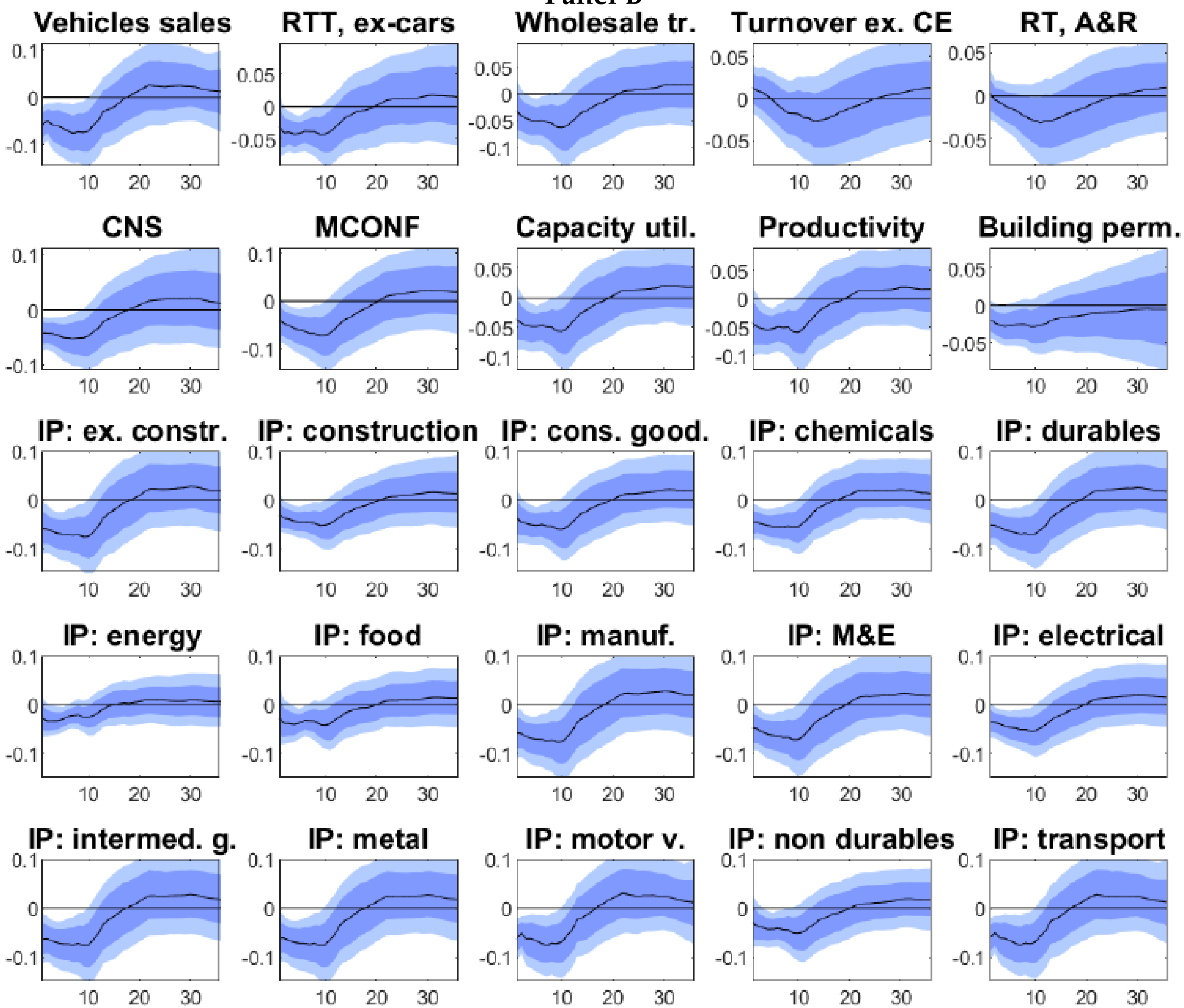
Fourth, as private consumption declines somewhat stronger on impact after the uncertainty shock than real disposable income, we find a muted, albeit insignificant upward effect on savings and the saving rate, suggesting a mild short-term upward impact on precautionary savings in the context of higher unemployment. In the medium term, we do not find any significant impact on uncertainty on either consumption, income or savings.

Fifth and turning to the impact of uncertainty on financial markets, share prices as proxied by the Eurostoxx decline significantly on impact and remain depressed by around 1.5 years after the uncertainty shock. This has an accompanying downward impact on shares issues by domestic residents. We also find a significant upward effects on systemic stress in financial markets as proxied by the CISS. Finally, the contractionary impact of uncertainty on activity involves a downward impact on oil prices and a depreciation of the euro against the dollar.

The data-rich nature of our approach allows us to shed light on the impact of uncertainty in even more detail and disaggregation. In Panel B we can observe the responses of disaggregated consumption and industrial output. First, both vehicle sales and retail trade excluding cars as well as wholesale trade decrease significantly after the uncertainty shock, with the first dropping most markedly as such purchases might be postponed most easily. In contrast, manufacturing turnover excluding energy and construction as well as retail trade in accommodation and restaurants do not exhibit significant impacts. Second, uncertainty implies an immediate downward impact on aggregate confidence and business confidence lasting for about 9-10 months, followed by a recovery and insignificant overshooting. Third, in the lower part of panel B we show the impact of an uncertainty shock on disaggregated industrial production. We find that the downward impact on durable consumer goods production is stronger and longer lasting than that on non-durable consumer goods, while there is a significant downward impact across industries producing intermediate and investment goods. Detailed information on the impact of manufacturing turnover as shown in Figure A3 in the appendix broadly confirms these findings. Finally, we find a short-lived, but significant downward impact on capacity utilisation in manufacturing and on productivity growth in manufacturing.

Figure 2 (cont.): IRFs to an uncertainty shock (+ 1 std. dev.), baseline FAVAR model.

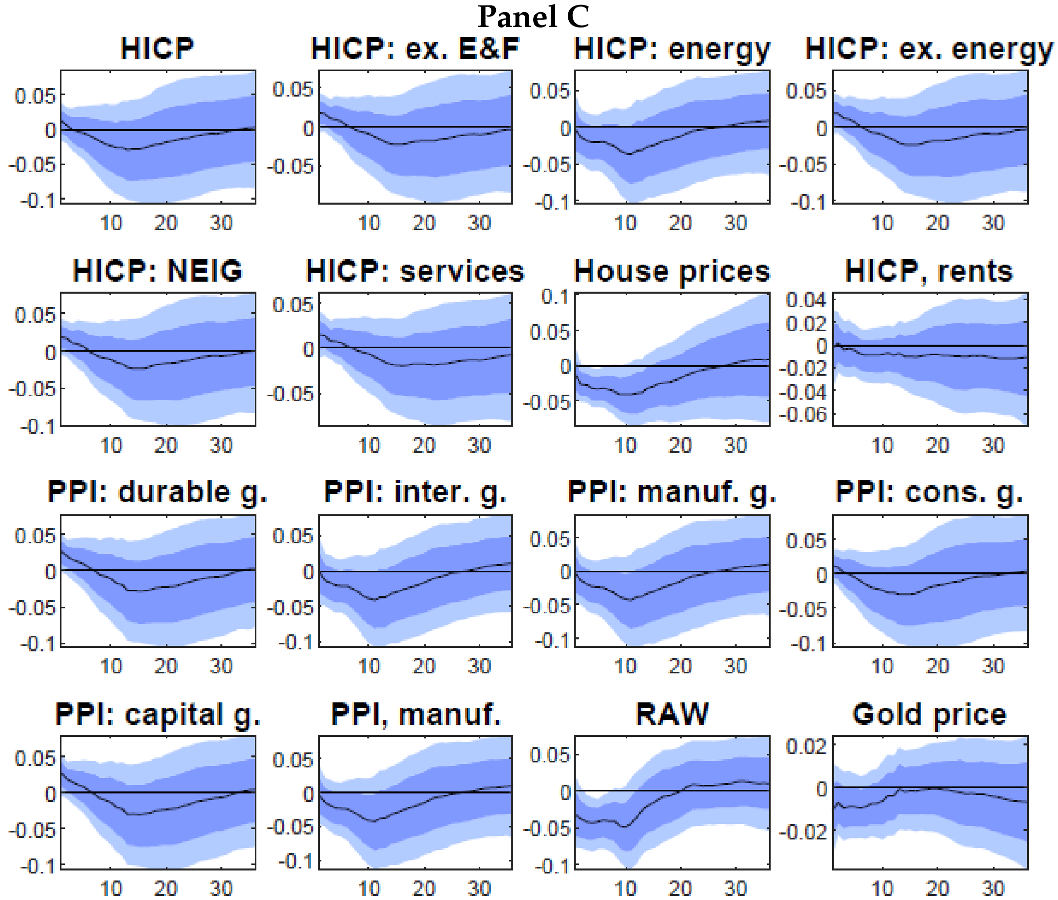
Panel B



Notes: Median (line), percentiles 32-68 (darker band), percentiles 10-90 (lighter band). See Table A2 for a complete description of the variables included. "RTT" is retail trade turnover, "tr." is trade, "CE" is construction and energy, "RT, A&R" is retail trade, accommodation and restaurants, "perm." means permits, "ex. constr." means excluding construction, "v." are vehicles, "manuf." is manufacturing, "M%E" means machinery and equipment.

The impulse responses in Panel C shed more light on the impact of uncertainty on inflation. Overall, we find insignificant impacts on both consumer prices and producer prices, at aggregated and disaggregated levels. In particular, housing rents as one of the biggest components of the HICP exhibit no significant impact, and energy prices hardly react despite the downward impact on oil prices. Turning to non-energy industrial goods and services prices as proxies for domestic core inflation, we find a weakly significant upward impact of uncertainty on impact lasting for a few months, followed by a more permanent, albeit insignificant downward impact in the following two years. We find a similar pattern for producer prices of capital and consumer goods.

Figure 2 (cont.): IRFs to an uncertainty shock (+ 1 std. dev.), baseline FAVAR model.

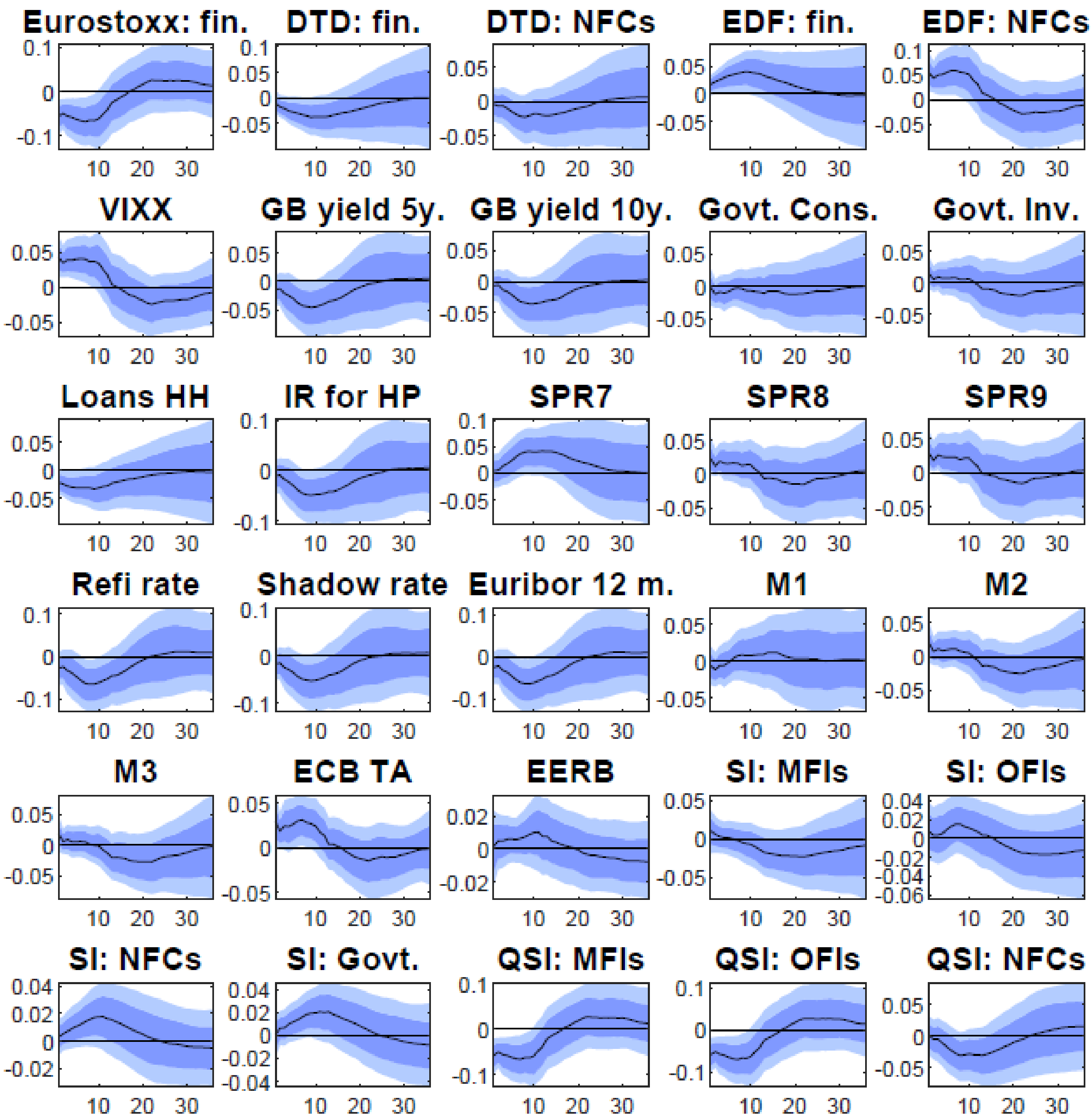


Notes: Median (line), percentiles 32-68 (darker band), percentiles 10-90 (lighter band). See Table A2 for a complete description of the variables included. "HICP: ex. E&F" is the HICP deflator excluding energy and food, "PPI" are producer price indexes, "g." means goods, "inter." means intermediate, "manuf." is manufacturing.

Turning in more detail to the impact of uncertainty on financial markets, Panel D suggests a broadly comparable significant upward impact on financial stress and equity volatility, as well as similar downward effects on the overall Eurostoxx and its financial subcomponent. We find a weakly significant response from monetary policy, with short-term interest rates slightly lower, money supply slightly up and ECB total assets significantly higher. Investors appear to re-direct their funds into non-equity securities, implying a downward impact on interest rates and bond yields across the maturity spectrum. MFI loans to non-financial corporations and the 10-year (euro area average) government bond yield spread don't react on impact, which suggests that we do not capture a financial shock in our identification, either via the banking system or the sovereigns' finances. On the other hand, loans to private households, and notably those aimed at house purchases, decline significantly on impact and over the following months, and the related credit spreads increase. We also find that both financial institutions and non-financial corporations tend to reduce the issuance of quoted shares in response to an uncertainty shock, while notably the latter appear to issue more other securities to maintain refinancing. The uncertainty shock appears to lower the distance to default and increase expected default rates for financial and non-financial companies, suggesting a possible channel by which uncertainty might affect financial stability. Finally, the gold price does not change significantly during the considered horizon, possibly suggesting that we are not confounding the uncertainty shock with a global shock.

Figure 2 (cont.): IRFs to an uncertainty shock (+ 1 std. dev.), baseline FAVAR model.

Panel D



Notes: Median (line), percentiles 32-68 (darker band), percentiles 10-90 (lighter band). See Table A2 for a complete description of the variables included. ”fin.” refers to financial companies, ”DTD” means distance to default, ”NFCs” are non-financial corporations, ”GB” stands for Government bond, ”HH” are households, ”IR for HP” are interest rates households' loans for house purchase, ”ECB TA” means ECB total assets, ”SI” refers to securities other than shares issued, ”MFIs” are monetary financial institutions and ”OFIs” stands for other financial institutions. ”QSI” means quoted shares issued.

Table 2: Overview of median responses to an uncertainty shock.

Variable	Peak impact (%)				Month	
	min.		max.		min.	max.
Industrial production	-0.43	**	0.15		9	30
Consumption	-0.10	*	0.03		11	36
Business investment	-0.37	**	0.11		10	32
Housing investment	-0.30	**	0.09		9	32
Imports (goods)	-0.48	**	0.16		9	30
Exports (goods)	0.00		0.00		13	36
Hours worked	-0.12	*	0.04		11	36
Employment	-0.06	*	0.02		11	36
HICP	-0.05		0.02		13	1
Real disposable income	-0.04	*	0.01		9	33
Savings	-0.13		0.29		36	10
Savings rate	-0.01	*	0.02		22	3
Dollar / Euro exchange rate	-0.33	**	0.10		1	22
Oil price	-1.86	*	0.50		10	31
Eurostoxx 50	-1.41	**	0.57		7	22
Systemic stress	-0.03		0.06	**	30	7
Shares issued	-1.42	**	0.58		7	22
House prices	-0.14	*	0.03		9	34
DTD, financial firms	-0.07	*	0.00		9	34

Notes: An uncertainty shock is an unanticipated positive shock to our survey-based uncertainty measure of one standard deviation. "Peak impact (%)" refers to the minimum and maximum percent change observed in response to the shock according to the median draw, and "Months" refers to the number of months after the shock it takes to reach those minimum and maximum impact, respectively, on the corresponding variable. DTD means "distance to default". * and ** mean that the minimum or maximum effect on the corresponding selected variable is statistically significant at the 32% or 10% significance level, respectively.

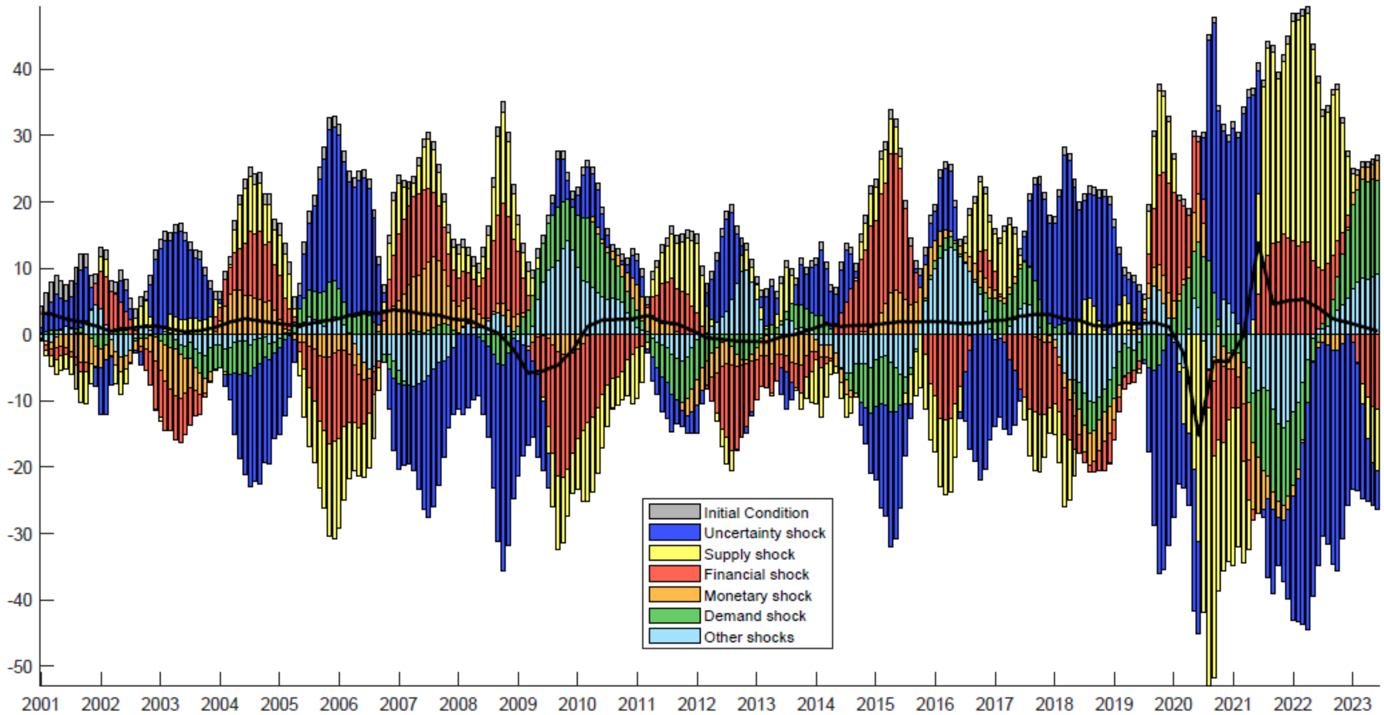
4.3 Historical decomposition

In order to assess the contribution of uncertainty shocks relative to the contribution of other shocks in the economy we plot the historical decomposition of shocks to real GDP in Figure 3. A few results stand out. First, macroeconomic uncertainty contributed negatively to activity during periods of economic weakness such as in the follow-up to the 9/11 attacks and around the turn of 2004/05, and it contributed significantly to the economic recessions that hit the euro area, notably the Great Financial Crisis (GFC) of 2008/09 and the euro area debt crisis of 2011/12. This is in line with Popp and Zhang (2016), who find that the macroeconomic effects of uncertainty shocks are quantitatively larger during recessions using US data. More recently, uncertainty contributed negatively to activity at the outset of the covid-pandemic and since the start of the war in Ukraine.

Second, the absence of uncertainty appears to have contributed positively to activity in periods of expansion, such as in 2005/06 and during recovery periods such as in 2009/10 after the GFR and in 2013/14 in the wake of the euro area debt crisis. Third, the chart suggests a few periods where uncertainty started to contribute negatively to activity well ahead of major economic crises. For example, uncertainty started to contribute negatively to activity from the second half of 2006 onwards, following a few years of robust growth and well ahead of the first signs of the GFR. Uncertainty also started to contribute negatively to activity during the course of 2019, after a long period of expansion and well ahead of the pandemic recession. In this context, the emergence of negative contributions of uncertainty to activity could possibly be interpreted as an early warning for forthcoming recession in activity.

Finally, our data-rich approach offers a new interpretation of the impact of shocks during the pandemic recession in the euro area. In particular, uncertainty seems to have stopped contributing negatively to activity rather early in 2020, with supply-side shocks relating to the introduction of lockdown measures and supply-chain disruptions taking over the major downward contributions.

Figure 3: Historical decomposition of uncertainty and other shocks to real GDP.



Notes: The uncertainty shock is defined as a positive one standard deviation shock to our uncertainty measure. The y-axis is in annual log-differences.

4.4 Forecast error variance decomposition

Additionally, we have computed the contribution of uncertainty shocks to the volatility of the observable factors in our FAVAR model. The resulting forecast error variance decomposition is displayed in Table 3. There are two main findings from this exercise. First, the contribution of uncertainty shocks to the volatility of our uncertainty measure is overwhelmingly dominant, which we take to suggest that our uncertainty measure captures actual uncertainty and is not primarily endogenous to other macroeconomic shocks. Second, the contribution of uncertainty shocks to the volatility of real GDP growth, government bond spreads, short-term interest rates and producer price inflation and the five factors is relatively low, but increasing with the length of the forecast horizon.

Table 3: Forecast error variance decomposition

	F 1	**F 2**	**F 3**	**F 4**	**F 5**	**YER**	**STR3**	**SPR4**	**PPIT**	**Unc.**
3 months ahead	1.51	1.31	0.59	0.28	0.38	0.23	0.12	0.13	0.27	68.80
6 months ahead	1.95	0.91	2.87	0.40	0.87	0.37	0.66	0.90	0.55	59.95
12 months ahead	1.06	2.26	2.95	1.37	1.87	1.01	1.26	2.40	0.39	34.05
24 months ahead	1.03	2.60	6.18	2.46	7.94	0.85	1.43	2.11	1.43	23.64
36 months ahead	1.79	3.44	15.48	6.82	10.30	2.15	2.50	6.66	4.10	24.88

Notes: F1 to F5 refer to the five factors summarizing our macro dataset. YER is real GDP, STR3 is the Euribor 3 months, SPR4 is the spread of the government bond yield 10 years versus the 12 months euro money market rate, PPIT is the producer price inflation (domestic) index (total excluding construction) and Unc. is our uncertainty measure Survey.

4.5 Robustness exercises

Overall, we conclude that our baseline model results in reasonable impulse responses to an uncertainty shock. Table A4 in the Appendix summarizes the results of various robustness checks derived from impulse responses on selected macro and financial variables using our baseline model with alternative uncertainty measures. Model (1) refers to our baseline model using a survey-based measure of uncertainty (i.e. SURVEY). Models (2)–(4) use the JLN Macro, JLN Financial, and EPU uncertainty measures, respectively[26]. We can observe that the responses move qualitatively in the same direction irrespective of the uncertainty measure used. Quantitatively, the responses tend to be slightly more contractionary when using SURVEY and the JLN Macro uncertainty measures.

Additionally, Table A5 in the Appendix shows the contribution of uncertainty shocks to real GDP across Models (1) to (4) and horizons. Notably, there is substantial variation in this result across the uncertainty measures. While using our survey-based measure, this figure is between 0%-2% as reported earlier; the use of any of the other three uncertainty measures yields a much larger range of results, being between 0%-12% in the cases of the JLN Financial and EPU, while it rises to roughly 14%-68% using the JLN Macro. This is relevant, as the choice of the latter measure is quite extended in the literature (see Table A1), and might be one of the key reasons why several studies using euro area data find a large contribution of uncertainty shocks to the variability of real GDP or other economic output measures.

[26]Note that these are arguably very different uncertainty measures that might require even a specifically different identification schemes. The closest uncertainty proxy to our baseline is the JLN Macro measure.

5 Discussion

In this section, we will discuss some of our main findings in relation to the recent literature on uncertainty. We will focus on the following aspects: a) how large are the effects of uncertainty, and are there expansionary effects of uncertainty? b) what is the impact of uncertainty on inflation? c) what is the impact of uncertainty on euro area foreign trade and the exchange rate? And d) is there a link between uncertainty and banking as well as financial stability?

First, there is a widespread consensus in the literature that an exogenous uncertainty shock causes a significant, temporary slowdown in activity, with both the real options channel (Bernanke, 1983) and the risk premium channel (see e.g. Christiano et al., 2014; and Gilchrist et al., 2014) being at work. Our main results exhibit the theoretically expected adverse impact on activity, with the latter being significant, albeit relatively small, and we also find a stronger impact on investment than on consumption. Our results are also broadly in line with the findings in other recent empirical studies for the euro area (see Table A1 in the appendix). It is worth noting that, both in terms of the IRFs and the forecast error variance decomposition, our results are closer to studies that include a more comprehensive set of variables in their models (see ECB, 2016 and Gieseck and Rujin, 2020) than to those using small-scale VARs. Overall, the differences to other euro area studies appear to be rather limited, in particular when considering the differences in uncertainty proxies chosen, time periods estimated (mostly excluding the 2020 pandemic), and differences in identification schemes applied. A small, but statistically significant impact of uncertainty on activity is also found in a recent study by Alessandri et al. (2023), who show that a large part of the disagreement in the literature about the size othe impact of uncertainty can be related to identification problems linked to the use of financial data in low-frequency VAR models. One interesting reason for the weak response of activity in the euro area to uncertainty could relate to relatively tight employment protection rules in most euro area countries. Dibiasi and Sarferaz (2023) use a variant of the JLN macroeconomic uncertainty proxy across a large set of countries and show that uncertainty shocks have stronger adverse impacts in countries with low employment protection (such as the US, Canada and the UK) compared to countries with high employment protection (such as Germany, France and Italy). Another factor behind the relatively weak response of activity to uncertainty could be seen in the much more aggressive policy response to the recent uncertainty shocks. Pellegrino et al. (2022) first find that uncertainty shocks have been much larger during the Great Recession than during normal times, and then demonstrate that the more aggressive monetary policy response to the crisis (with respect to the one estimated to be in place in normal times) successfully curbed the output loss that would otherwise have materialised. Our results exhibit an expansionary ECB monetary policy in response to uncertainty, as reflected in the IRFs on short-term interest rates including the ECB's main refinancing operations rate and also on the ECB's total assets.

In terms of components of demand, our findings partly contrast with those of other recent studies. For example, Coibion et al. (2024) find that higher uncertainty causes a sharp reduction in households' spending on non-durable goods and services, notably spending for personal health and care products and services as well as entertainment, holidays and luxury goods. This is in some contrast to our finding of a relatively stronger impact on vehicle sales. Part of the difference could be related to the fact that Coibion et al. (2024) discuss the impact of a very specific uncertainty shock in the context of the pandemic recession across a limited sample of private households, while we look at the impact of uncertainty over a longer sample at the overall economy level. Our finding of a muted and insignificant increase of the savings ratio in response to uncertainty is a bit surprising, notably in the context of an increase in unemployment; other studies typically find an upward impact of higher unemployment on pre-cautionary savings (e.g. Dossche and Zlatanos, 2020; Campos and Reggio, 2015; and Ravn and Sterk, 2017). It is, however, consistent with our finding of both consumption and income moving broadly into the same direction.

Our findings of rising uncertainty significantly dampening investment in the euro area are broadly in line with those of other recent studies. For example, Kolev and Randall (2024) use firm-level survey data and find economically significant downward effects on firm-level investment; Meinen and Röhe (2017) also find mostly significantly negative effects of uncertainty on investment across the four largest euro area countries, albeit they also find that investment exhibits different IRFs across the various uncertainty measures analysed.

A recent strand in the literature assesses the possibility of "good" uncertainty effects, i.e. of an increase in uncertainty causing expansionary effects on activity (see e.g. Segal et al., 2015; Forni et al., 2024). In this case, the "growth options" channel operates dominantly, according to which a mean-preserving increase in upside uncertainty increases the opportunity of high profits, stimulating investment and growth. It has also been proposed to differentiate between good and bad uncertainty as well as between expected and unexpected uncertainty; Uribe and Chulia (2023) find that it is bad-unexpected uncertainty shocks causing significant declines in activity, while expected uncertainty or good uncertainty might induce more ambiguous effects on activity. While our paper does not focus on this part of the literature, we do not find any significant upside effects of uncertainty in any of our IRFs, probably related to the fact that our uncertainty measures are generally countercyclical.

Second, from a theoretical standpoint and in models featuring price rigidities, the impact of an uncertainty shock on inflation is a priori uncertain as there are two channels at work. The standard demand channel would induce inflation to move into the same direction as activity; with uncertainty typically dampening consumption and investment, it would thus cause deflationary effects. At the same time, a pre-cautionary pricing channel could work as firms subject to price rigidities may have the incentive to set prices above the level they would target in the absence of uncertainty to avoid losing profits in case favorable economic conditions realize in the future. Oh (2020) shows that the response of inflation to an uncertainty shock depends on the structural source of price rigidity: uncertainty causes inflation to increase in a Calvo setting, while to decline in Rotemberg setting. In the Rotemberg (1982) model, a firm can adjust its price whenever it wants after paying a quadratic adjustment cost. Since their pricing decision is symmetric, all firms behave as a single representative firm. Thus, the firms are risk-neutral concerning their pricing decision. This implies that only the aggregate demand channel is at work, and the decrease in marginal costs induces firms to lower their prices. Consequently, inflation decreases in the Rotemberg model. On the other hand, in the Calvo (1983) model, each firm may reset its price only with a constant probability each period, independent of the time elapsed since the last adjustment. This pricing assumption generates heterogeneity in firms' prices and implies that firms are risk-averse regarding their pricing decision. Thus, the pre-cautionary channel implies that higher uncertainty induces firms which are resetting their prices to increase them so as to self-insure against being stuck with low prices in the future. If firms lower their prices, they may sell more but at negative markups, thereby incurring losses. As a result, inflation increases in the Calvo model.

While our findings point towards the dominance of demand side effects in the euro area (output declines, unemployment increases), the impact on inflation is overall insignificant, along the lines of Meinen and Röhe (2018) which show an ambiguous response of inflation to both financial and uncertainty shocks in the US and the euro area. Nevertheless, our findings are somewhat in contrast to those of De Santis and Van der Veken (2022) who find a significant upward impact of uncertainty for inflation in the US, but also to those of Leduc and Liu (2016) as well as Haque and Magnusson (2021) who find a deflationary impact of uncertainty. One possible explanation for our finding of insignificant impacts on inflation could be that our sample is dominated by a period of very low inflation, and in such a setting firms might not respond to higher uncertainty by increasing their markups. This points to the need for further research to uncover whether higher uncertainty significantly contributes to higher inflation only during periods when inflation is already high. Another reason for our tentative finding of uncertainty acting in the sense of demand shocks could be that our sample is limited to the period since early 2001; using rolling samples, Choi (2017) shows for the US that the nature of uncertainty shocks changed from supply-side shocks in earlier periods, closely related to oil price movements, to demand-side shocks in more recent periods. In our case, it is noteworthy that we find a demand-side impact on oil prices, while a small, albeit insignificant upward impact on the effective exchange rate of the euro counteracts imported inflation.

Third, from a theoretical standpoint, the impact of uncertainty on foreign trade is unclear. Baley et al. (2020) demonstrate in a theoretical model that hikes in uncertainty increase both the mean and the variance in returns to exporting. This implies that trade can increase or decrease with uncertainty depending on preferences. Higher uncertainty may lead to increases in trade because agents receive improved terms of trade, particularly in states of nature where consumption is most valuable. Empirical studies tend to exhibit a downward impact of uncertainty on trade (e.g. De Sousa et al., 2020, with the majority of papers using indicators of trade policy uncertainty. We do not find a significant downward impact of macroeconomic uncertainty on exports, while imports decline broadly in line with industrial production and probably related to the adverse shock on investment, but less so than could be expected following the typical import multiplier. The response of imports relative to output is also smaller than in Novy and Taylor (2020) who find that in the US imports respond five times stronger to a shock in trade uncertainty than industrial production and relate this to higher fixed costs for imported inputs than for domestically produced inputs. Concerning the exchange rate of the euro, our results show a depreciation of the euro against the US dollar, while the euro exhibits no significant impact against a broader set of exchange rates. This is in some contrast to the model of Akinci et al. (2022) which indicates an appreciation of the U.S. dollar after an uncertainty shock in the US owing to an increase in risk premium.

Finally, there is a rich literature on the interaction between uncertainty shocks and financial frictions. To give only a few examples, Juelsrud and Larsen (2023) find empirical evidence for an adverse impact of macroeconomic uncertainty on bank lending in Norway. Alessandri and Bottero (2020) analyse the impact of economic uncertainty on credit supply using monthly data on corporate loan applications received by Italian banks between 2004 and 2012. They find that an increase in aggregate uncertainty lowers the likelihood that firms' applications will be successful, and it prolongs the time firms have to wait for their loans to be disbursed. Our findings broadly concur: loans to households and non-financial companies decline following an uncertainty shock, and the spread on interest rates to such loans over 12-months euro money market rates tend to increase.

There is also theoretical and empirical evidence suggesting that financial frictions amplify the adverse effects of uncertainty on economic activity. Bonciani and van Roye (2016) use a DSGE model with heterogenous agents and a stylized banking sector and show that frictions in credit supply (mostly stickiness in banking retail interest rates) amplify the effects of uncertainty shocks on economic activity in the euro area. Similarly, Alfaro et al. (2024) build a general equilibrium heterogeneous firms model with real and financial frictions and find that financial frictions (i) amplify uncertainty shocks by doubling their impact on output, (ii) increase persistence by doubling the duration of the drop; and (iii) propagate uncertainty shocks by spreading their impact onto financial variables. Turning to empirical papers, Alessandri and Mumtaz (2019) apply a non-linear VAR for US data and find that the impact of uncertainty on economic activity is six times larger when the economy is going through a financial crisis. Our results deviate. On the one hand, we do find that uncertainty increases financial stress in the euro area, as exhibited by the upward impact on systemic stress and implied equity price volatility as well as the downward impact on equity prices and house prices. However, as argued above, we do not find particular large adverse effects of uncertainty on activity in the euro area. In this context it is again worthwhile to look at the impulse responses by ECB interest rates and of ECB total assets. Even though the uncertainty shock does not induce any significant inflationary or deflationary effects, the downward impact on the refinancing rate and the upward impact on ECB total assets could be interpreted that the ECB reacted with monetary policy tools to mitigate any adverse effects of the uncertainty shock in terms of financial stability.

6 Conclusions

This paper estimates the effects of uncertainty shocks on a large set of economic and financial variables in the euro area. To provide estimates that are robust to substantial empirical challenges, we adopt the following approach. First, we build a large macro dataset with euro area wide data, which we summarize by principal components. Second, we estimate a FAVAR model using a survey-based measure of uncertainty and our large summarized dataset. This method has several advantages. It allows us to mitigate the issue of omitting relevant variables in the model, while it gives us room to use more candidate variables for shock identification purposes and to report impulse responses. Third, we identify five shocks by employing a new identification scheme based on sign restrictions exploiting our large dataset, including uncertainty shocks, financial shocks, standard monetary policy shocks, aggregate demand shocks, and supply shocks. Fourth, we show more than one hundred impulse responses to an uncertainty shock, which allows us to contribute to several discussions in the uncertainty literature. Additionally, we provide a forecast error variance decomposition in this FAVAR model, as well as a historical decomposition of shocks to real GDP growth.

Our study concludes that uncertainty shocks have a negative and significant impact on economic activity in the euro area, particularly affecting industrial production, imports, and both business and housing investments. The effects on inflation and savings are muted. We also find that uncertainty shocks increase systemic and financial stability risks. During the Covid-19 recession, the impact of uncertainty shocks waned early as a supply shock became the primary driver of output contraction. Notably, the average contribution of uncertainty shocks to output is relatively low, significantly lower than the range of estimates found in benchmark studies.

Two policy implications stand out in our view. First, uncertainty does not seem to be a major threat to price stability in the euro area. Therefore, there is not clear need to include a measure of uncertainty into forecasting models of inflation. Second, uncertainty can be a threat to financial stability. Therefore, it may be advisable to consider uncertainty in the countercyclical policy tools with the aim of mitigating the impact of uncertainty on credit and financial frictions. We provide evidence that conventional and non-standard monetary policy may have been used with that motive.

Future research could develop our framework further to explore two additional points. First, by using a time-varying model, an interested researcher might study whether the effects of uncertainty on inflation vary with time[27]. Second, it could be explored whether the effects of uncertainty on the euro area economy are state-dependent, where dependencies might come from being in good or bad times and also from financial frictions.

[27] We thank an anonymous referee for this suggestion.

Appendices

A Overview of related studies.

Table A1: Overview of studies on the effects of uncertainty on the euro area economy.

Study	**B (13)**	**ECB (16)**	**GL (16)**	**GR (17)**	**V (18)**	**BB (18)**	**MR (18)**	**GR (20)**
Sample	1996 - 2011	1987 - 2016	1999 - 2015	1999 - 2014	1996 - 2016	1999 - 2017	1999 - 2017	1999 - 2020
Uncertainty measure(s)	M, P	M	M, F, P, SS	S	S, F, P	M	M	M, F
Model	ECM	BVAR	SVAR	SVAR	BVAR	BVAR	BVAR	BVAR
Frequency	Q	Q	Q	Q	Q	Q	Q	Q
N. variables	3, 4	21	5	9	6	6	6	11
Identification	-	Chol.	Chol.	Chol.	-	SR	SR	Chol.
Volatility treat.								LP (20)
Effect IRF on:								
GDP		-0.2%, 2Q	-0.2%, 2Q	-0.3%	-0.2%, 2Q	-0.3%, 4Q	-0.3%, 5Q	-0.1%, 1Q
Consumption	-2%		-0.1%, 3Q					
Investment	-1.6%		-0.5%, 2Q					
Prices							0.15%, 8Q	
FEVD GDP	-	20%	-	11%-41%	-	30%	23%	-

Notes: Regarding uncertainty measures: M = macro uncertainty, P = policy uncertainty, F = financial uncertainty, SS = systemic stress, S = survey-based uncertainty. Chol. means Cholesky identification. B (13) is Balta et al. (2013), GL (16) is Gieseck and Largent (2016), GR (17) is Girardi and Reuter (2017), V (18) is Vasicek (2018), BB (18) is Bundesbank (2018), MR (18) is Meinen and Roehe (2018), GR (20) is Gieseck and Rujin (2020) and LP (20) means Lenza and Primiceri (2022). Reported results on Vasicek (2018) are referred to the survey-based uncertainty proxy. Meinen and Roehe (2018) results on the IRFs effects refer to the survey-based business measure. FEVD GDP stands for the average contribution of uncertainty shocks to real GDP fluctuations using a forecast error variance decomposition. Comparative results for the FEVD need to be taken with care, given that modeling details across studies differ.

B Overview of variables in the FAVAR model.

Table A2: Variables in the macro dataset, group 1: Output and income

N	tcode	Variable	Description
1	4	YER	Real GDP
2	4	WIN	Compensation of employees
3	4	PYR	Real disposable income
4	4	CEX	Compensation per employee
5	4	PCR	Real private consumption
6	4	IHR	Real housing investment
7	4	IPR	Real business investment
8	2	INWR	Indicator of negotiated wages
9	4	JIP	Industrial production
10	4	JIPC	Industrial production: construction
11	4	JIPCG	Industrial production: consumer goods
12	4	JIPCH	Industrial production: chemicals
13	4	JIPDCG	Industrial production: durable consumer goods
14	4	JIPE	Industrial production: energy
15	4	JIPFD	Industrial production: food
16	4	JIPIG	Industrial production: investment goods
17	4	JIPM	Industrial production: manufacturing
18	4	JIPMA	Industrial production: machinery and equipment
19	4	JIPME	Industrial production: electrical
20	4	JIPMG	Industrial production: intermediate goods
21	4	JIPML	Industrial production: metal
22	4	JIPMV	Industrial production: motor vehicles
23	4	JIPNCG	Industrial production: non-durable consumer goods
24	4	JIPTR	Industrial production: transport
25	4	JIPX	Industrial production excl. construction
26	4	JIPXE	Industrial production excl. construction and energy
27	4	UCAP	Capacity utilization in manufacturing
28	4	GCR	Government consumption
29	4	GIR	Government investment
30	1	INV_GDP	Private investment / output ratio

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 2: Labour market

N	tcode	Variable	Description
1	2	URX	Unemployment rate
2	4	UNN	Unemployed, level
3	4	LNN	Employment
4	4	LHN	Hours worked
5	4	LFN	Labour force

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 3: Trade, turnover and sales

N	tcode	Variable	Description
1	4	RTURN	Retail trade turnover
2	4	RTURNMV	Sales of motor vehicles
3	4	RTURNX	Retail trade turnover, excluding cars
4	4	TURNCE	Turnover: chemicals
5	4	TURNDCG	Turnover: durable consumer goods
6	4	TURNIG	Turnover: investment goods
7	4	TURNMA	Turnover: machinery and equipment
8	4	TURNMAN	Turnover: manufacturing
9	4	TURNMV	Turnover: motor vehicles
10	4	TURNNDCG	Turnover: non-durable consumer goods
11	4	TURNTR	Turnover: transport
12	4	TURNTXCE	Turnover: total excl. construction and energy
13	4	ACCR	Retail trade: accommodation and restaurants
14	4	CARS	Car registrations: passenger cars
15	4	DTURNTXC	Turnover: domestic excl. construction
16	4	WTURN	Wholesale trade
17	3	BUILDNR	Building permits: all non-residential
18	3	BUILDO	Building permits: office buildings
19	3	BUILDT	Building permits: all residential

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 4: Interest rates, credit spreads and exchange rates

N	tcode	Variable	Description
1	2	MRO	ECB main refinancing operations reference rate
2	2	SIR	Shadow interest rate (Wu and Xia, 2017)
3	2	STR1	Euribor 1 month
4	2	STR3	Euribor 3 months
5	2	STR6	Euribor 6 months
6	2	STR12	Euribor 12 months
7	2	IR_LHP	Interest rates, loans to households for house purchase (new business)
8	2	IR_LHC	Interest rates, loans to households for consumption (new business)
9	2	IR_LNFC	Interest rates, loans to corporations (new business)
10	2	GBY10	Government bond yield, 10 years
11	2	GBY5	Government bond yield, 5 years
12	1	SPR7	Credit spread = IR_LHP - Euro money market rate 12 months
13	1	SPR8	Credit spread = IR_LHC - Euro money market rate 12 months
14	1	SPR9	Credit spread = IR_LNFC - Euro money market rate 12 months
15	1	SPR4	Credit spread = GBY10 - Euro money market rate 12 months
16	2	EXR	USD/euro exchange rate
17	4	EERB	Nominal effect. exch. rate of euro vs. EER-42 group of trading partners
18	4	EERN	Nominal effect. exch. rate of euro vs. EER-12 group of trading partners
19	1	OIS_3M	OIS changes around PRW, 3 months
20	1	SPR9_UM	SPR9 / SURVEY (uncertainty measure) ratio

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively. PRW means press release window, from the EA-MPD dataset (see Altavilla et al., 2019).

Table A2 (cont.): Variables in the macro dataset, group 5: Prices

N	tcode	Variable	Description
1	4	HIC	HICP
2	4	HEFX	HICP: excluding energy and food
3	4	HEG	HICP: energy
4	4	HEX	HICP: excluding energy
5	4	NEIG	HICP: NEIG
6	4	SERV	HICP: services
7	4	IHX	House price index
8	4	PPICG	Producer price inflation (domestic): capital goods
9	4	PPIDCG	Producer price inflation (domestic): durable consumer goods
10	4	PPIIG	Producer price inflation (domestic): intermediate goods
11	4	PPIM	Producer price inflation (domestic): manufacturing
12	4	PPIT	Producer price inflation (domestic): total excl. construction
13	4	PPITCG	Producer price inflation (domestic): consumer goods
14	4	PCD	Private consumption deflator
15	4	HICH	HICP: housing rents
16	4	RAW	Industrial prices: raw materials
17	4	GOLD	Gold price
18	4	OIL	Oil price

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 6: Financial market

N	tcode	Variable	Description
1	4	STOXX	Eurostoxx price index
2	4	STOXF	Eurostoxx price index: financial companies
3	1	SSCI	Systemic stress
4	2	VIXX	VIXX volatility index
5	4	SECUR2	Securities other than shares issued: MFIs
6	4	SECUR3	Securities other than shares issued: OFIs
7	4	SECUR4	Securities other than shares issued: NFCs
8	4	SECUR5	Securities other than shares issued: General government
9	4	SECUR51	Quoted shares issued: total economy
10	4	SECUR52	Quoted shares issued: MFIs
11	4	SECUR54	Quoted shares issued: NFCs
12	4	SECUR55	Quoted shares issued: OFIs
13	1	DTFFIN	Moody's distance to default: financial companies
14	1	DTFNFC	Moody's distance to default: NFCs
15	1	EDFFIN	Moody's expected default frequency: financial companies
16	2	EDFNFC	Moody's expected default frequency: NFCs
17	4	ECB_TA	ECB total assets
18	1	STOX_50	Stoxx50 changes around the press release window (PRW)

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively. MFIs are monetary financial institutions, OFIs stands for other financial institutions and NFCs are non-financial corporations. PRW means press release window around monetary policy events from the EA-MPD dataset (see Altavilla et al., 2019).

Table A2 (cont.): Variables in the macro dataset, group 7: Confidence

N	tcode	Variable	Description
1	3	PMICOMEMP	PMI: composite employment
2	3	PMICOMNEW	PMI: composite new orders
3	3	PMICOMOUT	PMI: composite output
4	3	PMIMANEMP	PMI: manufacturing employment
5	3	PMISEREMP	PMI: services employment
6	1	MCONF	Industrial confidence indicator
7	1	CNS	Confidence: average of consumer, manufacturing and constr. surveys

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 8: Money, credit, and savings

N	tcode	Variable	Description
1	4	MONEY1	M1 money stock
2	4	MONEY2	M2 money stock
3	4	MONEY3	M3 money stock
4	4	LNFC	Loans to NFCs
5	4	LHH	Loans to household
6	4	LHPR	Loans to households: housing purchase
7	4	LNHPR	Loans to households: other loans
8	1	SAX	Savings rate (%)
9	4	SAV	Savings

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

Table A2 (cont.): Variables in the macro dataset, group 9: Foreign trade and productivity

N	tcode	Variable	Description
1	4	MGR	Real imports of goods
2	4	XGR	Real exports of goods
3	4	FTURNTXC	Turnover: foreign, excl. construction
4	2	PRO	Productivity
5	2	GON	Gross operating surplus
6	1	GOX	Profit share

Notes: tcodes equal to 1, 2, 3 and 4 refer to no transformation, differences, logs and log-differences, respectively.

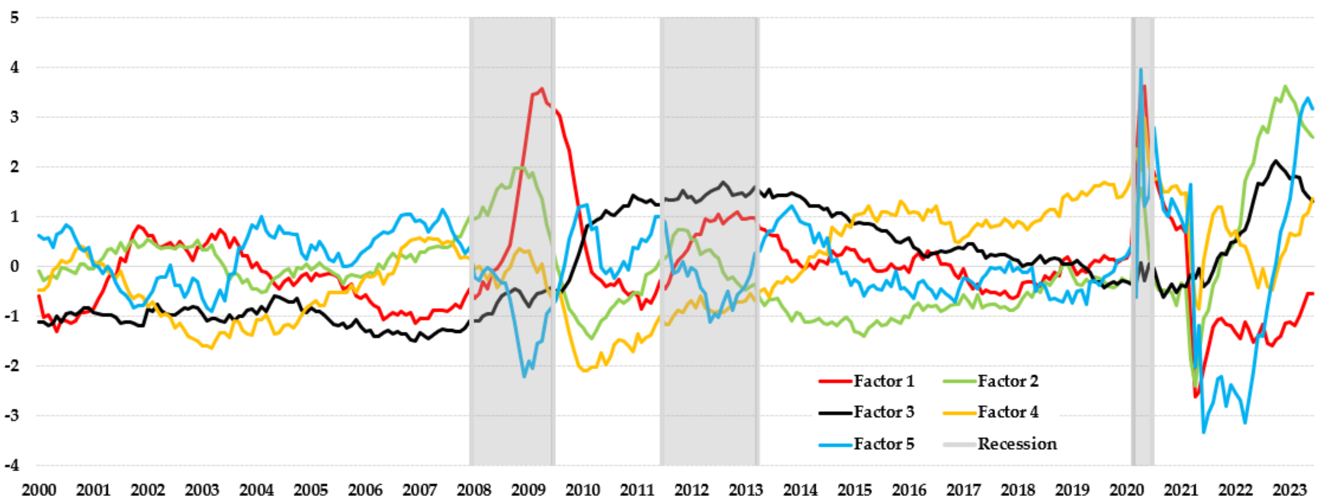
C Principal component analysis.

Table A3: Top 10 variables in the dataset in terms of explanatory power of each factor

	Factor 1	mR2	Factor 2	mR2	Factor 3	mR2	Factor 4	mR2	Factor 5	mR2
1	TURNMAN	0,90	HEX	0,74	LHH	0,76	SECUR55	0,65	PCR	0,22
2	DTURNTXC	0,86	HEFX	0,70	BUILDNR	0,70	SPR9	0,56	CEX	0,21
3	TURNMA	0,81	SERV	0,64	BUILDT	0,70	SPR8	0,51	SAV	0,20
4	MCONF	0,80	PPIDCG	0,63	LNFC	0,62	DTFNFC	0,37	LHN	0,19
5	WTURN	0,79	HIC	0,62	LHPR	0,56	TURNTXCE	0,30	JIPMV	0,18
6	PMIMANEMP	0,78	NEIG	0,60	DTFFIN	0,55	XGR	0,29	IRLNFC	0,18
7	JIPXE	0,77	PPITCG	0,59	MONEY3	0,55	UNN	0,27	STR6	0,16
8	JIP	0,77	PPICG	0,58	GCR	0,53	URX	0,27	MRO	0,16
9	JIPM	0,77	PCD	0,58	MONEY2	0,50	SECUR3	0,21	STR1	0,16
10	MGR	0,77	SPR7	0,43	GIR	0,48	HICH	0,16	STR12	0,15

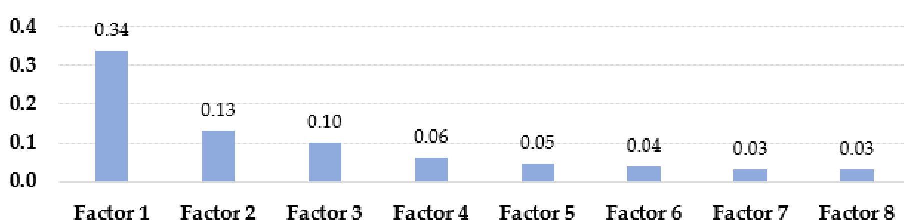
Notes: Each double column refer to each factor, as plotted in Figure A1. The variables codes refer to those specified in Table A2. mR2 refers to the marginal R^2 of each variable in explaining each factor.

Figure A1: The 5 factors summarizing our euro area dataset



Notes: See Section 4 and Table A2 for the detailed description of variables summarized by these five factors.

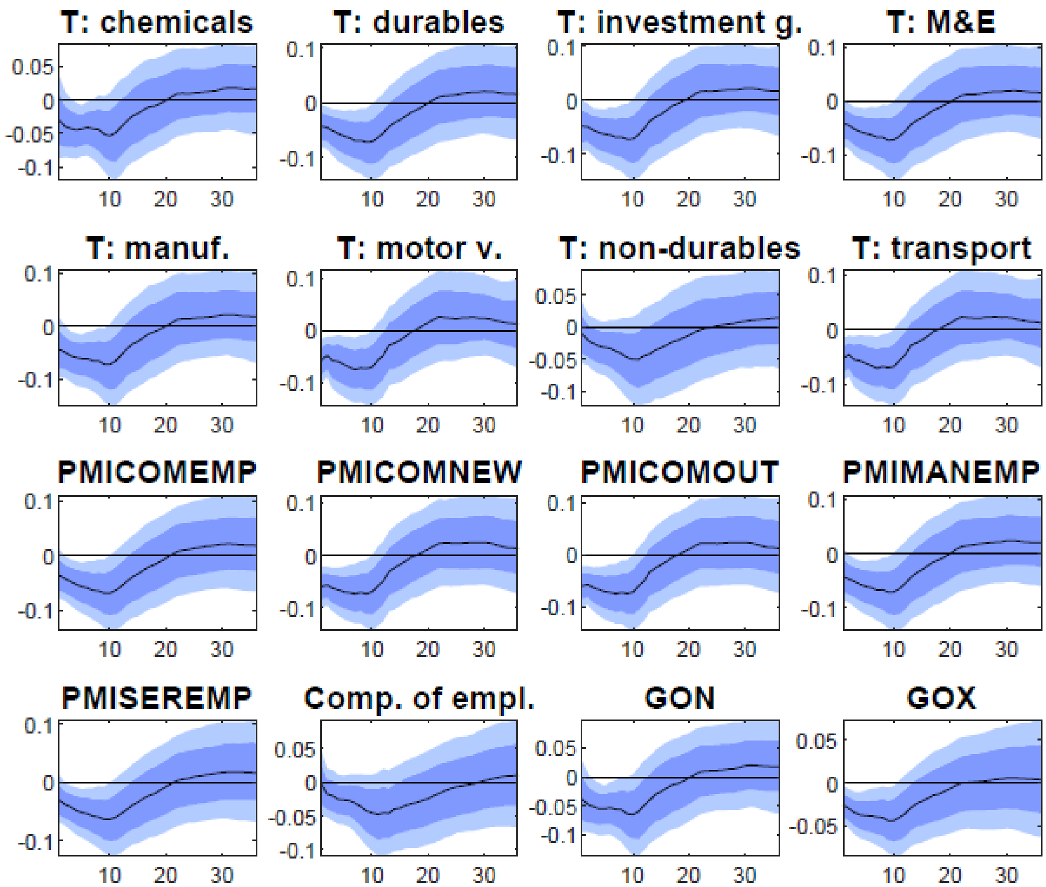
Figure A2: Scree plot of the marginal R^2 for each factor



Notes: y-axis is the marginal R^2, x-axis is each of the first eight factors summarizing our dataset.

D Additional impulse responses.

Figure A3: IRFs to an uncertainty shock (+ 1 std. dev.), baseline FAVAR model.



Notes: Median (line), percentiles 32-68 (darker band), percentiles 10-90 (lighter band). See Table A2 for a complete description of the variables included. "T" stands for turnover, "M&E" means machinery and equipment, "motor v." are motor vehicles.

E Robustness exercises.

Table A4: Overview of median responses to an uncertainty shock across models.

Model	**(1)**				**(2)**				**(3)**				**(4)**			
Uncertainty measure	**SURVEY**				**JLN Macro**				**JLN Financial**				**EPU**			
Variable	**Peak impact (%)**				**Peak impact (%)**				**Peak impact (%)**				**Peak impact (%)**			
	min.		**max.**		**min.**		**max.**		**min.**		**max.**		**min.**		**max.**	
Industrial production	-0.43	**	0.15		-0.31	*	0.15		-0.41	**	0.15		-0.36	**	0.13	
Consumption	-0.10	*	0.03		-0.05		0.05		-0.11	**	0.04		-0.08	*	0.01	
Business investment	-0.37	**	0.11		-0.27	*	0.15		-0.37	*	0.14		-0.29	*	0.13	
Housing investment	-0.30	**	0.09		-0.20	*	0.13		-0.29	**	0.09		-0.23	**	0.09	
Imports (goods)	-0.48	**	0.16		-0.34	*	0.16		-0.47	**	0.17		-0.41	**	0.14	
Exports (goods)	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	
Hours worked	-0.12	*	0.04		-0.07		0.06		-0.13	*	0.04		-0.09	*	0.03	
Employment	-0.06	*	0.02		-0.04		0.03		-0.06	*	0.02		-0.04	*	0.02	
HICP	-0.05		0.02		-0.05		0.02		-0.06		0.03		-0.04		0.02	
Real disposable income	-0.04	*	0.01		-0.02		0.03		-0.04	**	0.00		-0.03	*	0.01	
Savings	-0.13		0.29		-0.09		0.20		-0.27		0.41	*	-0.16		0.30	
Savings rate	-0.01	*	0.02		-0.01		0.03	**	-0.03		0.03	*	-0.01		0.03	*
Dollar / Euro exc. rate	-0.33	**	0.10		-0.30	**	0.16		-0.22	*	0.07		-0.35	**	0.05	
Oil price	-1.86	*	0.50		-1.29	*	0.53		-1.86	**	0.72		-1.74	**	0.41	
Eurostoxx 50	-1.41	**	0.57		-1.05	**	0.64		-1.25	**	0.52		-1.12	**	0.54	
Systemic stress	-0.03		0.06	**	-0.03		0.04	*	-0.02		0.06	**	-0.02		0.05	**
Shares issued	-1.42	**	0.58		-1.04	**	0.63		-1.25	**	0.52		-1.13	**	0.53	
House prices	-0.14	*	0.03		-0.06		0.08		-0.13	*	0.02		-0.10	*	0.01	
DTD, financial firms	-0.07	*	0.00		-0.04		0.03		-0.06	*	0.02		-0.05	*	0.01	

Notes: An uncertainty shock is an unanticipated positive shock to our survey-based uncertainty measure of one standard deviation. "Peak impact (%)" refers to the minimum and maximum percent change observed in response to the shock according to the median draw on the corresponding variable. DTD means "distance to default". * and ** mean that the minimum or maximum effect on the corresponding selected variable is statistically significant at the 32% or 10% significance level, respectively. "SURVEY" is our baseline survey-based uncertainty measure. "JLN Macro" and "JLN Fin." are the macroeconomic and financial uncertainty measures we compute along the lines of Jurado et al. (2015). "EPU" stands for economic policy uncertainty. See section 2.3 for a discussion about these uncertainty measures. Model (1) is our baseline model, while Models (2)-(4) are models used in our robustness exercises, in which we use of a different uncertainty measure.

Table A5: Forecast error variance decomposition on real GDP across models.

Model	**(1)**	**(2)**	**(3)**	**(4)**
Uncertainty measure	**SURVEY**	**JLN Macro**	**JLN Fin.**	**EPU**
Response variable	**YER**	**YER**	**YER**	**YER**
3 months ahead	0.23	13.80	0.35	0.45
6 months ahead	0.37	59.28	4.00	3.03
12 months ahead	1.01	68.40	2.79	15.63
24 months ahead	0.85	54.37	11.01	14.75
36 months ahead	2.15	50.65	11.57	12.57

Notes: YER is real GDP. "SURVEY" is our baseline survey-based uncertainty measure. "JLN Macro" and "JLN Fin." are the macroeconomic and financial uncertainty measures we compute along the lines of Jurado et al. (2015). "EPU" stands for economic policy uncertainty. See section 2.3 for a discussion about these uncertainty measures. Model (1) is our baseline model, while Models (2)-(4) are models used in our robustness exercises, in which we use of a different uncertainty measure.

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