UNIVERSITA' DEGLI STUDI DI PADOVA

DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI "M.FANNO"

CORSO DI LAUREA MAGISTRALE IN ECONOMICS AND FINANCE

TESI DI LAUREA

"MACROECONOMIC UNCERTAINTY: A NEW MEASURE FOR ITALY"

RELATORE:

CH.MO PROF. EFREM CASTELNUOVO

LAUREANDO: SUKHANJEET SINGH

MATRICOLA N. 1240447

ANNO ACCADEMICO 2021 – 2022

Dichiaro di aver preso visione del "Regolamento antiplagio" approvato dal Consiglio del Dipartimento di Scienze Economiche e Aziendali e, consapevole delle conseguenze derivanti da dichiarazioni mendaci, dichiaro che il presente lavoro non è già stato sottoposto, in tutto o in parte, per il conseguimento di un titolo accademico in altre Università italiane o straniere. Dichiaro inoltre che tutte le fonti utilizzate per la realizzazione del presente lavoro, inclusi i materiali digitali, sono state correttamente citate nel corpo del testo e nella sezione 'Riferimenti bibliografici'.

I hereby declare that I have read and understood the "Anti-plagiarism rules and regulations" approved by the Council of the Department of Economics and Management and I am aware of the consequences of making false statements. I declare that this piece of work has not been previously submitted – either fully or partially – for fulfilling the requirements of an academic degree, whether in Italy or abroad. Furthermore, I declare that the references used for this work – including the digital materials – have been appropriately cited and acknowledged in the text and in the section 'References'.

Firma (signature)   *Singh Sukhanjeet*

Table of contents

Introduction

This thesis aims to create an alternative measure of time-varying macroeconomic uncertainty for Italy, to the commonly used proxies, and to analyse the role it plays in macroeconomic fluctuations. Although the literature on measuring uncertainty is still in its early stages, recent events, like the Great Recession of 2007-08, have highlighted the importance of its study.

Uncertainty is defined as the time-varying conditional volatility of a disturbance common to various macroeconomic indicators that is unforecastable from the perspective of economic agents.[1] An increase in uncertainty has a negative impact on three main economic agents and areas: consumers, businesses, and financial markets. Consumers unsure about future labour income postpone consumption and investment to insure against temporary shocks to their revenue (precautionary savings). Businesses cut back on production and employee compensation, and delay investment decisions, particularly if they are characterized by (partial) irreversibility (labour market distortions and investment dynamics).[2] Financial markets are strongly affected by uncertain times since investors require a higher rate of return on their capital through higher risk premia. Also, as we have seen, an increase in uncertainty depresses private and firms' investments. In all these cases policymakers have an important role to play: they can reduce (at least partially) the level of uncertainty in the economy. For example, recessions are characterized by increased macroeconomic uncertainty and so an economic recovery may require management of expectations and assurance by policymakers. An accurate measure of uncertainty is therefore crucial for the purpose of developing adequate policy responses.

The lack of an objective measure of uncertainty makes it scientifically difficult to evaluate its behaviour and its relationship to macroeconomic activity. Until now, the empirical literature has mainly relied on proxies or indicators of uncertainty, such as the stock market volatility (Italian Stock Market Volatility), stock returns, cross-sectional dispersion of subjective (survey based) forecasts, or the appearance of certain "uncertainty-related" keywords in news publications (Italian Economic Policy Uncertainty Index or Italian World Uncertainty Index).[3] While most of these measures have the advantage of being easily observable, their usefulness

---

[1] Definition taken from Jurado et al. (2015).

[2] See Bloom et al. (2006) on Uncertainty and Investment Dynamics. Their paper shows that, with (partial) irreversibility, higher uncertainty reduces the impact effect of demand shocks on investment. Uncertainty increases real option values making firms more cautious when investing or disinvesting

[3] We will later explain in detail these uncertainty proxies and where we retrieve them.

as uncertainty proxies is determined by how strongly they are correlated with this latent stochastic process.

As we will see, the correctness of these proxies and their link to the usual theoretical notion of macroeconomic uncertainty can be seriously questioned. For instance, the stock market volatility can change overtime even if there is no change in uncertainty about the macroeconomy, if risk aversion or sentiment are important drivers of asset market fluctuations. Survey based proxies can present significant divergences given by different views of the same economic phenomena or even by the heterogeneity of sectors of competence of the surveyed economic agents. Also, the news-based proxies are not very reliable since they could present (and do present) extreme peaks for some periods followed by no movement at all in the following periods.[4] This can be simply given by the "news" factor of these proxies, meaning that once the topic has been covered the proxies will quickly drop to low values until a new event of uncertainty arises. Of course, this does not mean that in the meantime the uncertainty has drastically diminished as the news-based proxies would make it seem, but rather that the media has lost interest in the subject.

The objective of our thesis is to provide a new measure of Italian macroeconomic uncertainty, superior econometrically to the common proxies and as free as possible from dependencies on a single (or few) economic variable, and to analyse its macroeconomic dynamics. We begin by assuming that what matters for economic decision-making is whether the economy has become more or less predictable (uncertain), rather than whether any of the specific economic indicators has grown more or less variable.

To formalize our notion of uncertainty we follow the econometric framework presented by Jurado et al. (2015). We define h-period ahead uncertainty in the variable $y_{jt} \in Y_t = \left(y_{1t}, \dots, y_{N_y t} \right)'$, denoted by $\mathcal{U}_{jt}^y(h)$, to be the conditional volatility of the purely unforecastable component of the future value of the series. Specifically,

$$\mathcal{U}_{jt}^y(h) \equiv \sqrt{E\left[\left(y_{jt+h} - E[y_{jt+h}|I_t] \right)^2 \middle| I_t \right]} \tag{1}$$

where the expectation $E(\cdot \mid I_t)$ is based on the information I_t available to economic agents at time *t*. If the expectation today (conditional on all available information) of the squared error in forecasting y_{jt+h} rises, uncertainty in the variable increases as well. A measure of the

---

[4] We will further discuss and show these flows of news- based measures in the following sections.

macroeconomic uncertainty can then be constructed aggregating individual uncertainty for each date (t) using aggregation weights w_j :

$$\mathcal{U}_t^y(h) \equiv \text{plim} N_y \rightarrow \infty \sum_{j=1}^{N_y} w_j \mathcal{U}_{jt}^y(h) \equiv E_w\left[\mathcal{U}_{jt}^y(h)\right] \qquad (2)$$

Two important aspects of these uncertainty definitions are highlighted. First, there is an important distinction to be made between uncertainty in a series y_{jt} and the conditional volatility of that series. Before computing the conditional volatility, is necessary remove the forecastable component $E[y_{jt+h}|I_t]$ for a proper measure of uncertainty. If this is not done, the estimates will erroneously categorize forecastable variations as "uncertain". It is of crucial importance to remove the entire forecastable component. It is worth noting that nearly none of the uncertainty proxies take this fact into consideration. Second, macroeconomic uncertainty is not equal to the uncertainty in any single series y_{jt} . Instead, we define it as the measure of common variation in uncertainty across all the variables we take into account. The existence of an underlying, common variation in uncertainty over a large number of series is frequently required by uncertainty-based business cycle theories. This component is also thought to be countercyclical.[5] This common variation is critical for the study of business cycles because if the variability of the idiosyncratic shock were purely idiosyncratic, it would have no influence on the macroeconomic variables. If the prior assumptions are valid, we would expect to uncover an aggregate uncertainty factor, or common component in uncertainty fluctuations that affects a large number of series, markets and sectors contemporaneously.

In our thesis we therefore want to estimate (1) and (2), analyse the new time-varying macro uncertainty measure and its macroeconomic dynamics. Three key components are required to make these uncertainty measures operative.

First, we require an estimate of the forecast $E[y_{jt+h}|I_t]$. For this, we form factors from a large set of predictors $\{X_{jt}\}$, $i = 1,2, \ldots , N$, whose measure is as close as possible to I_t . Using these factors, we approximate $E[y_{jt+h}|I_t]$ by diffusion index forecast. This technique allows us to predict the common tendency within a group of numbers or statistics.

Second, defining the h -step- ahead forecast error to be $V_{jt+h}^y \equiv y_{jt+h} - E[y_{jt+h}|I_t]$, we require an estimate of the conditional, on time t information, volatility of this error, $E\left[\left(V_{t+h}^y\right)^2\Big|I_t\right]$.

---

[5] See Bloom (2009), Arellano et al. (2010), Bloom et al. (2010), Herskovic et al. (2014), Bernstein et al. (2021a), Bernstein et al. (2021b).

For this we specify a parametric stochastic volatility model for both the one-step-ahead prediction errors in y_{jt} and the analogous forecast error of the factors. These volatility estimates are used to recursively compute the values of $E\left[\left(V_{t+h}^{y}\right)^{2}\middle| I_{t}\right]$ for h > 1. This technique takes into account a key feature of the multistep-ahead forecasts, namely that the time-volatility of the errors of the predictor variables creates additional unforecastable variation in each variable y_{jt+h} , therefore contributing to its uncertainty.[6]

Third, an estimate of macroeconomic uncertainty $\mathcal{U}_{t}^{y}(h)$ is derived from the individual uncertainty measures $\mathcal{U}_{jt}^{y}(h)$. We will implement the equally weighted average of the individual uncertainties to construct our estimate, although it might be interesting attributing different weights to the different economic indicators as a topic of future research.

We estimate our measure of macroeconomic uncertainty from a dataset of the main macroeconomic variables available from different sources, namely ISTAT (Italian National Statistical Institute), FRED (Federal Reserve Economic Data), OECD (Organization for Economic Co-operation and Development), and ECB (European Central Bank). Due to the difficulty of finding monthly data for Italy for most of the interesting economic indicators, the dataset we created for our research is composed by quarterly data, extending from the first quarter of1996 to the fourth quarter of 2019. We decided not to include the recent COVID-19 crisis due to the fact that the sanitary emergency and consequent economic crisis continue to unfold and this could heavily bias our results.

Our main findings can be summarized as follows. Our measure of uncertainty shows significant independent variance when compared to commonly used proxies for macroeconomic uncertainty. In addition, our estimates imply substantially fewer large uncertainty episodes than any of the regularly used proxies we looked at. For instance, the Italian Stock Market Volatility proxy we take into account presents several peaks at the threshold of 1.65 standard deviations above its trend, representing significant increases in uncertainty. By contrast, in a sample extending from the first quarter of 1998 to the fourth quarter of 2019, our measure of macroeconomic uncertainty exceeds 1.65 standard deviations from its mean only one time, during the Great Recession of 2007-09. Furthermore, our estimate of macroeconomic uncertainty is far more persistent than the Italian Stock Market Volatility proxy: even during the most important event of uncertainty, the recession caused by the financial crisis of 2007-2008, the stock market proxy presents significant deviations from the mean only for a few

---

[6] We will review in detail this claim in the Econometric Framework chapter.

months, advocating a fast return to the pre-crisis level of uncertainty, whereas our uncertainty indicator presents significant deviations from the mean for almost two years, declining very gradually over the next several quarters. Our findings suggest that most of the fluctuations in conventional uncertainty proxies, such as the stock market volatility and news-based measures, are not associated with broad-based shifts in economic uncertainty as described in (2). This is compelling because it implies that macroeconomic uncertainty does not drive most of the variation in commonly used uncertainty proxies. Additionally, we study the correlation between the different measures of macroeconomic uncertainty and real economic activity. Particularly we focus on the industrial production growth rate, the employment growth rate and the unemployment growth rate, and we find that our estimate is the most accurate in following the economic theory's expected countercyclicality.[7]

Another relevant piece of analysis we conduct suggests that the Italian macroeconomic uncertainty follows roughly the trend of the U.S. measure of uncertainty found by Jurado et al. (2015) but presents significant differences in magnitude as well as recovery speed. We will further discuss this investigation, but these are mainly due to the major role that the United States play in the global economy, as well as the efficiency of the American policy makers in responding to the different crisis as opposed to the renowned Italian policy makers' inefficiency.

We also conduct a sensitivity analysis of our macroeconomic uncertainty measure, removing each time a different group of variables and computing a partial uncertainty measure to compare with the baseline indicator. The findings imply that the partial measure removing one at a time consumer price index, production price index, labour market and international trade variables present the highest variation with respect to the baseline uncertainty measure. This means that particularly these groups of variables tend to significantly influence the creation of our uncertainty estimate. We will further discuss these results in the following chapters.

Now that we found our uncertainty measure the question is: how important is time- varying economic uncertainty, and how closely is it correlated with macroeconomic fluctuations? As we already stated, our measure of macroeconomic uncertainty reveals one big episode of uncertainty in the period analysed. Large positive shocks to uncertainty result in a sizable and enduring fall in real activity (industrial production, employment, unemployment). These impacts are much bigger and last much longer than what observed when the stock market

---

[7] We compute the real activity growth rates based on the data available from the aforementioned different sources. The growth rate is computed based on 4 quarters values, i.e., q1 2000 – q1 1999 etc.

volatility (or one of the news-based measures) is employed as the proxy for uncertainty. Furthermore, they do not show the "overshooting" trend observed in the stock market volatility case, if not for a slight overshoot in industrial production. Using a 9- variable quarterly macro vector autoregression (VAR) and a recursive identification procedure with the uncertainty measure placed last, we find that common macro uncertainty shocks account for up to roughly 22 percent of the forecast error variance in industrial production, maintaining a mean value of 14 percent across five years of forecast horizon. By contrast, the other uncertainty proxies account for at most around 4 percent of the forecast error variance in industrial production, maintaining a mean value below 3 percent in all cases. Again, our macro uncertainty measure explains up to 17 percent of the forecast error variance in employment and up to 8.5 percent of the forecast error variance in unemployment. On the other hand, the common uncertainty proxies account for at most 6 percent of the forecast error in employment and 6 percent of the forecast error in unemployment.

These findings highlight the relevance of carefully considering how aggregate uncertainty is measured when assessing its relationship with the macroeconomy. Our estimates suggest that quantitatively important uncertainty events occur far less frequently than what is indicated from conventional uncertainty proxies, but that, when they do occur, they display larger and more persistent correlations with real activity. By contrast, common uncertainty proxies are less persistent and spike far more frequently, often in non-recession periods, or in periods of relative macroeconomic calm. Although we find that positive shocks to uncertainty are associated with large declines in real activity, our results do not specify whether macro uncertainty is a cause or an effect of such declines. Our goal is to develop a coherent and data-based measure of time-varying macroeconomic uncertainty that can be tracked overtime and related to fluctuations in real activity.

Our findings can represent a benchmark with which to evaluate theories where uncertainty plays a major role in business cycle. The measure can be computed regardless of the fact that the theory implies that uncertainty is the cause or the effect of recessions.

Evaluated the importance of time-varying macro uncertainty and its macroeconomic dynamics, we now focus our attention to the effects policy makers' decisions have on the real economic activity and how these changes are captured by our uncertainty measure. It is important to underline that the political context in which Italy lies is very particular. The European Central Bank is the policy maker for excellence and its policy decisions are influenced by the European Union as a whole and not by single countries (even if some countries have a higher consideration). We use a 6 variable quarterly macro vector autoregression (VAR) with the

uncertainty measure placed last. As the theory predicts we find that a positive shock to the short-term interest rate of the ECB depresses real economic activity, namely reducing the European industrial production and employment, and increasing the European unemployment. We find that an increase in EU's short-term interest rate leads to an increase in Italian uncertainty. This is in line with what one might expect since the reaction to contractionary fiscal policy, especially if unexpected, will consist in consumers and businesses cutting back on expenses or delaying investments, at least until they comprehend the reasons behind the ECB intervention or until the uncertainty about the situation decreases.

As a final step, we want to create a measure of uncertainty given by the thoughtful combination of multiple approaches. Computing the correlation between our uncertainty measure and the common proxies, we find that the Italian Stock Market Volatility proxy is highly positively correlated (43 percent) with our estimate, meaning that they roughly capture similar uncertainty events. The Italian Economic Policy Uncertainty Index has a very low, negative correlation (-15 percent) with our estimate, meaning that this news-based measure of uncertainty captures at some extent different uncertainty events. The World Uncertainty Index for Italy, however, shows a very high negative correlation (- 47 percent) with our estimate, meaning that this news-based uncertainty proxy captures very different uncertainty events compared to our measure (this last point can also be seen comparing the time series of the two measures in question). We decide to combine our time-varying macro uncertainty measure, which is data-based, and the World Uncertainty Index for Italy, which is a news-based proxy. As for the method of aggregation, we opted for the maximum value for each quarterly period of reference between the two measures. This is because we want to capture every uncertainty event that both measures identify, while maintaining the persistent effects of our main uncertainty measure. The macroeconomic dynamics of our new combined macroeconomic uncertainty index, studied through a VAR-9 similar to the one previously constructed for our analysis, are in line with the theoretical models. Again, a positive shock to the combined uncertainty index leads to a depression of real economic activity. Strikingly, we find that common macro uncertainty shocks given by the combined estimate account for up to roughly 34 percent of the forecast error variance in industrial production, maintaining a mean value of around 22 percent across five years of forecast horizon. Although, the forecast error variance in employment is explained better in our original measure (13.5 percent against 10.5 percent on average across the 5 years), the combined uncertainty measure accounts for an average of 4.4 percent of the forecast error variance in unemployment, versus the 2.7 percent on average explained by the original measure. Through the 6 variables VAR previously mentioned, we also study the impact that a European

policy shock has on the combined estimate of time-varying uncertainty and find similar results to the ones previously discussed and predicted by the theory, namely an increase in macro uncertainty, and a depression of consumption and investment decisions. While the results for this new combined measure of uncertainty are satisfying, we want to state a few important points. First, our original macro uncertainty measure cannot be discarded by these results. On the contrary, it should be clear that our original estimate is the driving force of these findings. Second, the fact that the combined measure accounts for a larger portion of the forecast error decomposition of the industrial production or unemployment doesn't necessarily mean that it a better representation of the real underlying uncertainty di per se. A combined measure of uncertainty proxies might be an interesting topic for future research, as long as it has a real method supporting it and it is not a naïve combination of different measures.

The thesis will be organized as follows. In chapter 1 we briefly present the macroeconomic uncertainty literature. In chapter 2 we describe the general econometric framework employed in our study and the construction of our uncertainty measure. In chapter 3 we discuss our dataset construction and its empirical implementation. In chapter 4 we present our time-varying macroeconomic uncertainty measure and the relative analysis. Particularly, we study the role of predictors in our estimate. We then compare our measure with the commonly used proxies of uncertainty for Italy: economic policy uncertainty, world uncertainty index, and a measure of stock market volatility. We also study their relationship with the real economic activity. In chapter 5 present identification strategies generally used in the literature, and the problems and benefits surrounding the VAR models, which we adopted for the macroeconomic dynamic analysis. We then present our VAR model and the results of macroeconomic dynamics analysis given by all the macro uncertainty measures. This chapter also includes the Forecast Error Variance Decomposition (FEVD) and the comparison of the findings given by our different indicators. In chapter 6 we inspect the effects of a positive shock to the European economic policy on the European real activity and our Italian macro uncertainty measure. In chapter 7 we present a new combined measure of macro uncertainty and discuss the relative analysis.

Chapter 1

Macroeconomic Uncertainty Literature

The literature on uncertainty measurement is still in its early stages, especially for Italy. The vast majority of the literature on uncertainty comes from studies on U.S. or global level analysis. Smaller countries are often neglected due to the limited impact they can have on a global level and due to difficulty on retrieving relevant and substantial data for the research. Nonetheless, the country-specific uncertainty has huge effects on the macroeconomic environment of said country. We focus our research on Italy.

As proxies for uncertainty, previous research has generally focused on measures of volatility and dispersion (Bloom, 2009; Grier et al., 2004; Benigno et al., 2012; Bachmann et al., 2013; Colombo, 2013; Fernandez- Villaverde et al., 2011; Caldara et al., 2016). Bloom (2009) reported a substantial countercyclical link between real activity and uncertainty as proxied by stock market volatility. In a simple vector autoregression (VAR) framework, his results suggest that uncertainty has a significant effect on output and employment six months after a change in these measures, with a rise in volatility initially depressing real activity and then increasing it, leading to an overshoot of its long-run level, which is consistent with the predictions of models that use uncertainty as a driving force of macroeconomic fluctuations. Also, Bloom et al. (2012) found a link between real activity and uncertainty, as measured by dispersion in firm-level earnings, industry-level earnings, total factor productivity, and forecaster's predictions. The fact that the uncertainty proxies are significantly countercyclical is a common aspect of these and other, similar research. While these analyses are good places to start and significant cases to learn about, it's worth noting that the metrics of dispersion and stock market volatility explored may or may not be closely linked to genuine economic uncertainty. Bekaert et al. (2013) have shown how one of the most recognized proxies for U.S. uncertainty, the VIX, which is strongly tied to financial market volatility, contains a major component that appears to be driven by characteristics associated with time-varying risk-aversion rather than economic uncertainty.[8] We have reasons to believe that these results apply for any country's financial

---

[8] The Cboe Volatility Index, or VIX, is a real-time market index representing the market's expectations for volatility over the coming 30 days. Investors use the VIX to measure the level of risk, fear, or stress in the market when making investment decisions (definition taken from Investopedia.com).

markets and not only to the U.S. case, given their similar functioning of financial markets around the world. [9]

While there are advantages to simultaneously estimating uncertainty and its impacts versus using exogenous and potentially noisy uncertainty proxies, there are still very few studies that do so (see, Jurado et al., 2015; Shin and Zhong, 2016; Mumtaz and Theodoridis, 2016; Mumtaz et al., 2016; Carriero et al., 2016). Jurado et al. (2015) create a measure of uncertainty using a framework based on a dynamic factor model and show that the behaviour of their measure of uncertainty differs from that of others typically used proxies in the literature. Their measure is then employed in an otherwise standard vector autoregression model (VAR) to analyse the dynamic consequences of an unanticipated shift in macroeconomic uncertainty on real activity and nominal indicators in a second phase. Although our econometric framework and our time-varying uncertainty measure construction follow the one provided by Jurado et al (2015), our research differs from theirs in several ways. First, Italy lays under a completely different economic and political context than United States. The United States have the largest economy in the world, accounting for over a quarter of worldwide GDP (at market exchange rates), one-fifth of global foreign direct investment, and more than a third of global stock market capitalization. The United States' dollar is the most frequently used currency in worldwide trade and financial operations, and changes in U.S. monetary policy and investor mood have a significant impact on global financing conditions. Moreover U.S. can autonomously implement their monetary policies through the Federal Reserve. On the other hand, Italy, despite not being a small country economically speaking by any stretch of the imagination, is far less influential in the world's economy. Also, the European context in which the country operates doesn't allow it to freely adopt monetary policies. This role is covered by the European Central Bank which manages the euro and frames and implements EU economy and monetary policy. Second, the availability of relevant economic data for Italy is far lower than that of the U.S. both in terms of number and time-length of the indicators. Also, our dataset is composed of quarterly data.[10] Third, we do not limit our analysis to the stock market volatility index as a comparative uncertainty proxy, but rather we add to the study two additional news-based measures: the Italian Economic Policy Uncertainty Index and the World Uncertainty Index for Italy. Fourth, the VAR model we implement for our macroeconomic dynamics analysis contains different variables than those used by Jurado et al. (2015).[11] Fifth, we implement additional analysis like the time-varying uncertainty measure sensitivity analysis to the removal of certain types of

---

[9] The so called "globalization of financial markets".
[10] As we will explain in detail in the following sections, our data is retrieved by various sources.
[11] We try to preserve the already proven economic interactions between the macroeconomic variables used.

variables, as well as the study of the effects of a change in the European policy on our Italian uncertainty estimate. Sixth, we try to improve our uncertainty measure carefully combining our data-based estimate with a news-based proxy that captures better different events of uncertainty, and analyse this new combined uncertainty estimate and its macroeconomic dynamics.

As a measure of uncertainty, a separate branch of the literature concentrates more on the cross-sectional dispersion in N_A analysts' or firm's subjective expectations. A big convenience in using this type of proxies is that the conditional, on the available information at time t, forecast of the y_{jt+h} variable is treated as directly observable. Even if analysts' forecasts and survey-based measures can be useful in evaluating certain types of phenomena, using them to measure uncertainty can have a number of relevant limitations. To begin with, subjective evaluations are available only for a few of the needed variables. Collecting expectations about dozens of variables would be extremely time consuming and inefficient for both the analysts and for the surveyed agents. To put into perspective, to construct our uncertainty measure we use over 50 variables. Another relevant issue is that it is unclear whether the results obtained from these surveys truly reflect the economy's conditional expectations. Practitioner forecasters are frequently sampled, and as So (2013) found, certain analysts' predictions are known to contain systematic biases and to omit crucial forecasting information. Analysts' may also have financial incentives to influence their forecasts in ways that economic actors would not. As Diether et al. (2002) and Mankiw et al. (2004) showed, a huge problem in survey data is that different opinions in economic predictions could be driven by a fundamental different point of view on the same topic rather than true uncertainty surrounding it. As behavioural finance thought us, psychological influences and biases affect the behaviour of different economic agents. In particular, prospect theory highlights that, under certain conditions, economic agents perceive even mathematical concepts, like probabilities, in different and incorrect ways. Not to mention that also other factors can heavily bias the results of survey studies, for instance different experiences, backgrounds, sectors of work and even personal traits of the answering subjects. Lahiri and Sheng (2010) show that, even if forecasts are unbiased, until the variance of accumulated aggregate shocks throughout the forecast horizon is zero, differences in experts' point forecasts does not equal to forecast error uncertainty (average across analysts). Using the Survey of Professional Forecasters, they demonstrate experimentally that the variance of aggregate shocks can produce a considerable wedge between uncertainty and disagreement in times of significant economic change. The European Commission recently came up with a new survey-based measure of economic uncertainty which shows a plausible empirical performance at the EU, country and sector levels. Although all the above critics of survey-based measures

apply, it will be interesting in the future to confront our measure of uncertainty with this new measure when enough data will be available for a significant analysis.[12] We focus on the uncertainty surrounding objective statistical forecasts for dozens of economic series, rather than the range in outcomes around subjective survey expectations of a few variables, as these studies do.

A distinct body of the literature focuses on news-based proxies of uncertainty. Of these measures, we analyse the Economic Policy Uncertainty index (EPUI) and the World Uncertainty index (WUI) for Italy. The first is a country-level index constructed drawing what are considered to be the two most economically relevant newspapers of the country: Corriere della Sera and La Stampa. The second is constructed analysing the Economist Intelligence Unit (EIU) country reports.[13] The use of these measures as macro uncertainty proxies can be heavily criticized. A striking example of these critics is their very low perceived uncertainty during the Great Recession of 2007-2009. Nonetheless these types of proxies can be very useful in perceiving certain specific categories of uncertainty shocks, namely political and event-specific shocks. In a recent paper, Donadelli et al. (2020), constructed a new daily and monthly measure of economic policy uncertainty for Italy using articles by the Sole 24 Ore. VAR investigations suggest that the new measure's positive shocks are detrimental for production and employment, but not significantly.

Our uncertainty measure also differs from proxies based on the unconditional cross-section dispersion of a particular variable. These types of measure can fluctuate without any change in uncertainty if there is heterogeneity in the cyclicality of firms' business activity.

Carriero et al. (2012) consider common sources of variation in the residual volatilities of a Bayesian Vector Autoregression (VAR), but differently from our measure of time-varying macroeconomic uncertainty, their estimation process presumes that individual volatilities have common shocks, and it is not conceivable for certain series to have homoscedastic shocks while others have heteroskedastic shocks.

The persistence of uncertainty shocks is a major unresolved problem in empirical uncertainty analysis. The majority of the proxies discussed above are not persistent enough to explain the prolonged levels of unemployment that occurred during and after the 2007-2009 recession: they present a depression of real economic activity quickly followed by a substantial recovery. Our

---

[12] The new survey- based measure is available since May 2021.
[13] We will explain in detail the development of these two news- based measures in later.

new measure of time-varying macro uncertainty is far more persistent than the common proxies that we analyse.

Chapter 2

Econometric Framework

Measure Estimation and Time-Varying Uncertainty

In this chapter we present the econometric framework we implemented in order to obtain our time-varying macroeconomic uncertainty measure. As we have already specified, we generally follow the econometric framework presented by Jurado et al. (2015).

An initial critical step in our research is the replacement of the conditional expectation, on information available at time t, in

$$\mathcal{U}_{jt}^{y}(h) \equiv \sqrt{E\left[\left(y_{jt+h} - E[y_{jt+h}|I_t]\right)^2 \Big| I_t\right]} \tag{1}$$

by a forecast, from which we create the forecast error that forms the basis of our uncertainty metrics. The forecast error is the difference between the actual or real value of a time series or any other event of interest and the expected or forecast value. It is important for our predictive model to be as rich as possible in order to identify the true forecast error and remove from its measure all the predictive content. A conventional strategy is to select a set of K predetermined conditioning variables given by the $K \ x \ 1$ vector W_t, and then estimate

$$y_{t+1} = \beta' W_t + \epsilon_{t+1}$$

by least squares. The one period ahead forecast is therefore $\hat{y}_{t+1}|t = \hat{\beta}' W_t$, where $\hat{\beta}$ is the least squares estimate of β. If economic agents, such as financial market players, have more knowledge than the conditioning variables, an omitted-information bias might occur.

The bias results in the model attributing the effect of the missing variables to those that were included. There are several approaches that can be taken in order to improve the forecasts. Lanwehr et al. (2021) try to raise awareness of the omitted variables bias and highlight its severity for causal claims. They discuss two remedies to reduce the risk of omitted information bias, namely the instrument variable or two-stage least squares estimator and the regression discontinuity design. However, we will follow a third approach that consists in improving the forecasts by augmenting best-fitting conventional forecasting equations with common factors

estimated from a large dataset.[14] Stock and Watson (2002) show that the forecasting process can then be split into two parts. First, the predictors are used to estimate a time series of the factors; second, a linear regression is used to estimate the connection between the variable to be forecast and the factors. Even under very generic assumptions about the cross-sectional and temporal dependency in the variables, exact estimates of the latent factors can be derived using simple approaches if the number of predictors is adequate. Ludvigson and Ng (2007) demonstrate how the empirical relation between the conditional mean and conditional volatility of excess stock market returns, often referred to as the risk-return relation, can be better explained by including in the model several estimated factors that contain important information not contained in commonly used predictor variables. Again, Ludvigson and Ng (2009) also find that several common factors estimated from a large dataset on U.S. economic activity have important forecasting power for future excess returns on U.S. government bonds. Solving the problem of omitted-information bias is particularly crucial in our case since relevant information not used to construct our forecasts would result in erroneous estimation of the macro uncertainty measure and, consequently, its dynamics. Therefore, we will employ the diffusion index forecasting method, which consists in adding a small number of factors estimated from a large number of economic time series to the typical forecasting model. Diffusion index forecasts are increasingly used in data rich environments. At the basic level, a diffusion index is a cross-sectional method to analyse and individuate common tendencies among multiple time-series. We will include in our forecasting model both the factors estimated as previously mentioned and non-linear transformation of these factors. This eliminates arbitrary reliance on a small number of exogenous predictors and allows for the use of data estimated from a large number of relevant economic variables, which are more likely to include economic agents' unobservable additional information.

The raw data used to form factors are always transformed to achieve stationarity. In the realm of time series analysis, stationarity is a crucial notion that has significant impact on how data is interpreted and forecasted. The statistical features of a system must not vary over time for data to remain stationary, which means that each series must have a constant mean and variance. Visually, the time series should not present trends or seasonality. Failure to render the data stationary will lead to spurious results and poor forecasting. Differentiating and logarithmic transformations are the most popular ways to ensure that the data present this property. Differencing is a transform that helps stabilize the mean of the time series by removing changes

---

[14] The common factors help us better represent the information available at time t as to reduce as much as possible the possible omitted variables (information) bias. Furthermore, they allow us to eliminate the forecastable, at time t, component.

in the level of a time series. The first-order difference transform involves subtracting the data point at time t from the previous point, $\Delta y_t = y_t - y_{t-1}$. If the first-order difference is stationary and random, then it is called a "random walk" model. In some cases, it is useful to perform the second order difference transform to reach the desired result, $\Delta'' y_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$. When differencing is not sufficient, we can perform the logarithmic transform that converts data into a logarithmic scale by taking the log of each point. It's vital to note that the logarithmic transform must always be followed by the difference transform. In addition, in the process of forming forecasting factors from our large macroeconomic dataset, we standardize the raw data before performing the principal component analysis, due to the different units of our data.

As anticipated, the factors are estimated by the method of static principal components (PCA). PCA is a statistical process that turns a series of observations of possibly correlated variables into a set of principle component values, which are linearly uncorrelated variables. In simpler terms, the principal component analysis is a dimensionality-reduction approach for reducing the dimensionality of large data sets by transforming a large collection of variables into a smaller one that retains the majority of the information in the large set. The PCA analysis is conducted through five main steps: i) ensure that the range of continuous initial variables is standardized; ii) compute the covariance matrix to identify correlations; iii) compute the eigenvectors and eigenvalues of the covariance matrix to identify the principal components; iv) create a feature vector to help you select which of the main components to maintain; v) recast the data along the principal components' axes. Bai and Ng (2006) show that, in large datasets, the estimates of the factors can be treated as they were observed in the subsequent forecasting regression.[15]

2.1 Construction of Forecast Uncertainty

Let $\boldsymbol{X}_t = (X_{1t}, \dots, X_{Nt})'$ signify the predictors that are available for our analysis. As previously mentioned, in order to work with the timeseries it is necessary to transform the series into stationary. We assume that the factor structure of X_{it} take the following form

$$X_{it} = \Lambda_i^{F'} \boldsymbol{F}_t + e_{it}^X , \qquad (5)$$

where $\boldsymbol{F}_t$ is an r_F x 1 vector of latent common factors, Λ_i^F is a corresponding r_F x 1 vector of latent factor loadings, and e_{it}^X is a vector of idiosyncratic errors, which in an approximate

---

[15] In particular, they show that the least squares estimates obtained from these factor-augmented regressions are root-T consistent and asymptotically normal if root(T)/N -> 0.

dynamic factor model like ours are allowed to have a limited amount of cross-sectional correlation. Factor loading are non-other than the correlation coefficient for the variable and factor. Loadings close to -1 or 1 indicate that the factor strongly influences the variable, while loadings close to 0 indicate that the factor has a weak influence on the variable. Importantly, the number of factors r_F is significantly lower than the number of series, N. In our case we have 2 factors, 2 additional predictors and 51 initial macroeconomic variables.

Let y_{jt} denote the generic series on which we wish to compute uncertainty in and whose value in period $h \geq 1$ is estimated from a factor augmented forecasting model

$$y_{jt+1} = \varphi_j^y(L)y_{jt} + \gamma_j^F(L)\widehat{F}_t + \gamma_j^W(L)W_t + v_{jt+1}^y \tag{6}$$

where $\varphi_j^y(L)$, $\gamma_j^F(L)$, and $\gamma_j^W(L)$ are finite-order polynomials in the lag operator L of orders p_y, p_F and p_W respectively, the elements of the vector $\widehat{F}_t$ are consistent estimates of a rotation of F_t, and the r_W dimensional vector W_t contains additional predictors that will be specified later. An important aspect of our analysis, that allows to generate time-varying uncertainty in the series y_{jt}, is that the one-step-ahead prediction error of y_{jt+1}, and of each factor $F_{k,t+1}$ and additional predictor $W_{l,t+1}$, is permitted to have time-varying volatility σ_{jt+1}^y, σ_{kt+1}^F, σ_{lt+1}^w, respectively.

When the factors are characterized by autoregressive dynamics, a better way to represent the system described above is the factor augmented vector autoregression (FAVAR). The FAVAR model, first proposed by Bernanke et al. (2005), is nowadays widely used in macroeconomics and finance. In this model, observable and unobservable factors jointly follow a vector autoregressive process, which further drives the comovement of a large number of observable variables. We will explain in depth the functioning and the literature around the general vector autoregressive model (VAR) later.[16] For now, let $z_t \equiv (\widehat{F}_t', W_t')'$ be a $r = r_F + r_W$ vector which contains the r_F estimated factors and r_W additional predictors, and define $Z_t \equiv (z_t', ..., z_{t-q+1}')'$. Let $Y_{jt} = (y_{jt}, y_{jt-1,\cdots}, y_{jt-q+1})'$. Then forecasts for any $h > 1$ can be obtained from the FAVAR system, stacked in first-order companion form

$$\begin{pmatrix} Z_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^Z & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} Z_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^Z \\ \mathcal{V}_{jt}^Y \end{pmatrix} \tag{7}$$

$$\mathcal{Y}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{jt-1} + \mathcal{V}_{jt}^{\mathcal{Y}}$$

---

[16] In particular, when discussing the macroeconomic dynamics of our uncertainty measure in chapter 5.

where Λ'_j and Φ^Y_j are functions of the coefficients in the lag polynomials in (6), Φ^Z stacks the autoregressive coefficients of the components of Z_t. Note that these specifications assume that the coefficients are time-invariant.[17] The highest eigenvalue of Φ^Y_j is smaller than one under the assumption of stationarity, and the conditional mean is the best h-period forecast under quadratic loss.

$$E_t \mathcal{Y}_{jt+h} = \left(\Phi^Y_j\right)^h \mathcal{Y}_{jt}.$$

The forecast error variance at t is

$$\Omega^Y_{jt}(h) \equiv E_t\left[\left(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h}\right)\left(\mathcal{Y}_{jt+h} - E_t\mathcal{Y}_{jt+h}\right)'\right].$$

Time variation in the mean squared forecast error in general arises from the fact that shocks to both y_{jt} and the predictors z_t may have time-varying variances. We now turn to these ramifications. When h = 1 we have that

$$\Omega^Y_{jt}(1) = E_t\left(\mathcal{V}^Y_{jt+1} \mathcal{V}^{Y'}_{jt+1}\right). \tag{8}$$

When h > 1, the forecast error variance of $\mathcal{Y}_{jt+h}$ changes according to

$$\Omega^Y_{jt}(h) = \Phi^Y_j \Omega^Y_{jt}(h-1)\Phi^{Y'}_j + E_t\left(\mathcal{V}^Y_{jt+h} \mathcal{V}^{Y'}_{jt+h}\right). \tag{9}$$

As $h \to \infty$ the forecast is the unconditional mean and the forecast error variance is the unconditional variance of $\mathcal{Y}_{jt}$. This means that $\Omega^Y_{jt}(h)$ is less variable as h increases.[18]

We want to study the expected forecast uncertainty of the scalar series y_{jt+h} given the information available at time t, denoted by $\mathcal{U}^y_{jt}(h)$. This is the square-root of the appropriate entry of the forecast error variance $\Omega^Y_{jt}(h)$. With 1_j being a selection vector, our uncertainty measure for each variable y_{jt} is given by,

$$\mathcal{U}^y_{jt}(h) = \sqrt{1j'\Omega^Y_{jt}(h)1j}. \tag{10}$$

To estimate the time-varying macroeconomic uncertainty, we form weighted averages of individual uncertainty estimates:

$$\mathcal{U}_t^y(h) = \sum_{j=1}^{N_y} w_j \mathcal{U}_{jt}^y(h) \, .$$

A trivial weighting scheme is to give every series an equal weight of $w_j = 1/N_y$. This will be the baseline case for our estimate of macroeconomic uncertainty. On the other hand, if the individual uncertainty has a factor structure, the weights can be defined by the eigenvector corresponding to the largest eigenvalue of the $N_y \times N_y$ covariance matrix of individual uncertainty. In this case we are talking about the PCA approach. We will also aggregate the individual uncertainties with this method as an alternative to the baseline case. In chapter 3 we will further explore the weighting scheme for measuring macro uncertainty.[19]

2.2 Statistical Decomposition of Time-Varying Uncertainty

We have already presented the construction of our uncertainty measure. In this section, we want to explain in depth how the stochastic volatility in the predictors z and in y_j contribute to its h period ahead uncertainty. The choice of stochastic volatility is critical because it allows for the creation of a second-moment shock that is independent of innovations to y_j itself. This is in line with much of the theoretical literature on uncertainty, which assumes the existence of an uncertainty shock that affects real activity in its own right. Some popular econometrical models, like the generalized autoregressive conditional heteroskedasticity (GARCH) type models, lack this property and instead have a shock that is not independent on y_j innovations. Let it be known that GARCH models are an extremely popular tool used by financial institutions to estimate the return volatility of stocks, bonds and other investment vehicles.

Consider the factors F_t , keeping in mind that the argument for W_t is similar. We suppose that each component of F_t is serially correlated and well represented by a univariate autoregressive model (AR (1)):

$$F_t = \Phi^F F_{t-1} + v_t^F$$

If v_t^F was a martingale difference with a constant variance $(\sigma^F)^2$, the forecast error variance $\Omega^F(h) = \Omega^F(h-1) + (\Phi^F)^{2(h-1)}(\sigma^F)^2$ increases with h but is the same for all t. We therefore allow the shocks to F to show time-varying stochastic volatility $v_t^F = \sigma_t^F \varepsilon_t^F$ where the log volatility has the following autoregressive structure:

$$log(\sigma_t^F)^2 = a^F + \beta^F log(\sigma_{t-1}^F)^2 + \tau^F \eta_t^F \, , \quad \eta_t^F \sim ii\,d\,N(0,1) \, .$$

As we previously mentioned, the stochastic volatility model allows for a shock to the second moment that is independent of the first moment, consistent with theoretical models of uncertainty. The model implies

$$E_t(\sigma_{t+h}^F)^2 = \exp\left[a^F \sum_{s=0}^{h-1}(\beta^F)^s + \frac{(\tau^F)^2}{2}\sum_{s=0}^{h-1}(\beta^F)^{2(s)} + (\beta^F)^h \log(\sigma_t^F)^2\right].$$

Since $\epsilon_t^F \sim ii\, d\, N(0,1)$ by assumption, $E_t(v_{t+h}^F)^2 = E_t(\sigma_{t+h}^F)^2$. This allows us to compute the $h > 1$ forecast error variance for F using the recursion

$$\Omega_t^F(h) = (\Phi^F)\Omega_t^F(h-1)\Phi^{F'} + E_t\left(v_{t+h}^F v_{t+h}^{F'}\right)$$

with $\Omega_t^F(1) = E_t(v_{t+h}^F)^2$. The h-period-ahead predictor uncertainty at time t is the square root of the h-step ahead forecast error variance of the predictor

$$\mathcal{U}_t^F(h) = \sqrt{1F'\Omega_t^F(h)1F},$$

where 1_F is an appropriate selection vector. From the determinants of $E(\sigma_{t+h}^F)^2$, we find that the h-period-ahead uncertainty of $\boldsymbol{F}_t$ has a level-effect attributable to the homoscedastic variation in v_{Ft}, $\boldsymbol{a^F}$, a scale effect attributable to $\boldsymbol{\tau^F}$, and persistence determined by $\boldsymbol{\beta^F}$.

We now assume that the forecasting model for $\boldsymbol{y_j}$ has just one predictor $\widehat{\boldsymbol{F}}$, in order to explain how the uncertainty in the predictors affect uncertainty in the variable of interest y_j. The forecasting model is specified as follows:

$$y_{jt+1} = \varphi_j^y y_{jt} + \gamma_j^F \widehat{\boldsymbol{F}}_t + v_{jt+1}^y,$$

where $v_{jt+1}^y = \sigma_{jt+1}^y \varepsilon_{jt+1}^y$ with $\varepsilon_{jt+1}^y \sim ii\, d\, N(0,1)$ and

$$\log(\sigma_{jt+1}^y)^2 = a_j^y + \beta_j^y \log(\sigma_{jt}^y)^2 + \tau_j^y \eta_{jt+1}, \qquad \eta_{jt+1} \sim ii\, d\, N(0,1).$$

When h = 1, V_{jt+1}^y coincides with the innovation v_{jt+1}^y which is uncorrelated with the one-step-ahead error in forecasting F_{t+1}, given by $V_{t+1}^F = v_{t+1}^F$. When h = 2, the forecast error for the factor is $V_{t+2}^F = \Phi^F V_{t+1}^F + v_{t+2}^F$. The corresponding forecast error for y_{jt} is

$$V_{jt+2}^y = v_{jt+2}^y + \varphi_j^y V_{jt+1}^y + \gamma_j^F V_{t+1}^F,$$

which depends on the one-step-ahead forecasting errors made at time t, but V_{t+1}^y and V_{t+1}^F are uncorrelated. When h=3, the forecast error is

$$V_{jt+3}^y = v_{jt+3}^y + \varphi_j^y V_{jt+2}^y + \gamma_j^F V_{t+2}^F,$$

25

which clearly depends on V_{jt+2}^y and V_{t+2}^F. However, differently than the case of h = 2, the two components V_{jt+2}^y and V_{t+2}^F are in this case correlated because both depend on V_{t+1}^F.

Going back to the general case, when the predictors are $\mathbf{z}_t \equiv \left(\widehat{\mathbf{F}}_t', \mathbf{W}_t'\right)'$ and its lags, the h-step-ahead forecast error variance for Y_{jt+1} allows for the decomposition

$$\Omega_{jt}^Y(h) = \Phi_j^Y \Omega_{jt}^Y(h-1)\Phi_j^{Y'} + \Omega_{jt}^Z(h-1) + E_t(\mathcal{V}_{jt+h}^Y \mathcal{V}_{jt+h}^{Y'}) + 2\Phi_j^Y \Omega_{jt}^{YZ}(h-1), (11)$$

where $\Omega_{jt}^{YZ}(h) = \mathrm{cov}_t\left(\mathcal{V}_{jt+h}^Y, \mathcal{V}_{jt+h}^Z\right)$. The terms $E(\mathcal{V}_{j,t+h}^Y \mathcal{V}_{j,t+h}^{Y'})$ are computed using the fact that $E_t\left(v_{jt+h}^y\right)^2 = E_t\left(\sigma_{jt+h}^y\right)^2$, $E_t(v_{t+h}^F)^2 = E_t(\sigma_{t+h}^F)^2$, and $E_t(v_{t+h}^W)^2 = E_t(\sigma_{t+h}^W)^2$.

Equation (11) shows us how time variation in our uncertainty measure can be mathematically decomposed in four sources: i) an autoregressive component (first term); ii) a common factor/predictor component (second term); iii) a stochastic volatility component (third term); iv) a covariance component (fourth term). It is obvious that the predictor uncertainty plays a big role through the second term. Expression (11) clearly varies over time due to stochastic volatility in the factor innovations, and it is generally nonzero for multi-step-ahead forecasts, i.e., h > 1. As a final remark, estimates of stochastic volatility in the residuals of each series y_j, as well as in each component of the predictor variables $\mathbf{z}$, are required to compute the uncertainty measure of each variable of interest.

Chapter 3

Empirical Implementation and Macro Data

Macroeconomic Variables, Dataset Construction, Individual Uncertainty Aggregation Method

In this chapter we will present the dataset we constructed for forming the forecasts and the common macroeconomic uncertainty measure. Our dataset is composed of 51 of the main macroeconomic variables for Italy. Unfortunately, the main Italian statistical database does not contain all the indicators needed, therefore we need to collect data from a variety of sources: Italian National Statistics Institute (ISTAT), Federal Reserve Economic Data (FRED), Organisation for Economic Co-operation and Development dataset (OECD), European Central Bank dataset (ECB), and Italian Central Bank (BI).[20] We form 9 main group of macroeconomic data: consumer price index; producer price index; labour market; industrial production; gross domestic product, consumption and investment; international trade markets; interest rates; housing market; stock market.

Consumer Price Index (CPI). The Consumer Price Index (CPI) is a weighted average of prices for a basket of consumer goods and services including transportation, food, and medical care. It's calculated by considering the average price changes across all items in a predetermined basket of goods. The CPI is used to determine price fluctuations linked with the cost of living and it is one of the most widely used indicators for determining periods of inflation or deflation. The data we make us of for this group of variables include CPI for: all items (CPI- all); food and non- alcoholic beverages (CPI- fna); alcoholic beverages, tobacco, narcotics (CPI- atn); clothing and footwear (CPI- cf); housing, water, electricity, gas and other fuels (CPI- hwego); furnishing, household equipment, routine household maintenance (CPI- fherhm); health (CPI- h); transportation (CPI- t); communication (CPI- c); recreation and culture (CPI- rc); restaurants and hotels (CPI- rh); miscellaneous goods and services (CPI- mgs). All the variables are indexed at the year 2015 =100.

Producer price index (PPI). The producer price index (PPI) is a group of indexes that calculates and represents the average movement in selling prices from domestic production over

---

time. It is a measure of inflation like the CPI, but it differs from consumer price index in that it assesses costs from the perspective of the industries that produce the goods, whereas the CPI assesses prices from the standpoint of consumers. The data we use for this group of variables include PPI for: manufacturing (PPI- m); industrial activities (PPI- ia); mining and quarrying activities (PPI- mqa); manufacturing of food products (PPI- mfp); energy (PPI-e); investment goods (PPI-ig); intermediate goods (PPI- ing); consumer goods (PPI-cg); durable consumer goods (PPI- dcg); non- durable consumer goods (PPI- ndcg). Again, all the variables are indexed at the year 2015=100.

Labour market. The labour market, also referred to as the job market, is concerned with the supply and demand for labour, with employees providing the supply and employers providing the demand. It is a fundamental part of any economy and is intertwined with capital, goods, and service markets. The data we collect for this group of variables include: unemployment rate (Unemp), representing the percentage of labour force that is jobless; employment rate (Emp), defined as a measure of the extent to which available labour force population is being used; activity rate (Acti), meaning the currently active population as a percentage of the comparable total current population; compensation of employees by industry (Compemp); labour compensation per employed person (Labcomp); hourly earnings of the manufacturing sector (Hourear); unit labour cost in the economy (Labcost); hours worked in the economy (Hourwork); working positions in the economy (Workp). Unemployment, employment and activity rate are expressed in percentage terms. Labour compensation, hourly earnings and unit labour cost are indexed at the year 2015=100. Compensation of employees is expressed in millions of euros and hours worked and working positions are expressed in thousands. Although some of the variables might sound similar, it is crucial to understand that we need all the available information to correctly measure the labour market impact on the macroeconomy and infer an as accurate as possible measure of uncertainty.

Industrial production. Industrial production (or production index (PI)) measures the output of businesses integrated in the industrial sector of the economy. In Italy, manufacturing is the most important industry, accounting for up to 88% of the total output.[21] The data we use for this group of indicators include: PI of total industry (PI- ti); PI for manufacturing (PI- m); PI for electricity, gas, steam and air conditioning (PI- egsac); PI for total energy (PI- te); PI for construction (PI- c); manufacturing total orders value (Ordman); total retail trade (Tretailt). As for the inflation measures, all the variables are indexed at the year 2015=100.

---

[21] More details about italian industrial production on https://tradingeconomics.com/italy/industrial-production.

GDP, consumption and investment. GDP or gross domestic production is the total monetary or market value of all the finished goods and services produced within a country's borders in a specific time period. It is commonly used as a broad measure of overall domestic production and therefore adopted as a measure of a country's economic wealth. GDP can be computed in three different ways, through expenditures, production, and income. Despite its shortcomings, GDP is an important tool for policymakers, investors, and corporations to use when making strategic decisions. Consumption is defined as the final purchase of goods and services by economic agents. An asset or object purchased with the intention of generating income or appreciation is referred to as an investment. The term appreciation refers to an asset's value increasing over time. Any medium or method used to generate future revenue, such as bonds, stocks, real estate property, or a business, is considered an investment. The data we use for this group of indicators include: gross domestic product in millions of euro (GDP); GDP as an index based on the year 2015=100 (GDP- index); growth rate of private final consumption as percentage of GDP (GDP- pfc); growth rate of government final consumption as a percentage of GDP (GDP- gfc); gross investment for different economic sectors in millions of euro (Grossinv).

International trade markets. International trade refers to the exchange of goods and services between countries. International trade enables countries to extend their markets and gain access to commodities and services that might otherwise be unavailable in their own country. The variables we represent in our dataset are: exports of goods (Exp); import of goods (Imp); spot exchange rate of € to $ (Spotexc). While imports and exports are indexed at the year 2015=100, the spot exchange rate is expressed in terms of Euro/Dollar.

Interest rates. The variables we use for interest rates are short- term interest rates (Shortint) and long- term interest rates (Longint). OECD gives the following definitions regarding the indicators used. Short-term interest rates are the rates at which short-term borrowings are settled between financial institutions or the rate at which short-term government paper is issued or traded in the market. Short-term interest rates are generally averages of daily rates, measured as a percentage. Short-term interest rates are based on three-month money market rates where available. Typical standardised names are "money market rate" and "treasury bill rate". Long-term interest rates refer to government bonds maturing in ten years. Rates are mainly determined by the price charged by the lender, the risk from the borrower and the fall in the capital value. Long-term interest rates are generally averages of daily rates, measured as a percentage. These interest rates are implied by the prices at which the government bonds are traded on financial markets, not the interest rates at which the loans were issued. In all cases,

they refer to bonds whose capital repayment is guaranteed by governments. Long-term interest rates are one of the determinants of business investment. Low long-term interest rates encourage investment in new equipment and high interest rates discourage it. Investment is, in turn, a major source of economic growth. [22]

Housing market. The Housing Market refers to the supply and demand for houses, usually in a particular country or region (Italy in our case). We include in our dataset the indexes, with base year 2015=100, of housing prices (Housp) and rent prices (Housr). [23]

Stock market. The stock market refers to a collection of exchanges and other venues where shares of publicly traded firms can be bought, sold, and issued. Such financial transactions are carried out on institutionalized formal exchanges (physical or electronic) or over- the- counter (OTC) markets that are governed by a set of rules. A well-functioning stock market is crucial to economic development because it allows businesses to swiftly acquire funds from the general public. As a measure of stock market in our dataset we use the share prices (Stockp). According to the OECD dataset share price indices are calculated from the prices of common shares of companies traded on national or foreign stock exchanges. They are usually determined by the stock exchange, using the closing daily values for the monthly data, and normally expressed as simple arithmetic averages of the daily data. A share price index measures how the value of the stocks in the index is changing, a share return index tells the investor what their "return" is, meaning how much money they would make as a result of investing in that basket of shares. A price index measures changes in the market capitalisation of the basket of shares in the index whereas a return index adds on to the price index the value of dividend payments, assuming they are re-invested in the same stocks. Occasionally agencies such as central banks will compile share indices.

Our full macroeconomic dataset is composed of quarterly data and goes from the first quarter of 1996 to the fourth quarter of 2019, just before the COVID-19 pandemic. Although some indicators are available from a preceding date to 1996, we want to include as many variables as possible to represent at best the macroeconomic environment, at the same time reducing as much as possible the loss of data.[24] As previously mentioned, a transformation of the raw data

---

[22] A surge in investment can also have a multiplier impact if the economy has excess capacity. The first increase in investment boosts economic growth, but if businesses see higher sales and profits, they are more likely to reinvest in more investment.

[23] The importance of housing market variables for macroeconomic uncertainty has been clear since the U.S. housing prices bubble burst that caused the Financial Crisis and the consequent Great Recession.

[24] We want to avoid the reconstruction of Time Series Data with Missing Values in order estimate our uncertainty measure through authentic data. Estimating the uncertainty measure using these techniques in order to obtain a longer time series for the missing data could be an interesting topic for future research.

is necessary to work with the time series. After the necessary logarithmic and differencing transformations of the data, and after the lags in the factor augmented vector autoregression (FAVAR) model, we construct a macroeconomic uncertainty estimate for the period ranging from q1 of 1998 to the q4 of 2019, counting a total of 88 quarterly observations.[25]

The stochastic volatility parameters stated in chapter 2, a_j, β_j, τ_j are estimated from the least square residuals of the forecasting models using Markov chain Monte Carlo (MCMC) methods. [26]Markov Chain Monte Carlo sampling provides a class of algorithms for systematic random sampling from high-dimensional probability distributions. Unlike Monte Carlo sampling methods that are able to draw independent samples from the distribution, Markov Chain Monte Carlo methods draw samples where the next sample is dependent on the existing sample, called a Markov Chain. This allows the algorithms to narrow in on the quantity that is being approximated from the distribution, even with a large number of random variables. The average of these model parameters over the MCMC draws is used to estimate $\mathcal{U}_{jt}^y(h)$ in the base-case. Therefore, we use simple averaging in order to retrieve our measure of h- period- ahead macroeconomic uncertainty denoted as follows

$$\bar{U}_t^y(h) = \frac{1}{N^y}\sum_{j=1}^{N^y} \hat{\mathcal{U}}_{jt}^y(h), \qquad (12)$$

where $\hat{\mathcal{U}}_{jt}^y(h)$ indicates the estimated value of $\mathcal{U}_{jt}^y(h)$. Besides the assumptions on the latent volatility process, this measure of average uncertainty imposes no structure on the individual uncertainty measures.

As already anticipated in chapter 2, we estimate uncertainty also in an alternative way, as done by Jurado et al. (2015). Instead of giving each individual measure equal weight, we form a latent common factor estimate of macro uncertainty as the first principal component of the covariance matrix of individual uncertainties. To do so, we first of all entertain the chance that uncertainty has a factor structure. If this is the case, macro uncertainty at each time t is a vector given by the common factor $F_t^{\mathcal{U}}(h)$ in

$$\log \mathcal{U}_{jt}^y(h) = c_j^{\mathcal{U}}(h) + \Lambda_{h_j}^{\mathcal{U}'} F_t^{\mathcal{U}}(h) + e_{jt}^{\mathcal{U}}(h). \qquad (13)$$

Macro uncertainty is then summarized by $F_t^{\mathcal{U}}(h)$, while idiosyncratic uncertainty is given by $e_{jt}^{\mathcal{U}}(h)$. The method of principal components is applied to the logarithm of the individual

---

uncertainty assessments and then rescaled, in order to guarantee that the latent uncertainty factor is > 0. As a result of this logarithmic specification, the PCA estimate of macro uncertainty $\mathcal{U}_{jt}^{y}(h)$ is the exponential of the PCA estimate $\hat{F}_t^{\mathcal{U}}(h)$, therefore we can put $\hat{\mathcal{U}}_t^{y}(h) \equiv exp(\hat{F}_t^{\mathcal{U}}(h))$. To obtain this measure, first of all we need to estimate the common (log) uncertainty factor $F_t^{\mathcal{U}}(h)$. Given the fact that many individual uncertainty series do not appear stationary, the estimate we are trying to obtain is defined by

$$F_t^{\mathcal{U}}(h) = \sum_{k=2}^{t} \hat{f}_k^{\mathcal{U}}(h),$$

where $f_t^{\mathcal{U}}(h)$ is an $r_u \times 1$ vector constituted of the r_u principal components of $\Delta log\mathcal{U}_{jt}^{y}(h)$. As Bai and Ng (2004) showed, when the idiosyncratic errors are possibly non-stationary, our differencing- recumulating method assures that the factors are consistently estimated. Due to our differencing procedure, the first value of our sample of the common uncertainty factor $\hat{F}_1^{\mathcal{U}}(h)$ is not present. To ensure a comparison with our baseline case of simple averaging approach since q1 of 1998, we impose as initial value of the common uncertainty factor the average level of (log) uncertainty across all the N series. Formally,

$$\hat{F}_1^{\mathcal{U}}(h) = \frac{1}{N} \sum_{j=1}^{N} log\ \mathcal{U}_{j1}^{y}(h).$$

Because the various individual uncertainty measures are themselves estimated, the problem of estimating r_u, the number of common uncertainty factors, $f^{\mathcal{U}}(h)$, is non-standard. As a simple solution to this problem, and to facilitate the comparison with the baseline measure of macro uncertainty $\bar{\mathcal{U}}_t^{y}(h)$, we impose r_u to be equal to 1. Additionally, we fine-tune the uncertainty factor $\hat{\mathcal{U}}_t^{y}(h)$ to have the same mean and standard deviation as $\bar{\mathcal{U}}_t^{y}(h)$ over the sample time series.

Going back to our baseline uncertainty measure estimation, we remind that the additional factors used in the augmented forecasting equation are estimated through the method of principal component analysis (PCA). Bai and Ng (2006) reported that if $\sqrt{T} / N \to 0$, the estimates $\hat{F}_t$ can be treated as if they were actual observed indicators in the forecasting regression.

The augmented forecasting model's potential predictors are therefore

$$\hat{\boldsymbol{F}}_t = \left(\hat{F}_{1t}, \dots, \hat{F}_{r_F t} \right)', \text{ and } \boldsymbol{W}_t ,$$

where the latter consists of squares of the first element of $\widehat{\boldsymbol{F}}_t$, and factors in X_{it}^2 collected in the $N_G \times 1$ vector $\widehat{\boldsymbol{G}}_t$. We use these quadratic components in $\boldsymbol{W}_t$ in order to account for potential nonlinearities and the impact of conditional volatility on the conditional mean function. According to the work by Bai and Ng (2008), the final predictors are chosen to ensure that only those with considerable incremental predictive value are included. To do so, we use a strict thresholding procedure and a conservative t test to keep just the statistically significant predictors $\boldsymbol{F}_t$ and $\boldsymbol{W}_t$. To go into the details of the selection process, we start with a set of possible predictors that includes all the estimated factors in X_{it}, namely $\widehat{\boldsymbol{F}}_t$, the first estimated factor in X_{it}^2, namely $\hat{G}_{1t}$, and the square of the first factor in X_{it}, namely $\hat{F}_{1t}^2$. After that, we chose subsets from these candidate predictors through a regression of y_{it+1} on a constant, four lags of the dependent variable y_{it} , $\widehat{\boldsymbol{F}}_t$, $\hat{G}_{1t}$, $\hat{F}_{1t}^2$, with these last three components not lagged. As a last step, we keep the regressors that have a marginal t statistic greater than 2.575 in the multivariate forecasting regression of y_{it+1} on the potential predictors known at time t. [27]

Another important topic we want to discuss, before wrapping up our discussion about our data and its implementation, is the possible use of real-time data as opposed to our historical data. We chose to use historical data in the estimation of our uncertainty measure for a few reasons. First, for our study we make use of a large dataset of macroeconomic variables, counting 51 indicators divided in 9 macro-categories. Retrieving real-time data for all those variables is simply not possible, especially for a country like Italy. This problem is also encountered by Jurado et al. (2015) in their study of U.S. uncertainty measure, even though the United States are at the core of many studies being one of the driving forces of global economy. Furthermore, due to the cost-opportunity emerged during our data collection process that we have previously mentioned, we are able to collect mainly quarterly data for our dataset to be as rich as possible both in terms of time length and number of variables available. Therefore, we would be bounded anyways to collect 'non- real- time' data. Second, as time passes, earlier available estimates of many time series (including real- time data) are analysed and revised and, as a result, better estimates become available. Third, we want to create the most historically accurate estimations of uncertainty at each given point in time in our sample. Restricting information to real-time data is not at all appropriate for this goal because it's likely to be too limiting, underestimating the amount of information agents have at the time of the forecast. Fourth, we must take into account that even forecasting experts can predict a major portion of a future data release based on available data. In this sense, much of what is referred to as real-time data, with the exception

---

[27] 2.575 t statistic assures a confidence interval of 99 percent.

of data from financial markets, is actually recently revealed information on previously occurred events.

Chapter 4

Macro Uncertainty Measure and Analysis

Uncertainty Measure, Predictors, Common Proxies, Real Economic Activity and Countercyclicality, Interpretation

4.1 Macro Uncertainty Measure

We are finally ready to present our estimates of macroeconomic uncertainty. Since our dataset is composed of quarterly data, we estimate uncertainty for 2 horizons: $h = 1$ and $h = 4$ quarters.

4.1.1 CSA and PCA Uncertainty Measure

We start from our baseline case of simple averaging of the individual uncertainty estimates to form our macroeconomic uncertainty measure (cross sectional average). Figure 1 plots $\bar{\mathcal{U}}_t^y(h)$ over time for both $h = 1$ and $h = 4$ quarters.

Figure 1. Macroeconomic Uncertainty CSA: $\bar{\mathcal{U}}_t^y(h) for h = 1, 4.$ The horizontal dashed line indicates 1.65 standard deviations above the mean of both series. The data are quarterly and span from q1 1998 to q4 2019.

It appears immediately clear that $\bar{\mathcal{U}}_t^y(4)$ is greater than $\bar{\mathcal{U}}_t^y(1)$. This is intuitive since, as we explained in the econometric framework chapter, an increase in the forecast horizon will lead to less certain prediction of future circumstances, leading uncertainty to increase with h on average. As the time range covered by the forecast—the time horizon—increases, the forecast accuracy drops. Short-term forecasts, on average, face less uncertainty than longer-term forecasts, hence they are more accurate. A longer forecasting horizon increases the likelihood of changes that are still unknown having a significant impact on future variables. Another interesting feature captured in our estimate is that, as h increases, the variability of the uncertainty decreases, and this is due to the fact that the forecast tends to its unconditional mean as the forecast horizon tends to infinity. Macroeconomic uncertainty peaks substantially around the years 2007-2009, during the Great Recession. For both of our uncertainty forecast horizons, the Great Recession represents by far the most pronounced episode of high uncertainty across the 20+ years of the time frame taken into consideration. As a matter of fact, only during the greatest global crisis in recent times, the macro uncertainty exceeds 1.65 standard deviations above its mean in our sample.[28] Only during the 2001 Dotcom crisis and after the Twin Tower's terroristic attack does macroeconomic uncertainty measure come close to the 1.65 standard deviation threshold (not exceeding it). These results clearly state that there are way fewer instances of uncertainty, based on our measure, than what other popular proxies imply, as we show later.

The second method we used to aggregate the individual uncertainties weights to estimate the macroeconomic uncertainty measure is the principal component method (PCA). Figure 2 plots $\hat{\mathcal{U}}_t^y(h)$ over time for both $h = 1$ and $h = 4$ quarters.

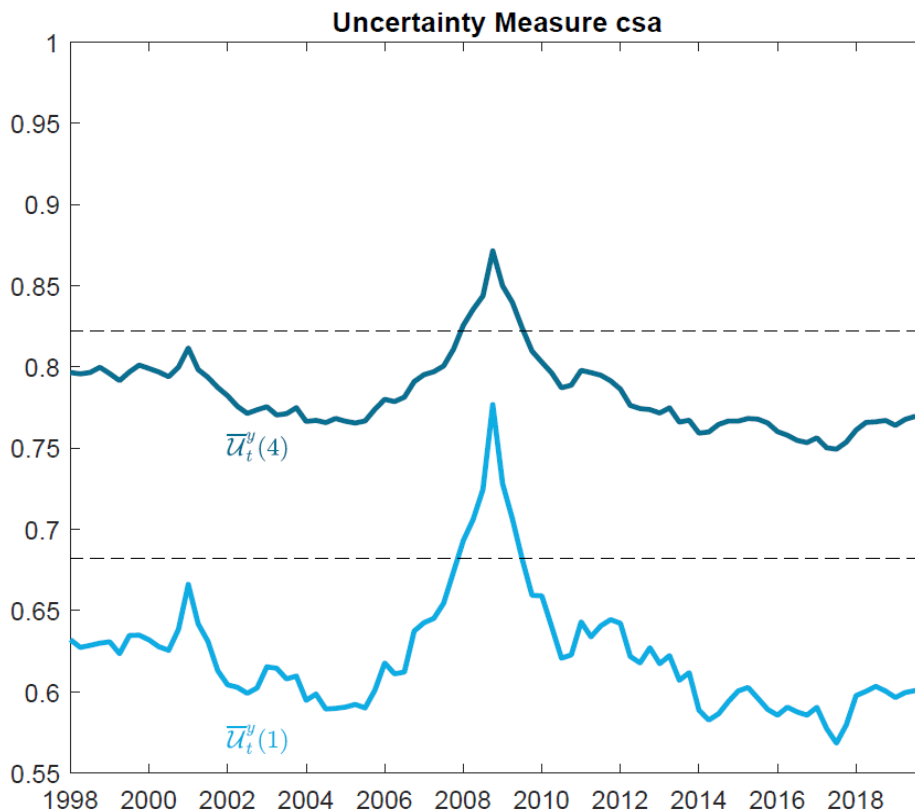[28] The value 1.65 belongs to the 90% confidence interval.
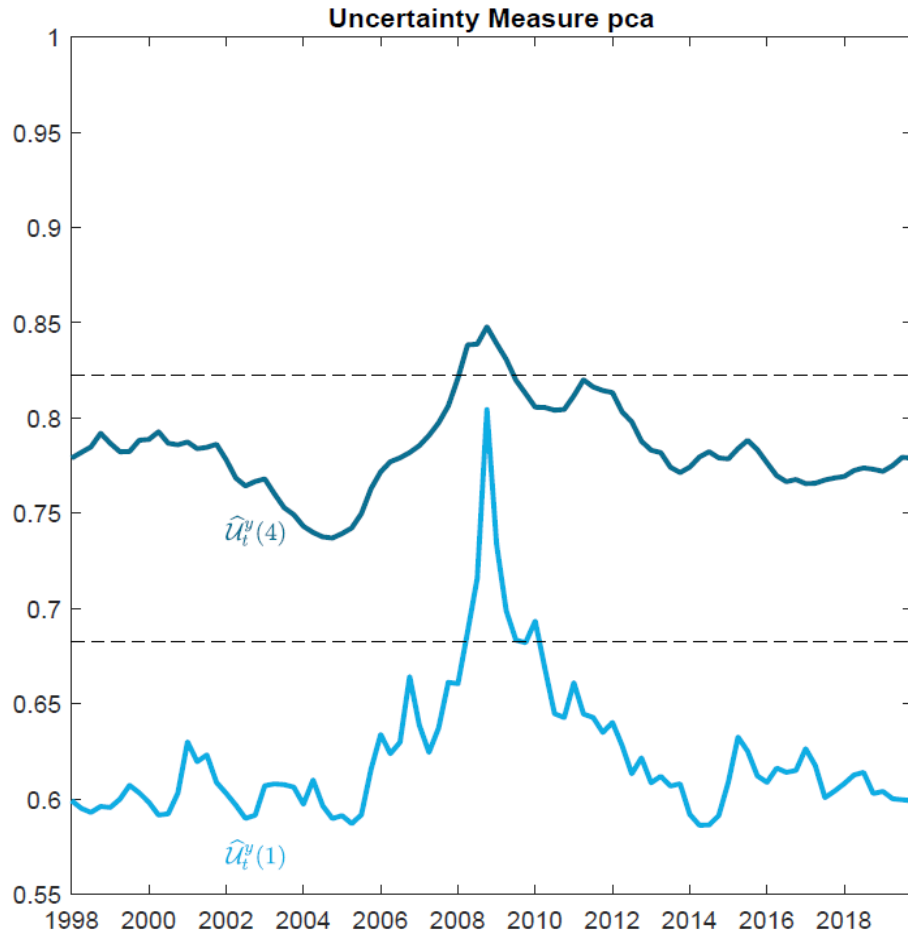
Figure 2. Macroeconomic Uncertainty PCA: $\hat{\mathcal{U}}_t^y(h) = 1, 4$. The horizontal dashed line indicates 1.65 standard deviations above the mean of both series. The data are quarterly and span from q1 1998 to q4 2019.

Again, the same considerations made for the simple average uncertainty case can be made for the PCA based aggregation method. $\hat{\mathcal{U}}_t^y(4)$ is evidently greater than $\hat{\mathcal{U}}_t^y(1)$ due to the longer forecast horizon. Also, as h increases, the variability of the uncertainty decreases since the forecast tends to its unconditional mean as the forecast horizon tends to infinity. The uncertainty measure exceeds its 1.65 standard deviation only once, during the recent financial crisis for both horizons. This consistency of our results between PCA and CSA methodology of aggregation of individual indicators goes to testify positively towards the validity of our results. Furthermore, we will give an economic interpretation to the majority of the peaks registered by our macro uncertainty measure towards the end of chapter 4.

Figure 3 shows the comparison between the two aggregation methods for the 1 period ahead forecast, $\overline{\mathcal{U}}_t^y(1)$ and the $\hat{\mathcal{U}}_t^y(1)$. Both measures are standardized towards the true mean and variance of the baseline case, in order to render the two measures comparable. The PCA presents a lower uncertainty metrics towards the beginning of the sampled period (1998-2001), while it presents higher uncertainty values towards the last years of the sampled period (2015-

2017).[29] In general, however the two measures follow the same trend: when uncertainty increases in the CSA case, it also increases in the PCA case (and vice-versa).

Uncertainty Measure (1) csa vs pca

$\overline{\mathcal{U}}_t^y(1)csa$

$\widehat{\mathcal{U}}_t^y(1)pca$
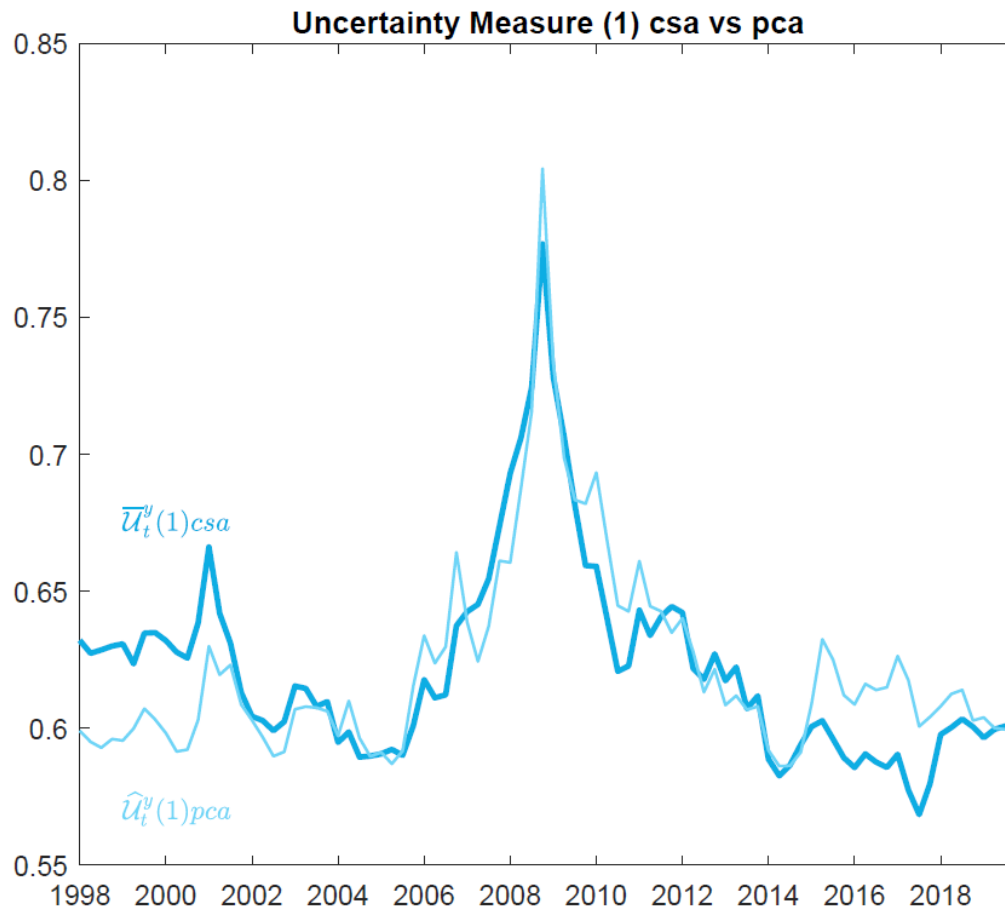
Figure 3. Macroeconomic Uncertainty CSA vs PCA for h =1. The data are quarterly and span from q1 1998 to q4 2019. The data is standardized on the mean and variance of the base case.

Figure 4 shows the comparison between the two aggregation methods for the 4 period ahead forecast, $\overline{\mathcal{U}}_t^y(4)$ and the $\widehat{\mathcal{U}}_t^y(4)$. Although almost everything we stated for figure 3 continues to be true, the PCA case seems to slightly accentuate the increases and the decreases in uncertainty measurement with respect to the CSA case. This is clearly due to the very structure of the measure, giving more importance to certain component of the individual uncertainty measures. Nonetheless, all 4 cases presented are consistent with the uncertainty events and periods that concerned the Italian economy in the last two decades, as we will show later in the chapter.

---

[29] This is clearly do to the aggregation method of the two measures.

Uncertainty Measure (4) csa vs pca

$\overline{\mathcal{U}}_t^y(4)csa$

$\widehat{\mathcal{U}}_t^y(4)pca$
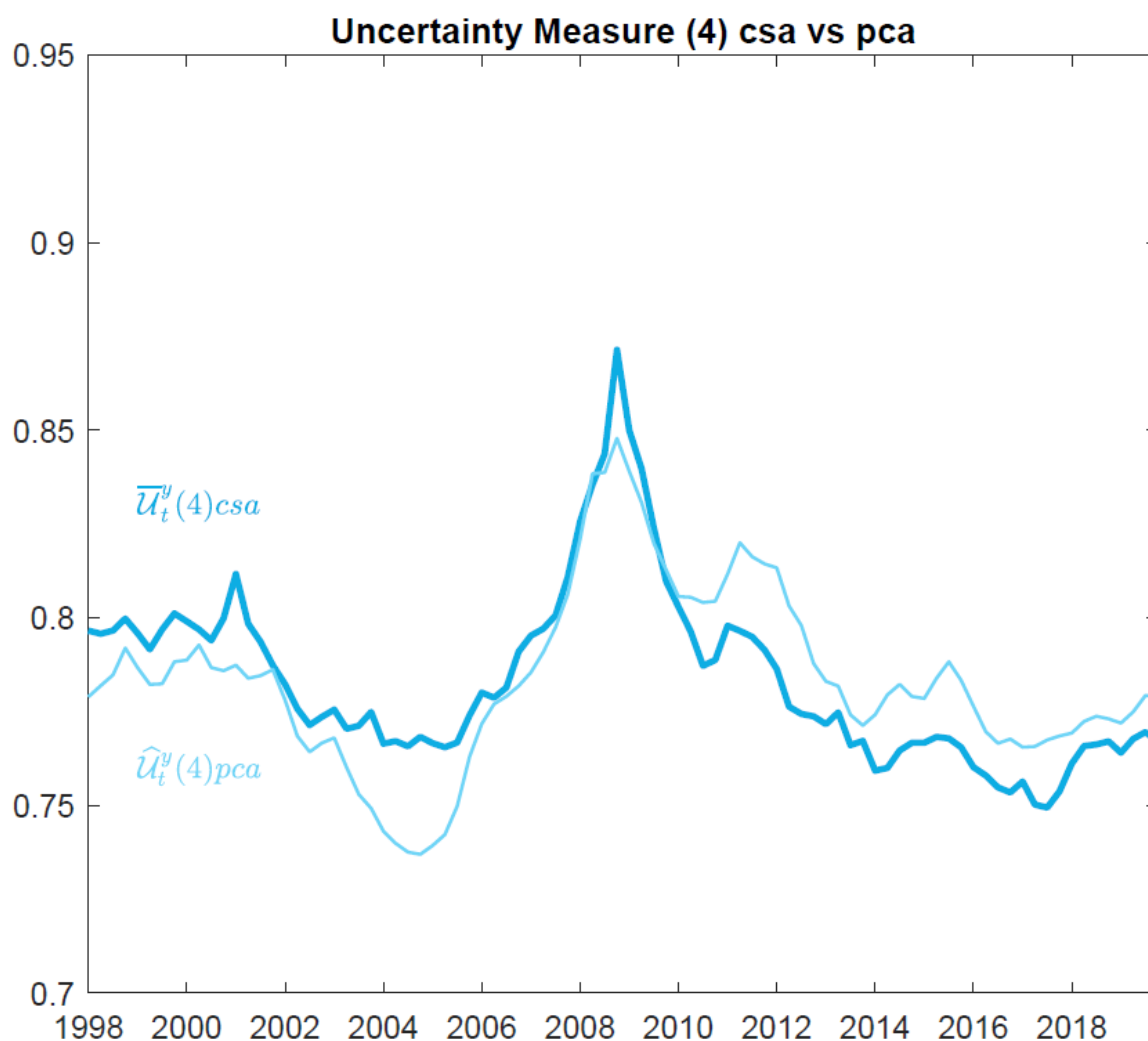
Figure 4. Macroeconomic Uncertainty CSA vs PCA for h =4. The data are quarterly and span from q1 1998 to q4 2019. The data is standardized on the mean and variance of the base case.

4.1.2 Italian Vs American Macro Uncertainty Measures

In this section we compare our Italian macro uncertainty measure with the U.S. measure of macro uncertainty obtained by Jurado et al (2015), with the updated data to the end of 2019.[30] We convert the monthly data of the American measure to quarterly data for a cleaner comparison with ours. We think it is fundamental to state that the results and points we will be making in this section are not data proved, besides our estimates, and leave space for a deeper analysis.

Figure 5 plots the macro uncertainty measures for Italy and for the U.S. for the one- period-ahead forecast (h=1). The aggregation of the uncertainty measures is based on the equal weighting (baseline case).

---

[30] Data retrieved at https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

Uncertainty(1) Italy vs USA
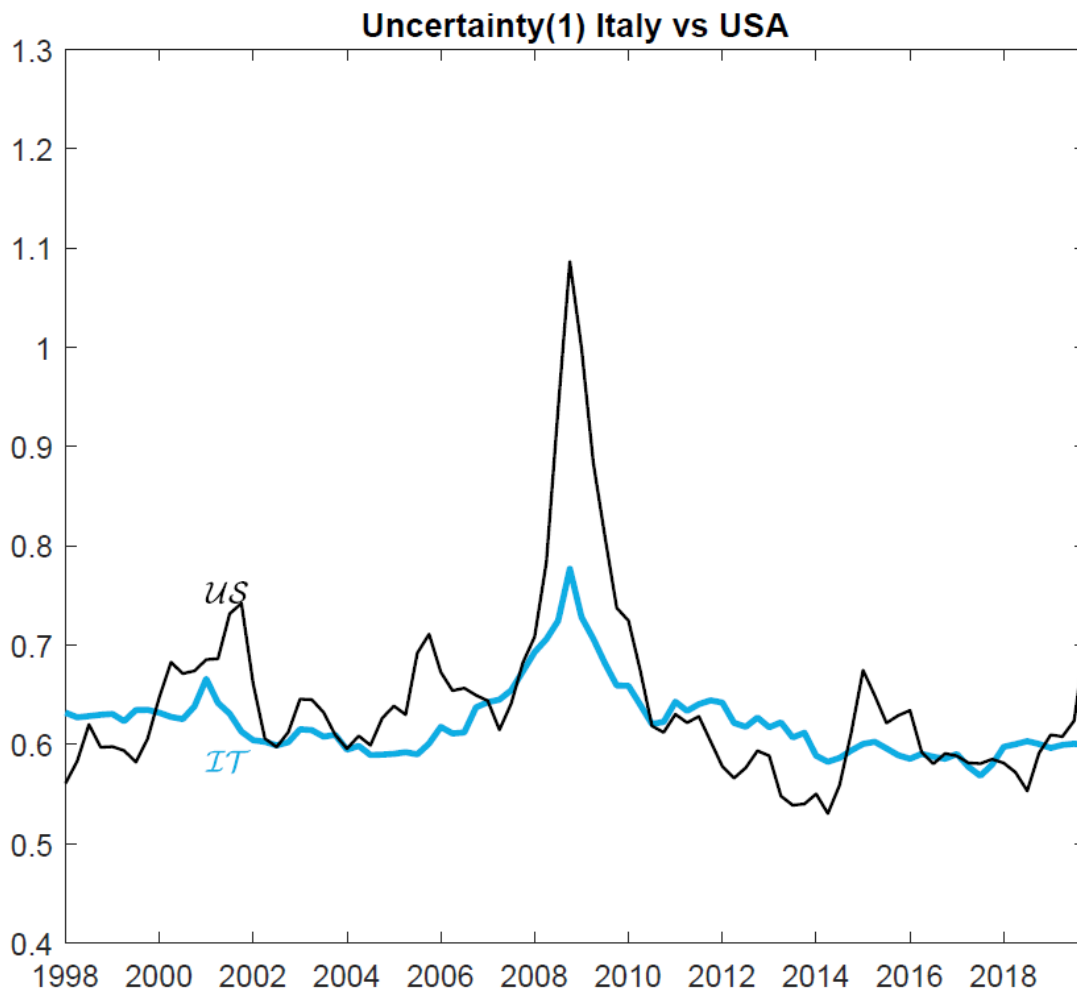
Figure 5. Macroeconomic Uncertainty of Italy and United States. The data are quarterly and span from q1 1998 to q4 2019.

There are a few interesting features of the two measures worth noting. First, in normal times, uncertainty seems to be generally lower in the U.S. than in Italy. One explanation of this could be that the United States are considered a very strong country in times of economic stability or progress. Businesses are thriving, jobs are created, and consumption rises, oiling the motor of the economy. Another possible explanation of this lower uncertainty in stable times can be found in the Uncertainty Avoidance Index (UAI), introduced by Geert Hofstede in 1980. The UAI is a cross- sectional phenomenon that describes the degree at which a society, or the members of said society, tolerate and cope with unpredictability. It reflects the reaction to ambiguity. The countries with a strong UAI are countries with traditional practices and standard approaches. On the other hand, countries with a low UAI are deemed to embrace alternative approaches and are comfortable with uncertainty. From a recent study, Italy is believed to have an uncertainty avoidance index of around 75 while the U.S. are believed to have an index around 46.[31] Second, United States' measure shows peaks of uncertainty higher than Italy. This is

---

[31] Data retrieved at https://clearlycultural.com/geert-hofstede-cultural-dimensions/uncertainty-avoidance-index/.

probably due to the fact that the U.S. are considered the main economic power of the world accounting for roughly 25% of the global GDP, therefore, every recession or stagnation period strongly negatively impacts the country. Furthermore, the role played by the U.S. dollar worldwide can amplify the effects of other countries' uncertainty and crisis on the American economic power. It is also important noting that the Financial Crisis and consequent Great Recession arose in the U.S., then having a domino effect on the rest of the world. Another important uncertainty increase, between 2000 and 2002, in both the Italian and the U.S. indexes is given by the terroristic attack of 9/11 and the burst of the Dotcom bubble. As the Great Recession, these events propagated to the world through the U.S. economy. There are numerous papers that study and explain the mechanisms of transmission of the States' cyclical developments to the rest of the world.[32] Third, although presenting impressive increases in the Uncertainty measure with respect to the Italian case, U.S. seem to be able to recover from uncertainty period faster than the European country. A big role in these speedy recoveries is probably played by the efficiency and relatively high trustworthiness of the American policy makers in responding to the different crisis, as opposed to the renowned Italian policy makers' inefficiency. Furthermore, the fact the communitarian environment in which Italy finds itself, although being overall positive, makes it difficult for the country's government to implement efficient policies without the monetary tool, mainly reserved to the European Central Bank.

Although some differences in the magnitude and in the speed of recovery of the uncertainty measures in the two countries, they both seem to follow roughly the same trend. Indeed, the two estimates present a very high positive correlation of 0.78. This confirms, as many studies found, that there is significant transmission mechanism from the U.S. to the rest of the World (and Italy).

4.2 The Role of Predictors in Determining the Uncertainty Measure

In the econometric framework description, we have greatly emphasized the importance of removing all the foreseeable variation in a series so as not to attribute its fluctuations to a movement in uncertainty. Now we want to show how relevant the predictors obtained actually are in the estimation of our macro uncertainty measure.

4.2.1 Predictors

As previously shown in equation (6), our forecasting regression is the following:

---

[32] See Dees and Saint- Guilhem (2011), Arora and Vamvakidis (2004), Dees and Vansteenkiste (2007), Bayoumi and Bui (2010).

$$y_{jt+1} = \varphi_j^y(L)y_{jt} + \gamma_j^F(L)\widehat{\boldsymbol{F}}_t + \gamma_j^W(L)\boldsymbol{W}_t + \sigma_{jt+1}^y \varepsilon_{jt+1} \, .$$

Our predictors $\mathbf{F}$ and $\mathbf{W}$ have uncertain future values, and each predictor is forecasted using an AR (4) model. We have previously shown how the time- varying volatility in the predictors forecast errors contribute to the h- step- ahead uncertainty of each series y_{jt} when the forecasting horizon is greater than 1. Figure 6 shows the estimated factor uncertainty $\mathcal{U}_{kt}^F(h)$ for the factors $\widehat{\boldsymbol{F}}_{kt}$ that were proved to be significant trough the hard thresholding rule, among all the factors estimated. [33]
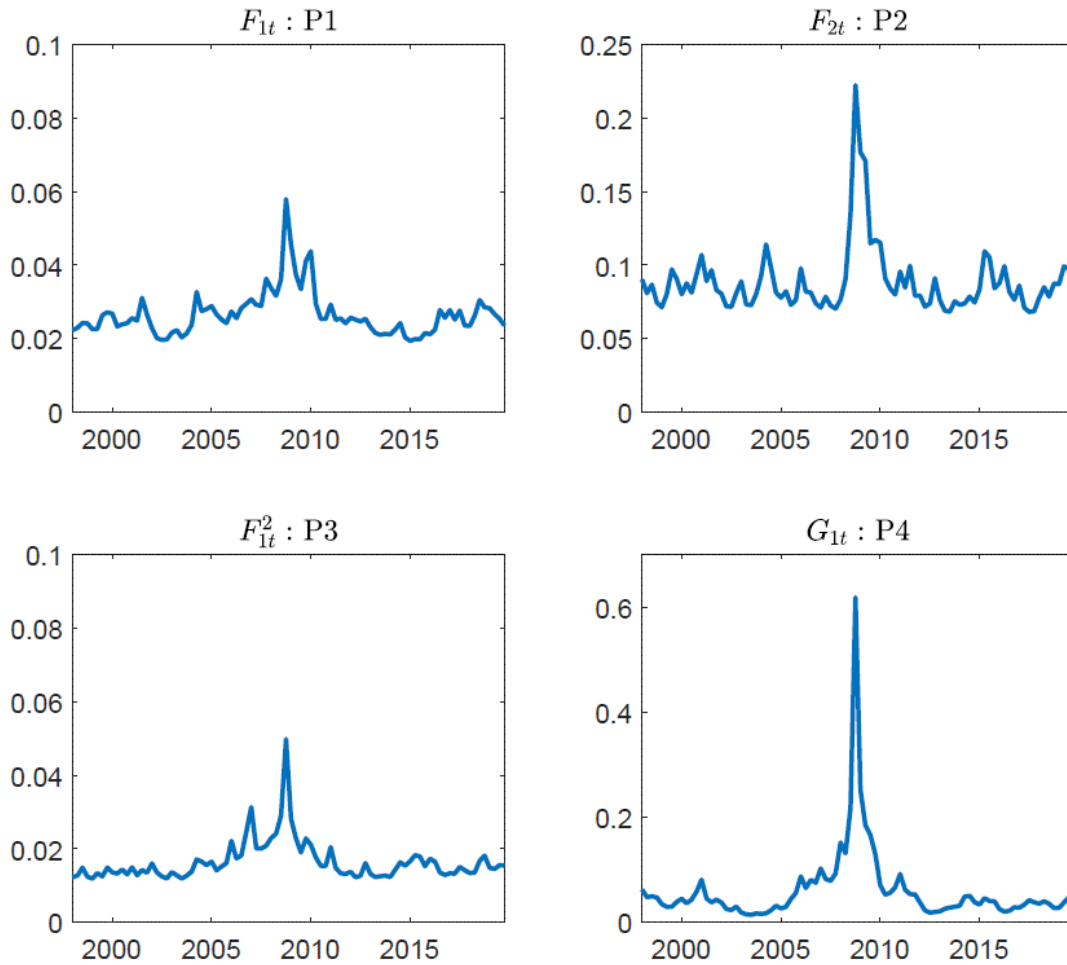
Figure 6. Predictors' uncertainty. The above results represent the predictors contained in $Z_t \equiv (F_t', W_t')'$. The data is quarterly and span the period q1 1998- q4 2019.

The top two predictors are the factors estimated in $\mathbf{F}$, namely F_{1t} and F_{2t} , while the third and fourth are plots of the predictors in $\mathbf{W}$, namely F_{1t}^2 and G_{1t}. From these findings we can clearly see that uncertainty in the predictor variables is crucial in contributing to uncertainty in the series y_{jt+h} to be forecasted. Although there are idiosyncratic features of the volatilities of all

---

[33] t statistics greater than 2.575, hence confidence interval of 99 percent.

the predictors, the 2007-2009 period is characterized by a strong increase of factors' uncertainty. The predictors have also a direct impact on the forecast level, besides the stochastic volatility effect described above. A key feature of our uncertainty measure is a forecasting model that exploits as much accessible information as possible in order to explain as accurately as possible the macroeconomic state of the country, thus eliminating all the forecastable variations from our estimates in each variable y_{jt+h}. Most commonly used uncertainty proxies ignore these systemic forecasting interactions.

4.2.2 Key Series Analysis

To further examine the role that our predictors play in our uncertainty estimation across the different series, we estimate for a second time the uncertainty for each variable based on a simple, not augmented, model with constant conditional mean:

$$y_{jt+1} = \mu + \tilde{\sigma}_{jt+1}\tilde{\varepsilon}_{jt+1} \ . \tag{14}$$

In figure 7 we plot the baseline measure of uncertainty and we compare them to the possibly mis- specified estimates resulting from the simple factor- less model (14), for a handful of key variables of our dataset. We do so for: total production index, GDP index, consumer price index, production price index for consumer goods, long term interest rate, short term interest rate, house prices and stock prices.

Keyseries
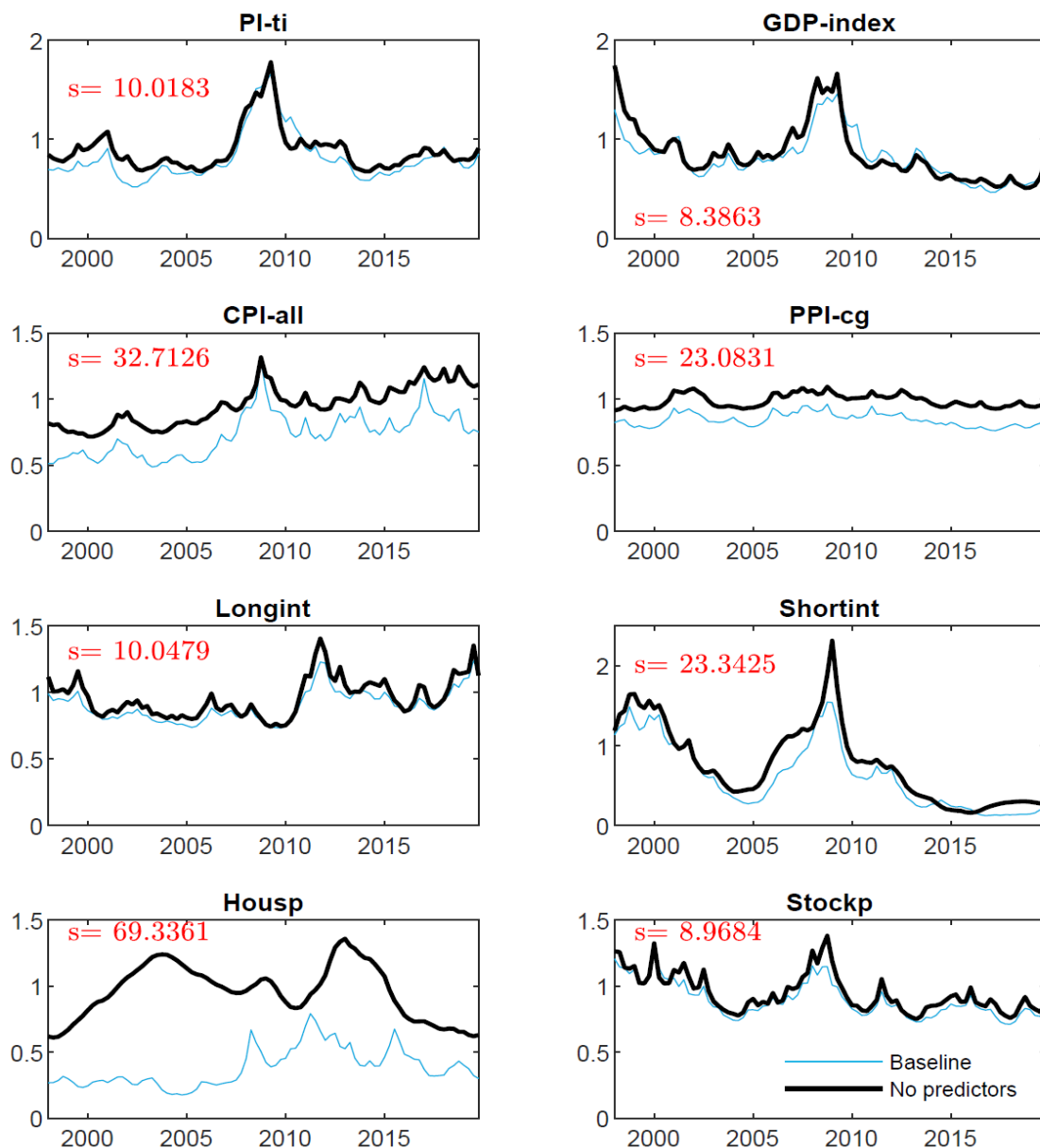
Figure 7. Role of Predictors in the key-series analysed. The plots show two estimates of $\bar{u}_{jt}^{y}(1)$ for several key-series in our dataset. The Baseline estimate uses the full set of predictors available, while the No predictors estimate does not use any of the predictors. The data are quarterly and span the period q1 1998- q4 2019.

There are a few things that this data tell us. First, there is meaningful heterogeneity in the time-varying uncertainty estimates across the different series. This means that a considerable part of the uncertainty is series- specific. Second, figure 7 further indicates that whether or not the forecastable variation is removed before computing individual uncertainty has a considerable impact on the estimations of uncertainty in these variables. Indeed, when it is removed through the information contained in our predictors, the uncertainty estimates tend to be lower, and in some instances, significantly lower. In some periods, the gap between the two estimates for

these variables is fairly large, implying that much of the variance in these series is predictable and should not be attributed to uncertainty. This is also shown by the spread measure present on each plot. The spread simply represents the sum, for each series, of the difference between the predictor- less estimate and the baseline augmented estimates of time- varying uncertainty, across the whole time series from q1 1998 to q4 2019. When the spread (s) is > 0, the potential mis- specified estimates are larger, in general, than the baseline case (and vice- versa). Now we can also numerically, and not only graphically, affirm that our predictor augmented estimates remove a big part of predictable variation, using all the available information (contained in the data) at time t. Furthermore, through the measure of the spread, we can see that the series, among those taken into account, that majorly benefit from our improved estimation is the housing price (s=69.34). This is understandable since the Financial Crisis, and consequent Great Recession, were led by the burst of the housing bubble in the 2000s. Examining briefly the series' estimates of uncertainty, it clear that every series, besides the PPI, the Housp and the Longint, experiences the highest increase during the 2007-2009 recession. The long interest rates show their most relevant increase of the estimate around 2012, due to the European Sovereign Debt Crisis. The housing prices show the biggest increase before the Financial Crisis, being one of its main causes, and during the communitarian debt crisis.

4.2.3 Macro Uncertainty Measure: Predictors vs No Predictors

To conclude our investigation on the role of the predictors in our model, in figure 8 we plot our macro uncertainty measure for h=1 computed in both ways, with and without the predictors.
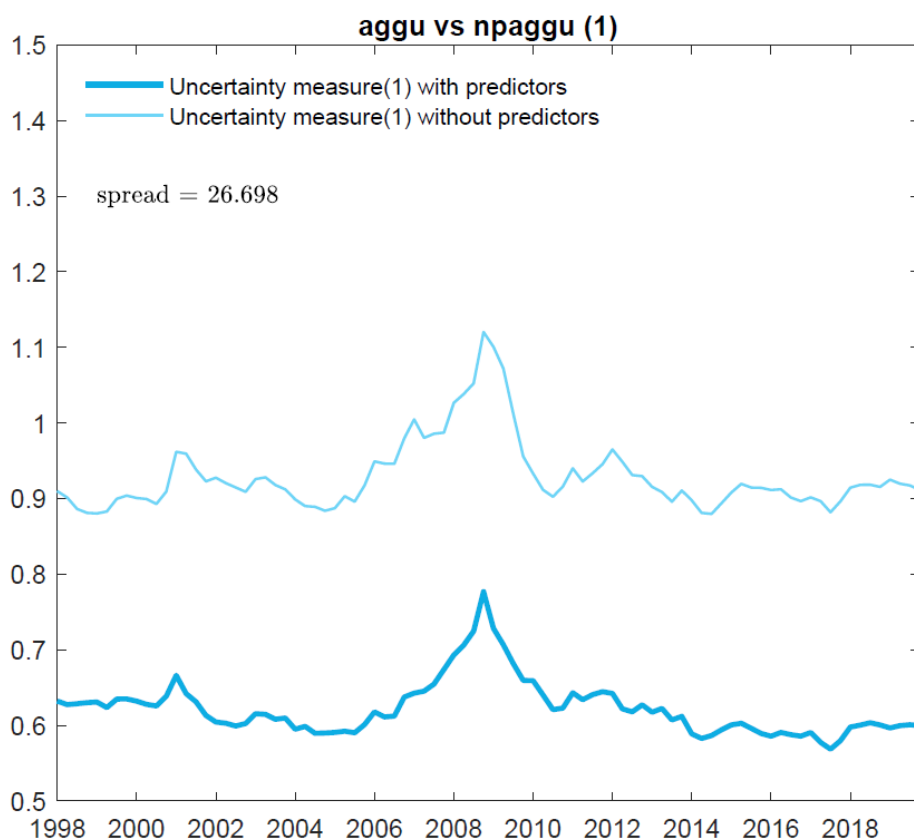
Figure 8. The role of Predictors in the Macro Uncertainty Estimate: $\bar{u}_t^y(1)$. The Baseline estimate aggregates the individual series that use the full set of predictors available, while the No predictors estimate aggregates the individual series that do not use any of the predictors. The data are quarterly and span the period q1 1998- q4 2019.

Again, the plots show that the macro uncertainty estimate, removing all the forecastable variation exploiting all the information (in our data) available at time t, is lower of about 30% across the period of reference, with respect to the possibly mis- specified no- predictors estimate. The general trend for both measures is roughly the same.[34]

4.3 Macro Uncertainty Versus Other Uncertainty Proxies

We have now presented our uncertainty measure, which overall is coherent with the economic theory and seems to present reliable results.[35] But how good is actually our uncertainty measure and how does it compare with commonly used uncertainty proxies for Italy?

The Italian proxies we chose for the comparison are the Stock Market Volatility Index, the Economic Policy Uncertainty Index and the World Uncertainty Index. All measures of

---

[34] The addition of predictors seems to influence more the level of uncertainty rather than the general pattern of uncertainty. This is in line with what we would expect since even a simple uncertainty predictor, if well-constructed and computed with the right data, should be able to show us the periods of high and low uncertainty. However, the level of uncertainty is higher since not all the predictable component is removed.
[35] More on this in the following sections.

46

Uncertainty are standardized to have $\mu = 0$ and $\sigma = 1$ in order to allow for a correct and easier comparison between them.

4.3.1 Macro Uncertainty vs. Stock Market Volatility Index

The first measure that we will analyse and compare to our macro uncertainty measure is the Stock Market Volatility Index (ISV, i.e., Italian Stock Volatility).

First and foremost, let's define stock market volatility. The volatility of the stock market is a measure of how much the market's overall value swings up and down. Individual stocks, in addition to the market as a whole, are also deemed to be volatile. Volatility is determined by looking at how much an asset's price departs from its average price. The standard deviation is a statistical measure of volatility that is often employed.

Bloom (2009) argues that a measure of stock market volatility can be used as a proxy for uncertainty. This is also stated or supported by numerous other papers on uncertainty.[36]

Figure 9 plots the standardized measure of uncertainty of both our estimation and the stock market volatility index. As proxy of the ISV, we take the relative measure for Italy elaborated by Castelnuovo and Caggiano (2021). They create their estimate of stock market volatility elaborating data on stock market returns, exchange rate returns, and 10-year Government bond yield returns for 42 countries for the period July 1992 - May 2020.[37]

---

[36] See Romer, (1990); Leahy and Whited (1996); Hassler (2001); Bloom, Bond, and van Reenen (2007); Greasley and Madsen (2006); Gilchrist, Sim, and Zakrajsek (2010); and Basu and Bundick (2012); Fang, Su, and Yin (2019); Liu and Zhang (2015), Leduc and Liu (2016).
[37] For our analysis we transform the data in quarterly and take the ISV measure from q1 1998 to q4 2019.
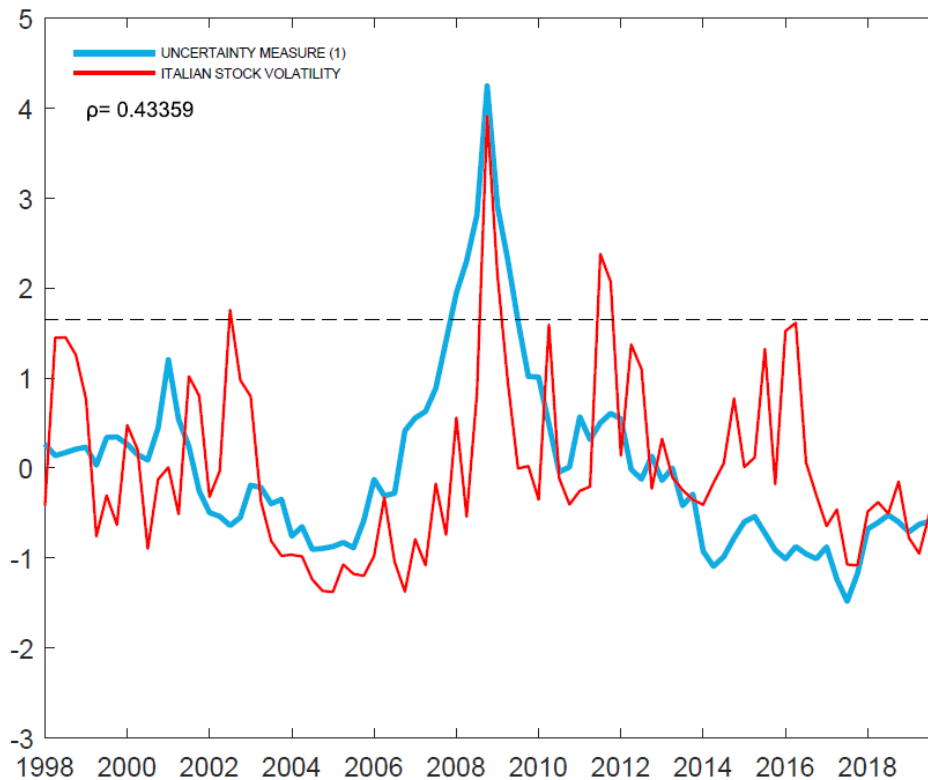
Figure 9. Uncertainty Measure (h=1) vs Italian Stock Market Volatility Index. Both measures are expressed in standardized units with $\mu = 0$ *and* $\sigma = 1.$. The horizontal line corresponds to the 1.65 standard deviations above the unconditional mean of each series. The data are quarterly and span the period q1 1998- q4 2019.

It is immediately clear that the ISV index is significantly more volatile than our estimate $\bar{u}_t^y(1)$, with many sharp peaks that are not correspondingly reflected by our macro uncertainty measure. The ISV is characterized by rapid increases in its volatility followed by rapid decreases. When used as a proxy of the macro uncertainty, the stock market volatility tells us that periods of recession are followed by speedy recoveries by the whole economy, going back to pre- crisis levels of uncertainty in a matter of a few months. Notably striking is the case of the Financial Crisis and subsequent Great Recession, in which the uncertainty period significantly over the 1.65 standard deviations above the unconditional mean only lasts for roughly 2 quarters. The macro uncertainty goes back to pre- crisis level in about 4 quarters. To put into perspective, our measure presents uncertainty significantly above the 1.65 threshold for more than 7 quarters, and takes more than 3 years, to go back to pre- crisis level. $\bar{u}_t^y(1)$ presents a realistic decrease rate of the macro uncertainty and a persistence that is in line with the theory around the subject. Additionally, the ISV presents two cases in which the proxy surpasses the 1.65 standard deviations, and three cases in which it is extremely close to do so, almost stating that there are additional five cases in which the macro uncertainty level arose extremely significantly, almost as much as during the Financial Crisis. Also these spikes, like the one analysed above, present an extremely fast recovery rate.

Furthermore, even if there is no change in economic fundamental uncertainty, i.e., if leverage increases, or if variations in risk aversion or sentiment are key drivers of asset market fluctuations, stock market volatility can vary over time. If there is heterogeneity in the loadings on common risk factors, cross-sectional dispersion in individual stock returns can fluctuate without any change in uncertainty.[38] Our uncertainty measure and the ISV seem to report, in general, on very similar uncertainty events presenting a positive, high correlation (0.43).

4.3.2 Macro Uncertainty vs. Economic Policy Uncertainty Index

The second commonly used proxy of uncertainty we are going to analyse is the Economic Policy Uncertainty Index (EPUI) for Italy, developed by Baker et al (2016). The EPUI is an index based on newspaper articles regarding policy uncertainty. For its estimation they draw on the two main newspaper per country, namely Corriere della Sera and La Stampa for Italy. According to the website they created for the policy uncertainty measures, they then count the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-relevant terms.[39] They conduct all searches in the native language of the newspaper in question. They scale the raw EPU count by a measure of the number of articles in the same newspaper and month. They standardize each newspaper-level monthly series to unit standard deviation prior to 2011 and average across newspapers by month to obtain country-level and European EPU indexes, which they normalize to a mean of 100 prior to 2011. We transform the data from monthly to quarterly and we standardize to have $\mu = 0$ and $\sigma = 1$.

Figure 10 plots the two standardized measures.

---

[38] Taken from Jurado et al. (2015).
[39] The website is: https://www.policyuncertainty.com/.

Figure 10. Uncertainty Measure (h=1) vs Economic Policy Uncertainty Index for Italy. Both measures are expressed in standardized units with $\mu = 0$ and $\sigma = 1.$. The horizontal line corresponds to the 1.65 standard deviations above the unconditional mean of each series. The data are quarterly and span the period q1 1998- q4 2019.

Looking at the graph, it is promptly evident that the Economic Policy Uncertainty Index shows little to no relevant movement during the Great Recession of 2007- 2009. By this fact alone, the usefulness of EPUI as macro uncertainty proxy can be put under serious questioning. Furthermore, the proxy exhibits sharp increases and likewise rapid decreases, hinting at the speedy dispersion of the macro uncertainty. There are a couple of instances in which EPUI exceeds the 1.65 standard deviations above the mean threshold, around 2012 and 2013, probably driven mostly by the European Sovereign Debt Crisis. In these particular cases, the uncertainty is three times bigger than the uncertainty that arose during the Great Recession. There are additional 5 peaks during the span of our timeseries analysis where the pinnacle of the uncertainty is higher than that caused by the biggest recession in recent times, adding to the inability of the measure to be a good proxy for the macro uncertainty. This type of behaviour of the news- based measure can be due to the very nature of its construction. The "news" factor could be such that, once the topic has been covered, the proxies will quickly drop to low values until a new event of uncertainty arises. Of course, this does not mean that in the meantime the uncertainty has drastically diminished as the news-based proxies would make it seem, but rather that the media has lost interest in the subject or already reported on it.

The difference between our uncertainty measure and the EPUI, namely the persistence and the far fewer relevant uncertainty events, it is also testified by the low, negative correlation between the two measures (-0.15).

4.3.2 Macro Uncertainty vs. World Uncertainty Index

The last measure we take into account as possible proxy of macro uncertainty is the World Uncertainty Index (WUI) for Italy, developed by Ahir et al. (2018). According to the website they created for the policy uncertainty measures (where also EPUI is reported), they construct quarterly indices of economic uncertainty for 143 countries from 1996 onwards using frequency counts of the word "uncertainty" (and its variants) in the quarterly Economist Intelligence Unit (EIU) country reports.[40] The EIU reports discuss major political and economic developments in each country, along with analysis and forecasts of political, policy and economic conditions. They are created by country-specific teams of analysts and a central EIU editorial team. We standardize WUI to have $\mu = 0$ and $\sigma = 1$.

Figure 11 plots the two standardized measures.
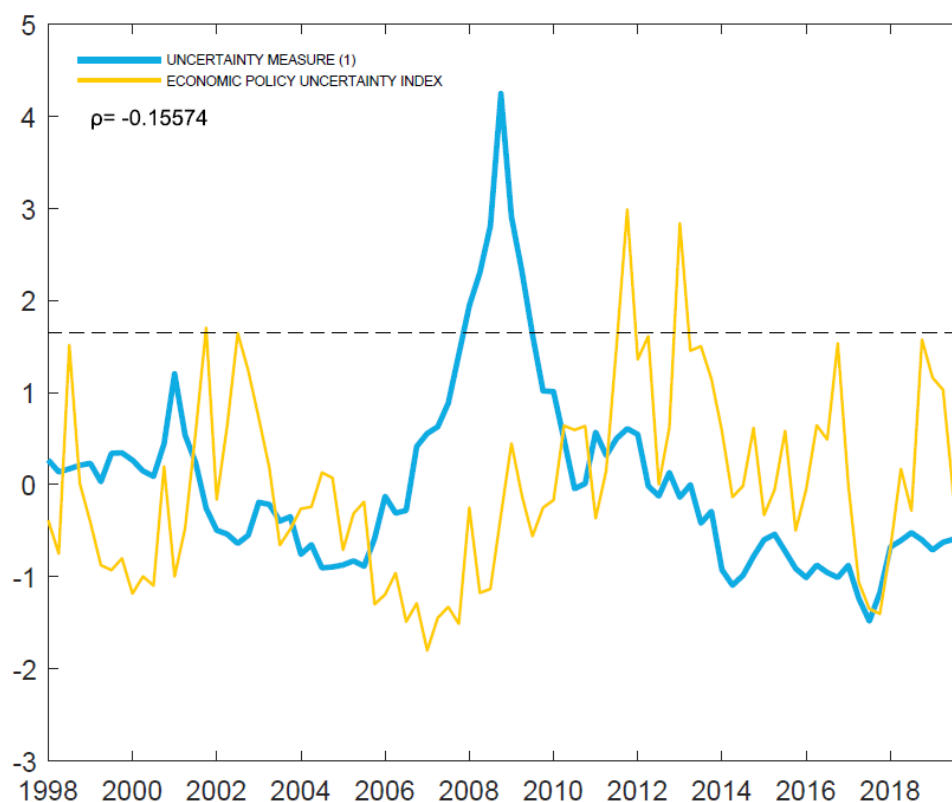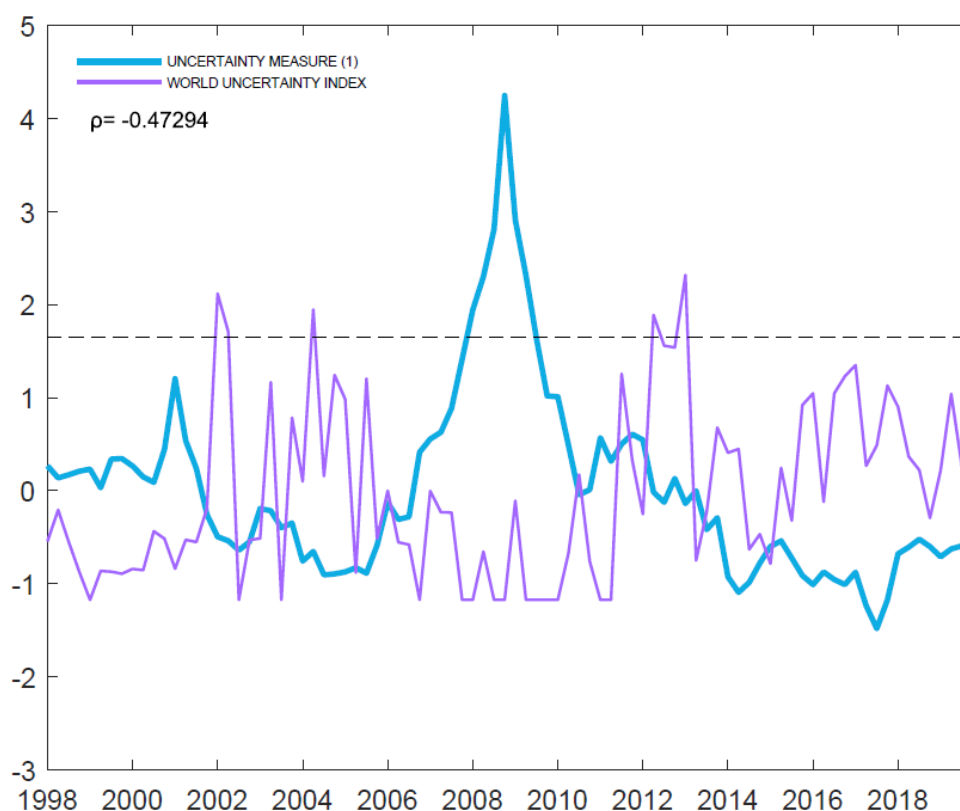

Figure 11. Uncertainty Measure (h=1) vs World Uncertainty Index for Italy. Both measures are expressed in standardized units with $\mu = 0$ *and* $\sigma = 1$. The horizontal line corresponds to the 1.65 standard deviations above the unconditional mean of each series. The data are quarterly and span the period q1 1998- q4 2019

---

[40] The website is: https://www.policyuncertainty.com/.

As for the EPUI, we can see an immediate problem with this measure when used as a proxy of macro uncertainty: during the Great Recession the measure shows extremely low to no movement at all. In this last proxy this is even more evident with respect to what was seen with the Economic Policy Uncertainty Index. However, there are a few cases of the measure crossing the significant 1.65 standard deviations above the mean threshold. Particularly, this happens after the 9/11 terroristic attack (2001), the start of the American invasion of Iraq (2003), the European debt crisis (2012-13) and during 2019 due to a series of reasons (intensification of trade tensions between USA and China, slowing down of the European economy, the resignation of the Italian government, etc.). All the above-mentioned events, and some others, are more relevant than the Uncertainty brought by the Financial Crisis of 2007-2009. As the ISV and the EPUI, the WUI presents rapid increases and decreases of its measure, alluding to a speedy recovery of the economy from uncertain situations. Also, the same news- based behaviour mentioned for the Economic Policy Uncertainty Index might apply (even if less strongly). WUI seems not to be a very good proxy of macroeconomic uncertainty due to its lack of persistence and the considerable number of significantly high uncertainty episodes. This is in contrast with what macro uncertainty theory suggests. The WUI presents a very high, negative correlation with our uncertainty measure (-0.47). This means that the two measures seem to capture fundamentally different uncertainty events. We will return to this point in chapter 7.

4.4 Macro Uncertainty Measures and Real Economic Activity

Existing empirical uncertainty research has frequently discovered significant dynamic correlations between real activities and numerous uncertainty proxies. In particular, uncertainty is considered to be countercyclical. In his seminar work, Bloom (2009) found a strong countercyclical relationship between real activity and the uncertainty as proxied by the stock market volatility. Bloom et al. (2012) also documented a relationship between real activity and uncertainty as proxied by dispersion in firm-level earnings, industry level earnings, total factor productivity, and the predictions of forecasters. Again, from their research, a strong countercyclicality emerges. Jurado et al. (2015) macroeconomic uncertainty measure for the U.S. also presents the same characteristics. With this in mind, we want to analyse the relation of the different macro uncertainty proxies for Italy, including our own, with real economic activity. The variables we chose to study are industrial production, employment and unemployment. It is important to quickly define the distinction between employment rate and unemployment rate. Employment rate refers people that are currently employed (employment- to- population ratio). On the other hand, unemployment rate refers to

people that are actively searching for a job but are still unemployed (unemployment- to-working force ratio). For instance, students not looking for a job are considered not employed based on the employment rate but are not considered unemployed based on the unemployment rate since they are not actively searching for a job.

The real variables are all expressed in yearly growth rate terms, i.e., growth rate of the 1st quarter of 1999 relative to the 1st quarter of 1998. All the data is quarterly and in standardized to have $\mu = 0$ and $\sigma = 1$.

The first real variable we consider is the industrial production growth rate. The series are plotted in figure 12.
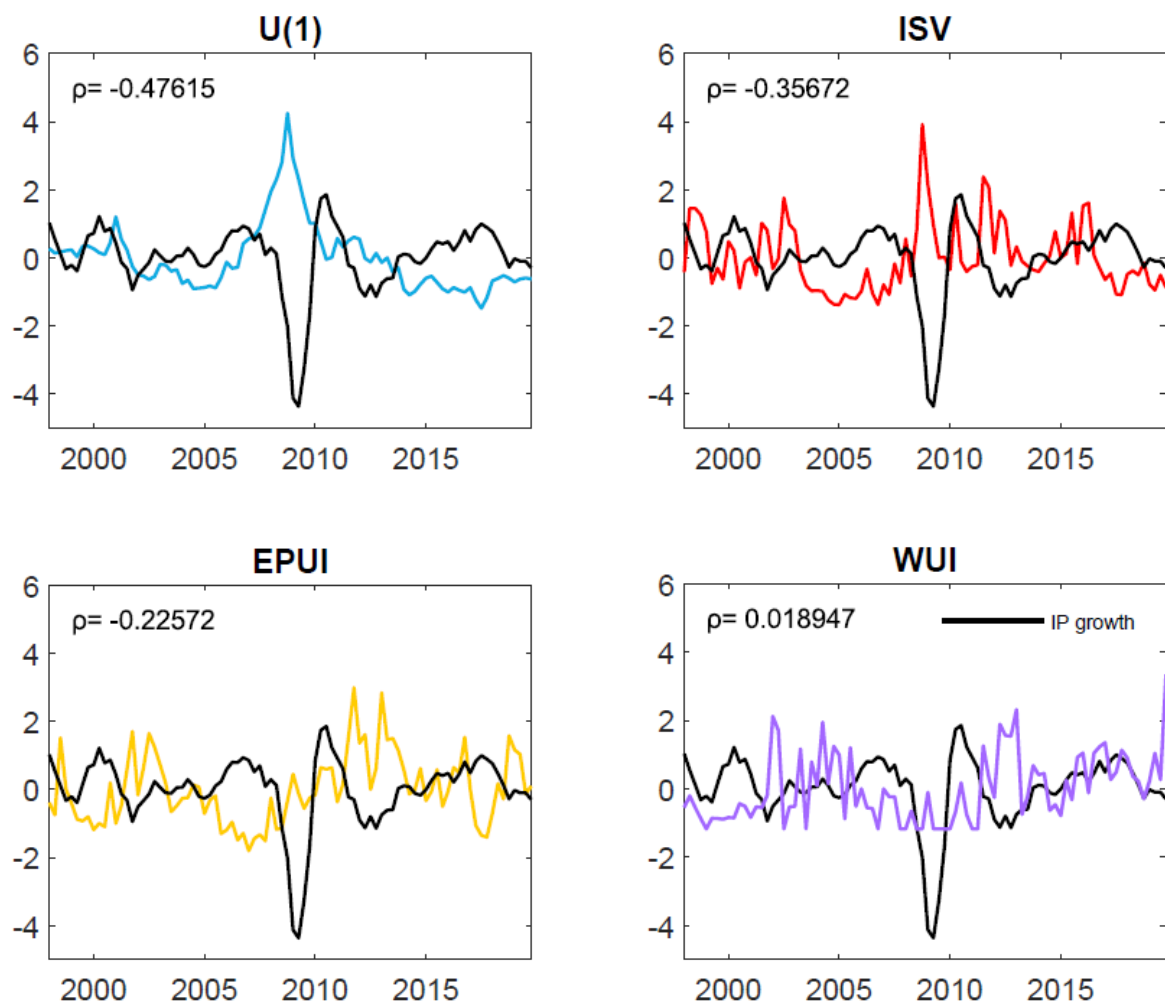
Figure 12. Uncertainty measures and Industrial production growth rate. All measures are expressed in standardized units with $\mu = 0$ and $\sigma = 1$. The correlation measures between IP and the different uncertainty measure are reported in the top left of each graph. The data are quarterly and span the period q1 1998- q4 2019.

Among the four uncertainty measures, our measure is the one that presents the highest countercyclicality $\rho = -0.47615$. During a recession or unstable times, the macro uncertainty measure increases and the industrial production declines. This is particularly evident during

the Great Recession. Furthermore, this is coherent with what previously reported and what the economic theory predicts. The ISV is the second-best measure of macro uncertainty in this sense, with a negative correlation of ρ = -0.35672. While the EPUI still shows some countercyclicality (ρ = -0.22572), the WUI shows basically no correlation at all with the industrial production growth rate (ρ = 0.018947), highlighting once more the flows of taking it as a macroeconomic uncertainty proxy.

The second real variable we study is the employment growth rate.

The series are plotted in figure 13.
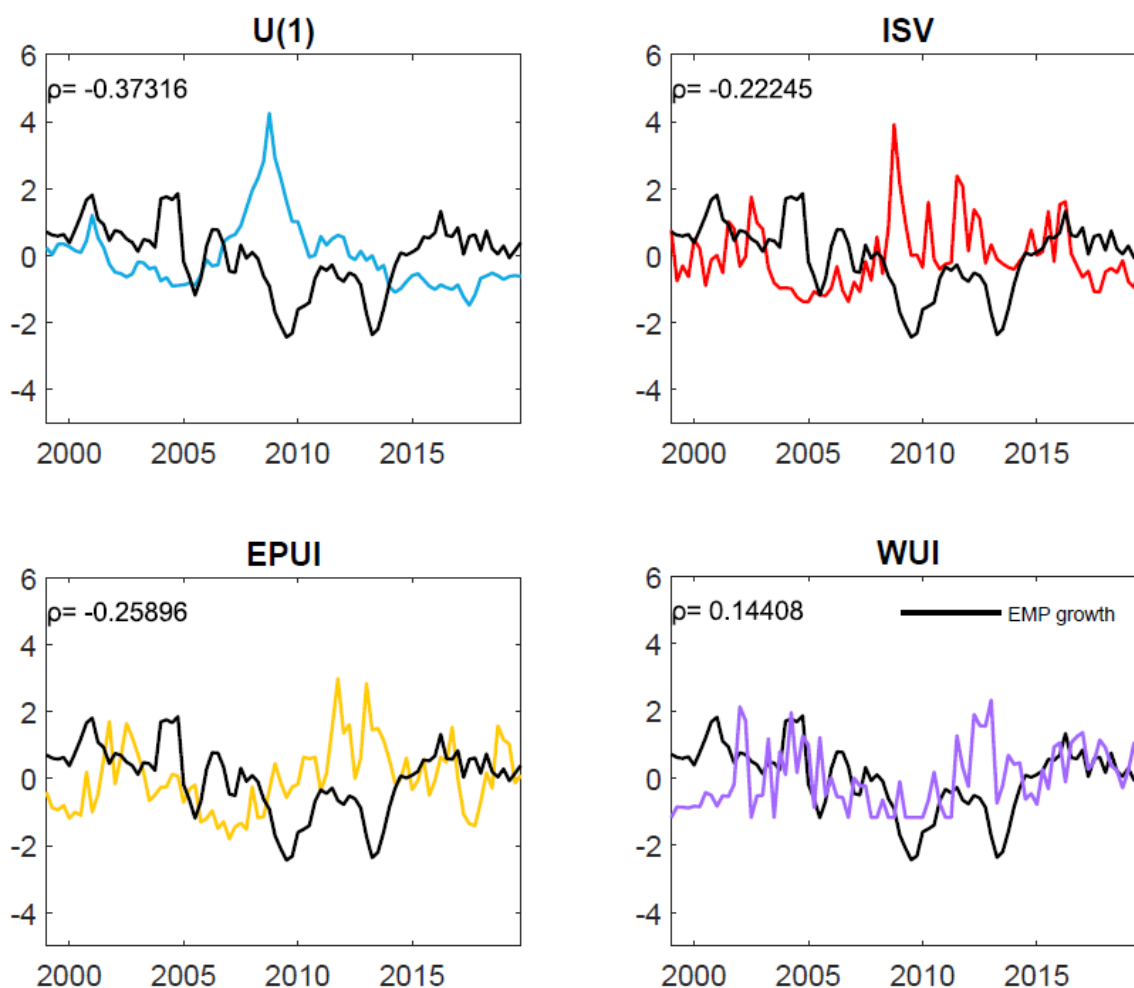
Figure 13. Uncertainty measures and Employment growth rate. All measures are expressed in standardized units with $\mu = 0 \; and \; \sigma = 1$. The correlation measures between EMP and the different uncertainty measure are reported in the top left of each graph. The data are quarterly and span the period q1 1998- q4 2019.

The results are generally a replica of the ones found for the industrial production case. In particular, our uncertainty measure presents the highest countercyclicality with ρ = -0.37316. When the economy experiences a recession period, uncertainty increases and the employment growth rate declines. This time the EPUI (ρ = -0.25896) seems to be slightly preferable to the

ISV proxy (ρ =-0.22245). The WUI shows a small positive correlation with the employment rate (ρ = 0.14408).

Lastly, we present the results concerning the unemployment growth rate, which are plotted in figure 14.
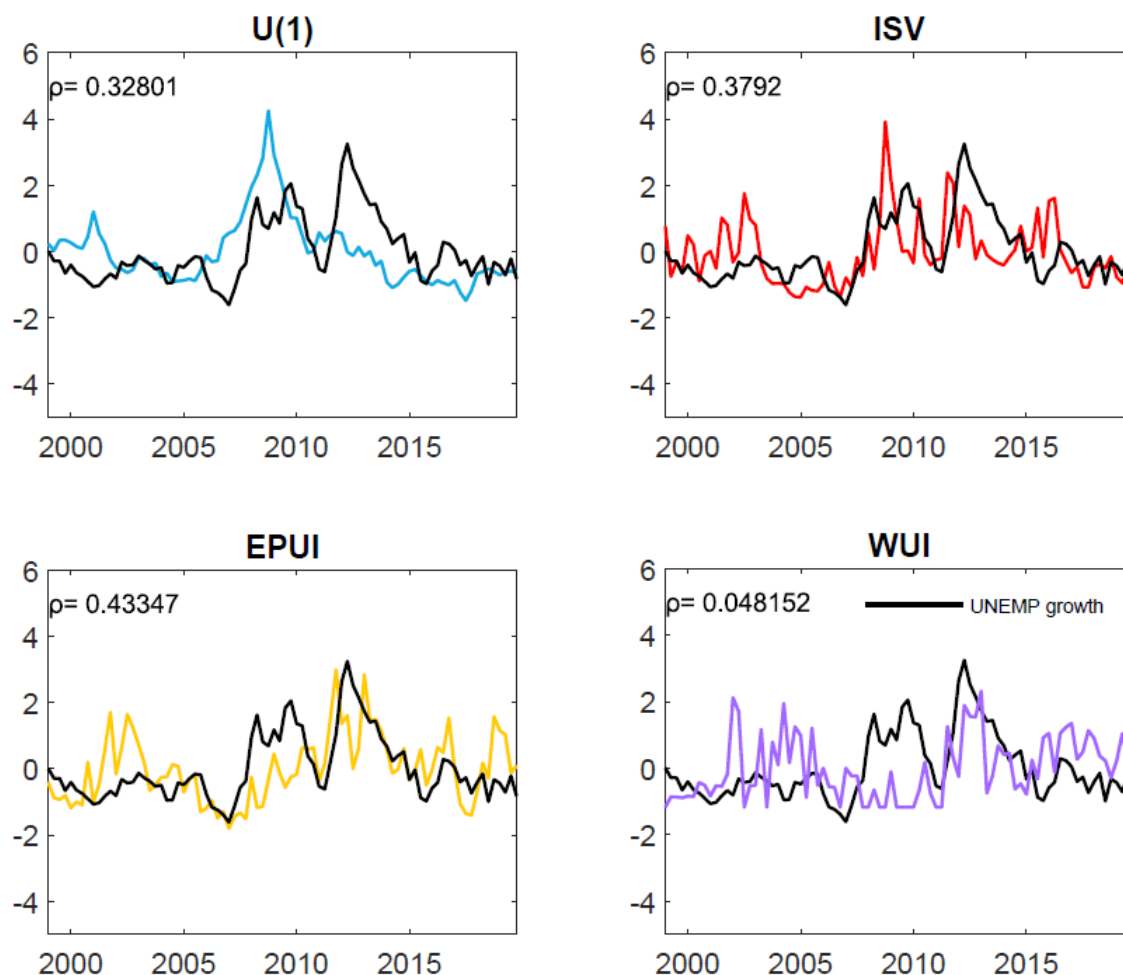
Figure 14. Uncertainty measures and Unemployment growth rate. All measures are expressed in standardized units with $\mu = 0$ and $\sigma = 1$. The correlation measures between UNEMP and the different uncertainty measure are reported in the top left of each graph. The data are quarterly and span the period q1 1998- q4 2019.

First of all, we have to keep in mind that Unemployment growth rate is also a countercyclical economic variable. Intuitively, when the economy is weak, businesses downsize their workers, and unemployment grows. In this case we expect the uncertainty measures to be positively correlated with the unemployment growth rate. This time, the EPUI is the measure with the highest correlation with the unemployment rate (ρ = 0.43347), with a big portion of the correlation due to the adequate capture of the increase in unemployment during the European Sovereign Debt Crisis. Next, we find the ISV with a positive correlation of ρ = 0.3792, followed by our uncertainty measure with a positive correlation of ρ = 0.32801. All these results are in line with what the economic theory on uncertainty envisions. Then again,

55

the WUI is the worst performer amongst our measures, showing basically no correlation with the unemployment growth rate ($\rho = 0.048152$).

Although these results do not define with certainty which is the best measure of macro uncertainty, they definitively give some important hints to which measure better represents it. [41]We will run further analysis to determine the best fitting measure of macro uncertainty, investigating the macroeconomic dynamics through VARs and FEVDs in chapter 5.

4.5 Macro Uncertainty Measure Interpretation and Sensitivity Analysis

In the previous sections we have discussed the validity of our macro uncertainty measure in relation with the other commonly used uncertainty proxies. Our measure seems to follow, better than the others, the economic theory and literature surrounding the topic. In this section we want to give a precise historical interpretation of our uncertainty measure to understand how well it represents the actual Italian macroeconomy and its relevant events, in addition to the general theoretical models. After that, we want to perform a sensitivity analysis of our estimate, in order to comprehend how removing different groups of variables, present in our dataset, from the estimation of the macro uncertainty measure influences it.

4.5.1 Macro Uncertainty Economic Interpretation and Rationalization

The process of describing, analysing, evaluating, and creating an explanation for previous economic events is known as economic historical interpretation. We now want to understand if our macro uncertainty measure well captures the relevant economical and uncertainty events that concerned Italy during the last two decades.

In figure 15 we plot our baseline, one- period- ahead macro uncertainty measure, with the interpretation of different relevant peaks and the Italian recession periods.

---

[41] Note, we are specifically interested in finding a reliable macroeconomic uncertainty measure. Some of the proxies discussed represent well other types of uncertainties.
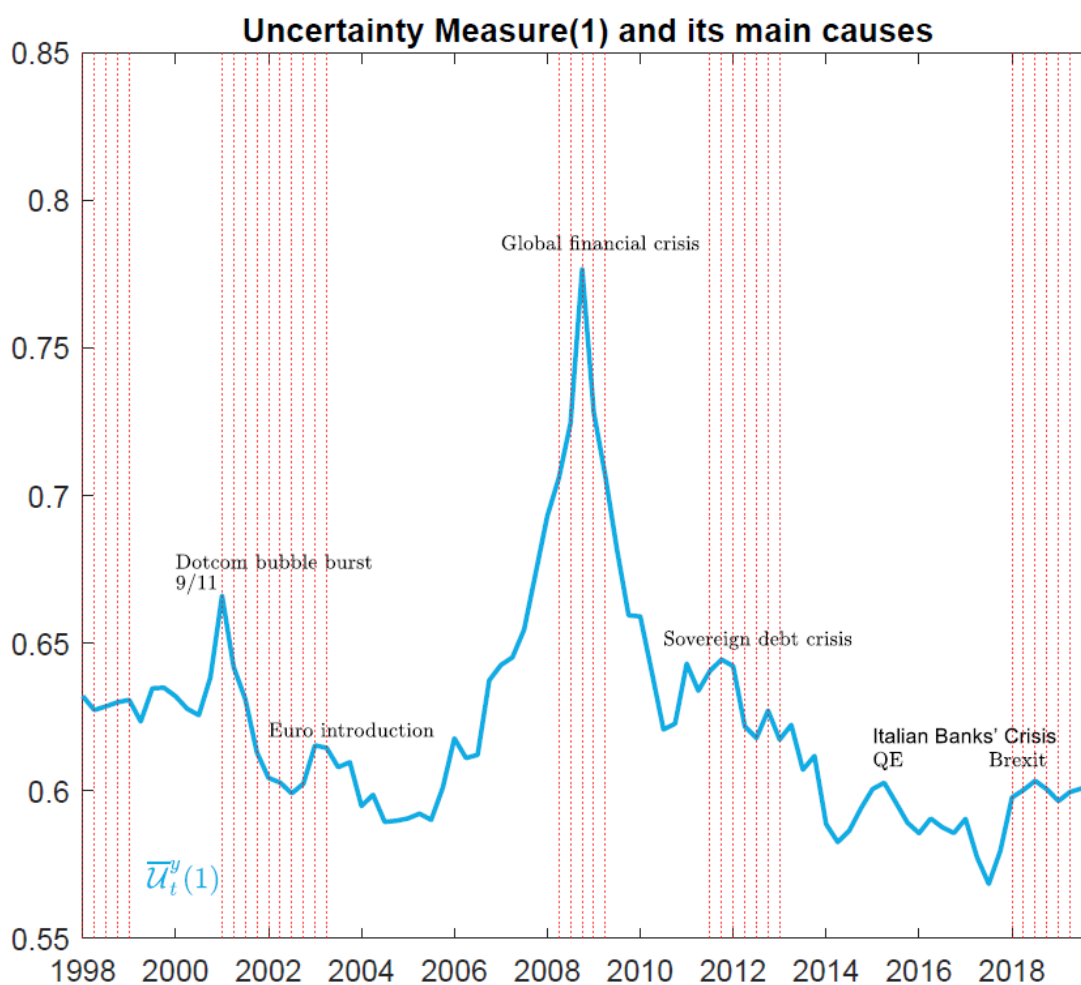
Figure 15. Uncertainty Measure and Interpretation. The red dashed lines represent regression periods as defined by the OECD Composite Leading Indicators. The data are quarterly and span the period q1 1998- q4 2019.

The first thing to notice in this plot, besides our macro uncertainty measure and the different interpretations of the peaks, are the red dashed lines which represent the recession periods for the Italian economy. The recession indicators for Italy are based on data elaborated by the Organization of Economic Development and reported on the Federal Reserve Database. As disclosed on the FRED website, the time series is an interpretation of the OECD Composite Leading Indicators.[42] The OECD identifies months of turning points without designating a date within the month that turning points occurred. The dummy variable adopts an arbitrary convention that the turning point occurred at a specific date within the month. The arbitrary convention does not reflect any judgment on this issue by the OECD. The time series is composed of dummy variables that represent periods of expansion and recession. A value of 1 is a recessionary period, while a value of 0 is an expansionary period. We plot the recession

---

[42] As defined on the OECD website, the composite leading indicator (CLI) is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long term potential level.

periods, all the periods in the time series contradistinguished by the dummy 1, with our uncertainty measure, to investigate if our findings are coherent with the different economic phases. We can clearly see that all the historical recession periods are either on the peaks of our estimate or closely following it. This gives enormous credibility to the validity of the macro uncertainty measure that we created.

We now focus on the interpretation of each recession period and each peak of macro uncertainty in the series.

90ies crisis. During the 90ies Italy experience several adverse events that severely impaired its future economic development. From the Italian Lira devaluation in 1992, to the political crisis and scandals, passing through the increase of the Italian public debt, all these events contributed to increase the level of macro uncertainty surrounding the country. As we can see from our graph, at the start of our measurements, Italy is already experiencing a period of recession based on the OECD measure we defined above.

Dotcom Bubble Burst. During the mid 90ies, the enthusiasm linked to the discovery of new technologies started the creation of a speculative bubble. Like every bubble, the Dotcom bubble followed a sequence of: i) extreme confidence by the investors in the potential of a product or company; ii) rapid increase in the products' prices; iii) an event that causes expectations of important earnings to waver; iv) mass selling and disinvestment; v) final collapse in the price of the product that dictates the burst of the bubble. In the case of the Dot-com bubble, unexpectedly, in March 2000, the financial statements published by several companies showed disappointing results, providing evidence that investing in these companies could prove unprofitable. In just three days, the Nasdaq, the benchmark equity index, lost nearly 9% of its value.[43] During 2001, many Dot-com companies closed or were subject to acquisitions and mergers. A typical element of speculative bubbles is the attitude of individuals to carry out herding behaviour inspired by common action and the most widespread practices among other investors. In fact, both in the growth phase and in the bursting phase of the bubble, market operators tend to make investment and disinvestment decisions based on the euphoria of the moment and widespread fear of losing the entire value of the securities in the portfolio in a few moments (so-called panic selling), rather than objective assessments of future returns prospects. [44]

---

[43] Between 1995 and its peak in March 2000, the Nasdaq Composite stock market index rose 400%, only to fall 78% from its peak by October 2002.

[44] FOMO, i.e., fear of missing out, is also another cause of investors irrational behaviour.

9/11 terroristic attack. When terrorists struck America on September 11, 2001, the whole business sector was hit hard. Stock markets plummeted immediately, causing economic damage to practically every area of the economy. Following the dotcom bubble, the US economy was already in a moderate slump, and the terrorist attacks added insult to injury to the suffering business community. Although not affecting Italy directly, the twin towers' terroristic attack had relevant economic indirect consequences. Dugan et al. (2006) state that despite the growth in research examining direct economic impacts of terrorism, the indirect impact of terrorism on the stability of local economies has generally been overlooked. The report explores the influence of terrorism on employment and business outcomes in Italy from 1985 to 1997 using panel data regression models and the most complete open- source database on terrorism at the time available to researchers. They find that terrorist attacks are proven to diminish the number of businesses and jobs in the year following the attack. When net outcomes are disaggregated into their component gross flows, it is discovered that the majority of the consequences are due to fewer firm formations and expansions. [45]

Euro introduction. Since the early 2000s, besides the afore mentioned adverse events, Italy also experienced a period of prolonged stagnation, that overall contributed to the uncertainty surrounding the macroeconomy. Throughout the year 2003, GDP grew of only about 0.3% and the taxations increased of about 0.9 %. Our measure also registers a small peak around 2002-2003 that, besides the relevant slow economic growth, could be also due to the introduction of the Euro in early 2002. Of course, the change of the currency and the transfer of monetary policy powers to the European Central Bank, depriving Italy itself of one of the crucial policy instruments, increased the macroeconomic uncertainty. Nonetheless, even at its peak, the total level of uncertainty during this period stayed lower than the one brought by the events above described. Additionally, there was a small increase in inflation after the introduction of the communitarian currency. However, the increase was more perceived increase in prices than actual increase in prices like figure 16 shows. Other international events occurred in this period contributed to further increase the level of uncertainty perceived.[46]

---

[45] The increasing globalization further accentuated the transmission of the indirect economic effects from the U.S. to the rest of the world.
[46] i.e., the U.S. invasion of Iraq.
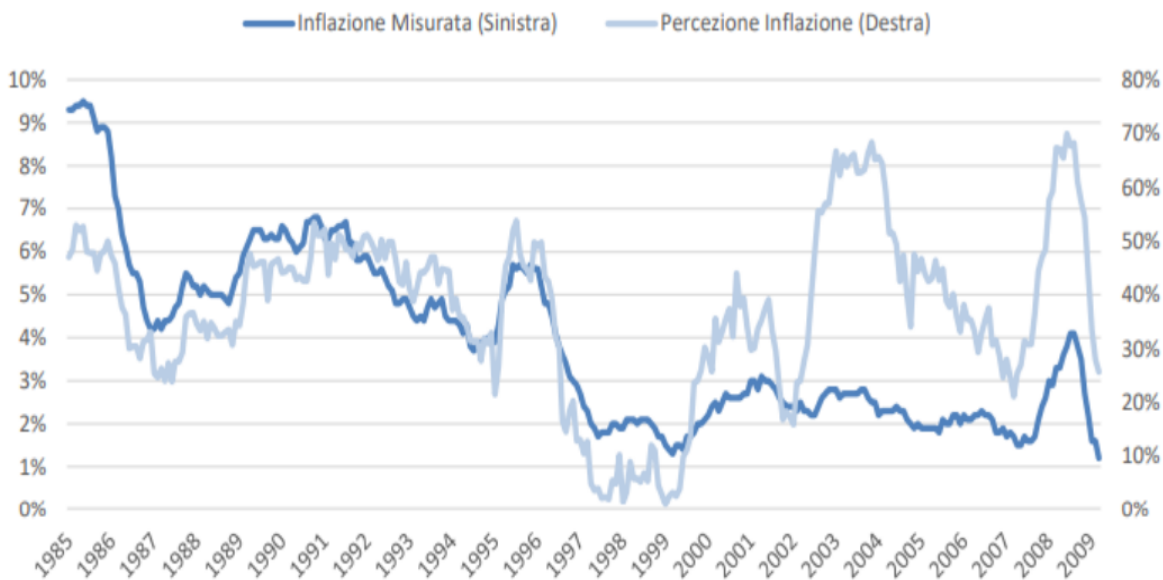
Figure 16. Italian actual inflation vs perceived inflation. Source: European commission.

The Global Financial Crisis and Great Recession. The Great Recession was the sharp decline in economic activity during the late 2000s. It is considered the most significant downturn since the Great Depression. In an effort to maintain economic stability following the 2001 recession and the 9/11/2001 World Trade Center attacks, the US Federal Reserve cut interest rates to the lowest levels observed in the post-Bretton Woods era. Until mid- 2004, the FED kept interest rates low. These low interest rates, when combined with federal policies encouraging home ownership, contributed to a fast rise of real estate and financial markets, as well as a huge increase in overall mortgage debt. New types of subprime and adjustable mortgages permitted borrowers, who would not have qualified otherwise, to get large home loans based on the belief that interest rates would remain low and property prices would continue to grow indefinitely. Nevertheless, from 2004 to 2006, the Federal Reserve slowly raised interest rates in order to keep the economy's inflation constant. As market interest rates rose in response, the flow of new credit into real estate via traditional banking channels reduced. Rates on existing adjustable mortgages and even more exotic loans began to reset at considerably higher levels than what borrowers had anticipated. Many Borrowers defaulted their loans and mortgages. The result was the bursting of a housing bubble, which was later widely acknowledged. As mentioned, financial institutions began promoting mortgage-backed securities and other sophisticated derivative products at unprecedented levels during the American housing boom of the mid-2000s. When the real estate market crashed in 2007, the value of these securities plummeted. As the credit crisis unfolded in 2007, the credit markets that had fueled the housing bubble swiftly followed housing prices into a collapse. With the downfall of Bear Stearns in March 2008, the solvency of over-leveraged banks and financial

60

institutions reached a breaking point. The failure of Lehman Brothers, the country's fourth-largest investment bank, in September 2008 further deteriorated the situation. The effects of the huge crisis started to quickly spread to other economies around the world, especially in Europe.[47] With the onset of the international financial crisis, the Italian financial system did not suffer immediate damage since Italian banks were relatively under-internationalized and had only a small number of toxic instruments in their portfolios. However, the financial crisis quickly affected also the real economy all around the world through decreases of investments, disposable income and consumption. International trade, and in particular exports that are a big part for the Italian GDP, took a deep dive. Italian GDP growth rate decreased in 2008 (-1.2%) and even more in 2009 (-5.5%). As we previously stated, the Great Recession represents the most striking case of increased macro uncertainty based on our measure, and it is the only time that our measure surpasses the 1.65 standard deviations above the unconditional mean threshold. This is in line with the expectations since this was indisputably the worst crisis in modern times.

Sovereign Debt Crisis. While Europe was still struggling with the aftermath of the Great Recession, a new crisis invested the old continent: the Sovereign Debt Crisis. The Sovereign Debt Crisis is characterized by an abnormally high rise in interest rates on government bonds, which are auctioned on a regular basis to fund the renewal and growth of public debt. The country may be required to raise the interest rate in order to sell its debt instruments, but an interest rate that is excessively high in the presence of a substantial quantity of debt can jeopardize the country's capacity to repay the debt. The crisis has deep roots in 2008 with the collapse of Iceland's banking system. The crisis then slowly spread towards other countries, namely Portugal, Italy, Ireland, Greece and Spain, leading to the somewhat offensive moniker of PIIGS. In particular, by the end of 2009, Greece, Spain, Ireland, Portugal, and Cyprus were unable to repay or restructure their government debt or bail out their struggling banks without the help of third-party financial institutions. The European Central Bank (ECB), the International Monetary Fund (IMF), and, finally, the European Financial Stability Facility (EFSF) were among them.[48] The Italian debt crisis became apparent in June 2011, shortly after Greece, Ireland, and Portugal, all on the verge of default, sought Europe for assistance, and it quickly worsened. The "spread," or the yield differential between Italian and German

---

[47] See Chudik and Fratzscher (2011).
[48] The European Financial Stability Facility (EFSF) was created as a temporary crisis resolution mechanism by the euro area Member States in June 2010. The EFSF has provided financial assistance to Ireland, Portugal and Greece. The assistance was financed by the EFSF through the issuance of EFSF bonds and other debt instruments on capital markets. The EFSF does not provide any further financial assistance, as this task is now performed solely by the European Stability Mechanism).

government bonds, began to rise month after month (with an exception in August due to the European Central Bank's purchase of a large quantity of Italian securities on the bond market), eventually reaching over 500 points in the month. The worldwide financial risk assessment organization Standard & Poor's had downgraded the "rating" (the judgment of reliability) on Italian public debt securities shortly before, in September. The growth of the spread put the Italian banking system in enormous difficulty since individual banks were holding large amounts, up to 60 %, of BOT (Buoni Ordinari del Tesoro).[49] A generalized crisis of trust worsened the banks' situation, leading to the collapse of European stock exchanges, particularly the Milan stock exchange, where bank equities suffered big losses. As can be seen in figure 15, the Sovereign Debt Crisis is captured by our macro uncertainty measure, although the uncertainty increase is not comparable to that of the Great Recession.[50]

Italian Banks Crisis. Tied to what has been said about the Italian banking system in the previous paragraph, a concatenation of events led to the bankruptcy or refinancing of several small-medium banks. A credit crunch, that added to the slow growth of the economy did not help their case. In 2015 alone, seven Italian banks filed for bankruptcy: Banca Romagna, Banca Padovana, Banca Brutia, Banca delle Marche, Cassa di Risparmio di Ferrara, Cassa di Risparmio della Provincia di Chieti and Banca dell'Etruria e del Lazio. This is also testified by an increase in our macro uncertainty estimate.

Quantitative Easing. Quantitative easing (QE) is an unconventional monetary policy tool in which a central bank buys longer-term securities on the open market to expand the money supply and boost lending and investment. On 22 January 2015, Mario Draghi, President of the European Central Bank, announced the European QE programme. Although this is an expansionary monetary policy, macro uncertainty saw a little surge, as can be seen by our uncertainty measure. [51]

Brexit. Brexit is a mix of the words "British" and "exit" coined to refer to the U.K.'s decision, in a June 2016 referendum, to leave the European Union. There is a significant impact with repercussions for both institutions with the British withdraw from EU policies on free movement of goods, persons, services, and capital, as well as the European Union Customs Union, criminal intelligence cooperation, and other similar matters. It is safe to say

---

[49] This created some sort of vicious cycle for which the bonds held by banks were slowly devalued, influencing the reliability of the banks in the country which in turn added uncertainty to the situation further depreciating the government bonds and increasing the long- term interest rate on them.
[50] The sovereign debt crisis seems to be better captured by the news- based uncertainty proxies, however, the level of uncertainty increase of these measures is greater than that of the Great Recession, which is not very representative of a reliable macro uncertainty measure.
[51] In addition to the Italian Banking Crisis.

that the exit from the EU of an important commercial and political partner brought to the increase of uncertainty, and this is especially evident moving towards the actual programmed exit date of 2020. In the last two years of transition out of the Union, the U.K. and Italy frantically tried to reach commercial agreement between the two countries, contributing to the pre-existing uncertainty of the period, as it can be seen in figure 15. [52]

4.5.2 Macro Uncertainty Measure Sensitivity Analysis

In this section we quickly report the results of a sensitivity analysis on our estimate of macro uncertainty $\bar{\mathcal{U}}_t^y(1)$.[53] We want to understand how a group of variables contributes to the creation of the uncertainty measure. To do so, we replicate the process explained previously, forecasting the individual series uncertainty and aggregating them with the equally- weighted aggregation scheme. However, in this case, we remove a group of variables at a time to analyse how the uncertainty measure changes with respect to our baseline case when all available information is used.

The results are plotted in figure 17.

The newly estimated measures of uncertainty without respectively the CPI variables, the labour market variables or the GDP related variables, report an increase of the estimate with respect to the baseline case. This seems to indicate that these groups of indices tend to decrease the overall macroeconomic uncertainty level when included.

On the other hand, the newly estimated measure of uncertainty without the PPI variables or the international trade variables, report a decrease of the estimate with respect to the baseline case. Again, this seems to indicate that these groups of indices tend increase the overall macroeconomic uncertainty level when included.

---

[52] We will add more to the recession dates by OECD of 2019 visible in figure 15 in the last chapter.
[53] A sensitivity analysis examines how changes in the assumptions- and in our case in the dataset used for the uncertainty measure estimation- of an economic model affect its predictions.
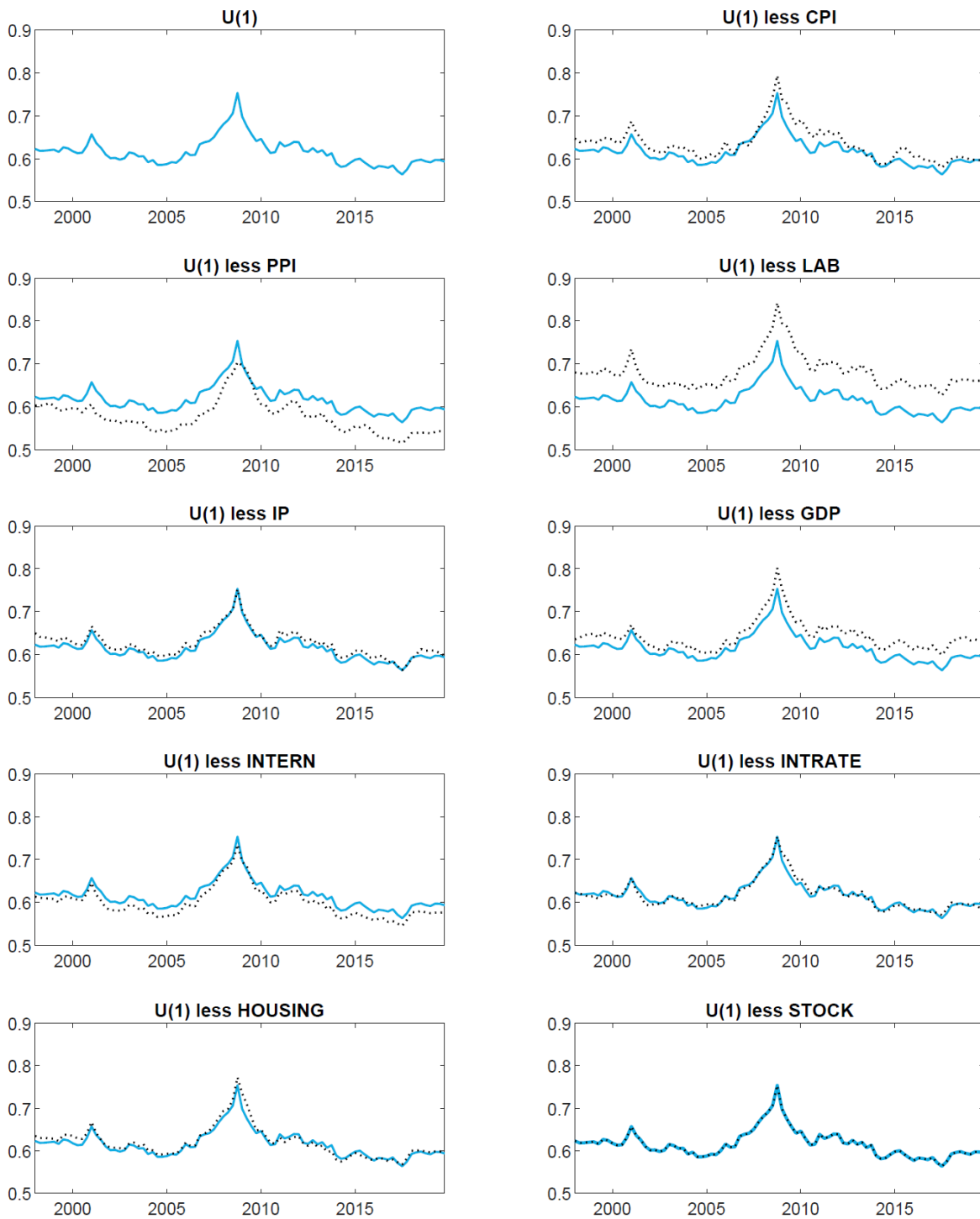
Figure 17. Sensitivity analysis of our uncertainty measure. The light blue line represents the baseline case estimated with all the available data. The pointed, black line represents the measure of uncertainty estimated without the corresponding group of variables.

Lastly, group of variables like the industrial production indexes, stocks, interest rates or housing variables seem to slightly deviate from the measure, but not consistently. This does not mean that these variables are superfluous or do not contribute to our final estimate of macroeconomic uncertainty, quite the opposite.

4.6 Remarks

The legitimacy of $\bar{\mathcal{U}}_t^y(h)$ as candidate measure for the Italian macroeconomic uncertainty appears to be clear. As we have shown in this chapter, our estimate proves superior to the commonly used proxies we analyse for Italy (ISV, EPUI and WUI) in several ways.

First, our measure is much more persistent than the other proxies. Second, our measure presents fewer episodes of significant uncertainty events with respect to the other proxies. Third, our uncertainty measure presents strong countercyclical behaviour. These first findings are in line with what the economic theory and the theoretical models predict. In addition to all that, it is safe to say that our uncertainty measure well encapsulates all the main macroeconomic events that forged the Italian economy during the last two decades.

In chapter 5, we will further investigate our estimate's adequacy through Macroeconomic Dynamics analysis.

Chapter 5

Macro Uncertainty Measures and Macroeconomic Dynamics

Var Models Characteristics and Implementation, Real Economic Activity IRFs comparison, FEVDs

5.1 VAR Models Introduction

Up to this moment we have explored and analysed the construction of our uncertainty estimate and the adequacy of our estimate as possible candidate as a macroeconomic uncertainty measure. In this chapter we focus on the role of uncertainty in the economy and its macroeconomic dynamics. To study the issue, we introduce the vector autoregression (VAR) analysis.

5.1.1 VARs and SVARs in the Literature

In their 2001 Journal of Economic Perspectives' article "Vector Autoregressions" Stock and Watson describe the job of macroeconometricians as consisting of the following tasks: describe and summarize macroeconomic time series; make forecasts; recover the structure of the macroeconomy from the available data; advice macroeconomic policy makers. Christopher Sims (1980) established vector autoregression (VAR) models to represent the combined dynamics and causal relationships among a set of macroeconomic variables. Before his work, the tasks described by Stock and Watson (2001) were carried out using a variety of methods that failed to produce reliable findings. The vector autoregressive (VAR) model is a simple multivariate time series model that connects current observations of a variable to previous observations of itself and other variables in the system. An n-variate VAR(p) is a linear system of n equations in which the n endogenous variables are explained by their own historical values as well as the current and past values of the remaining $n - 1$ variables, with p being the number of lags. Two forms of VARs can be distinguished based on the researcher's task and the stage of the analysis: reduced-form VARs and structural VARs.

Fry and Pagan (2011) well summarize the concepts behind the two VAR models.[54]

The reduced-form VAR is the baseline model, which is used to provide a representation and to summarize the data. The following is a depiction of an n-variate first order VAR:

$$z_t = A z_{t-1} + e_t$$

where z_t is a n x 1 vector of variables, z_{t-1} is the n x 1 vector of one-period lagged variables, A is a n x n matrix of parameters, and e_t is a n x 1 vector of errors. The errors must satisfy the following properties: i) $E(e_t) = 0$, namely errors have zero mean; ii) $E(e_t e_t') = \Sigma_e$, meaning that errors have a constant variance-covariance matrix; iii) $E(e_t e_s') = 0$ for $s \neq t$, stating that the errors are serially uncorrelated. They are, however, contemporaneously correlated. Finally, as Hamilton (1994) shows, they meet the criteria for being considered white noises.

The structural VAR (SVAR) gives an economic interpretation of the data. The VAR can be used to get the SVAR (and vice- versa). The SVAR is constructed as follows:

$$B_0 z_t = B_1 z_{t-1} + \varepsilon_t$$

where B_0 and B_1 are two n x n matrices of the parameters and ε_t is a n x 1 vector of shocks. The shocks must satisfy the following properties: i) $E(\varepsilon_t) = 0$, meaning that shocks have zero mean; ii) $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon = I_n$, stating that the variance-covariance matrix is constant; iii) $E(\varepsilon_t \varepsilon_s') = 0$ for $s \neq t$, namely the shocks are serially uncorrelated. In the SVAR, however, the shocks are also contemporaneously uncorrelated. Again, as Hamilton (1994) shows, they meet the criteria for being considered white noises.

Now, it can be shown from the previous two equations that $A = B_0^{-1} B_1$ and that $B_0 e_t = \varepsilon_t$. This means that the SVAR shocks are linear combinations of the errors of the VAR. Alternatively put, $e_t = B_0^{-1} \varepsilon_t$ and, given that $E(\varepsilon_t \varepsilon_t') = I_n$, we get that $E(e_t e_t') = B_0^{-1} B_0^{-1'} = \Sigma_e$. Through a recursive substitution we can obtain the following moving average (MA) construction from the VAR:

$$z_t = D_0 e_t + D_1 e_{t-1} + D_2 e_{t-2} + \cdots$$

where D_j is the *jth* period impulse response of z_{t+j} to a unit change in e_t, and $D_0 = I_n$.

Similarly, by recursive substitution we can obtain the following moving average (MA) construction from the SVAR:

---

[54] The remainder of this section is based on the work presented by Fry and Pagan (2011).

$$z_t = C_0 \varepsilon_t + C_1 \varepsilon_{t-1} + C_2 \varepsilon_{t-2} + \cdots$$

where C_j is the *jth* period impulse response of z_{t+j} to a unit change in ε_t, and $C_j = D_j B_0^{-1}$.

5.1.2 Identification Problem, Strategies and Restrictions

Analysts engaged in macroeconomic studies want to know how a shock (such as monetary policy shock, or uncertainty in our case) affects macroeconomic variables. Again, we will closely follow the critical review of Fry and Pagan (2011) on VAR models.[55] From the description of the vector autoregression models in section 5.1.1 it is obvious that the crucial objective is to estimate B_0^{-1}, and this is done through a process called identification. In particular, Σ_e has dimension n x n but it includes only $n(n-1)$ unique values. On the other hand, while B_0^{-1} still has dimension n x n, it is characterized by the presence of n^2 unknowns. This means that there are $n(n-1)$ equations and n^2 unknows, thus the system is under-identified.

To grasp better the concept, consider a SVAR (1) with three variables: real GDP (y_t), real interest rate (r_t) and inflation (π_t). Starting from the SVAR representation, we can write the following:

$$B_0 z_t = B_1 z_{t-1} + \varepsilon_t$$

$$z_t = B_0^{-1} B_1 z_{t-1} + B_0^{-1} \varepsilon_t$$

$$z_t = A z_{t-1} + B \varepsilon_t$$

where $A = B_0^{-1} B_1$, $B = B_0^{-1}$ and $B \varepsilon_t = e_t$.

Now, take $z_t = (y_t, \pi_t, r_t)'$, $z_{t-1} = (y_{t-1}, \pi_{t-1}, r_{t-1})'$, $B_0 = \begin{pmatrix} b_{011} & b_{012} & b_{013} \\ b_{021} & b_{022} & b_{023} \\ b_{031} & b_{032} & b_{033} \end{pmatrix}$,

$$B_1 = \begin{pmatrix} b_{111} & b_{112} & b_{113} \\ b_{121} & b_{122} & b_{123} \\ b_{131} & b_{132} & b_{133} \end{pmatrix}, \quad A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix},$$

$$\varepsilon_t = (\varepsilon_{yt}, \varepsilon_{\pi t}, \varepsilon_{rt})' \text{ and } e_t = (e_{yt}, e_{\pi t}, e_{rt})'.$$

Since $\Sigma_e = B_0^{-1} B_0^{-1'}$, we can write the following:

$$\begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} = \begin{pmatrix} b_{011} & b_{012} & b_{013} \\ b_{021} & b_{022} & b_{023} \\ b_{031} & b_{032} & b_{033} \end{pmatrix}^{-1} \begin{pmatrix} b_{011} & b_{012} & b_{013} \\ b_{021} & b_{022} & b_{023} \\ b_{031} & b_{032} & b_{033} \end{pmatrix}^{-1\prime}.$$

Note that there are 6 equations in 9 unknowns, thus the model is under-identified. As we have explained before this is the identification problem posed by structural VAR models. To solve this identification problem, we need more equations which come in the form of restrictions.

Generally, there are three identification schemes that can be used to solve the under-identification of the VAR model: sign restrictions, zero long-run restrictions and zero short-run restrictions (or Cholesky identification). It can be difficult to choose the right restrictions to identify SVAR models, however, the guiding factor in determining them should always be the theoretical background and literature.

The idea behind sign restriction is straightforward: it suggests that some shocks only induce increases or decreases in one or more endogenous variables. In oil price modelling, sign restrictions are widely utilized. Kilian and Murphy (2012), for example, employ a SVAR model to investigate the effects of oil supply, aggregate demand, and oil-specific demand shocks.

The zero long-run restrictions identification scheme is built on the theory that some shocks have no long-run cumulative effects on one or more of the endogenous variables, i.e., money neutrality is an economic theory that states that monetary policy has no long-run effects on output.

For our macroeconomic dynamic analysis, we will implement the zero short-run restrictions (or Cholesky identification), therefore we will focus on explaining this identification scheme in detail in the remainder of this section. This identification scheme assumes that some shocks have no contemporaneous effect on one or more of the endogenous variables. As well explained by Foroni (2015), $\boldsymbol{B}_0^{-1}$ is assumed to be lower triangular and, therefore, a number n of unknows is "artificially" set to zero. In this way, we obtain a system of $n(n-1)$ equations in $n(n-1)$ unknowns. This allows us to correctly identify the model. Since $\boldsymbol{\Sigma}_e = \boldsymbol{B}_0^{-1}\boldsymbol{B}_0^{-1\prime}$ with $\boldsymbol{B}_0^{-1}$ being lower triangular, the variance-covariance matrix $\boldsymbol{\Sigma}_e$ represents a Cholesky decomposition, hence the name Cholesky identification.[56]

We can now represent $\boldsymbol{\Sigma}_e = \boldsymbol{B}_0^{-1}\boldsymbol{B}_0^{-1\prime}$ as follows:

---

[56] Cholesky decomposition or factorization is a powerful numerical optimization technique that is widely used in linear algebra. It decomposes an Hermitian, positive definite matrix into a lower triangular and its conjugate component. These can later be used for optimally performing algebraic operations. Source: https://www.sciencedirect.com/topics/engineering/cholesky-decomposition.

$$
\begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} = \begin{pmatrix} b_{011} & 0 & 0 \\ b_{021} & b_{022} & 0 \\ b_{031} & b_{032} & b_{033} \end{pmatrix}^{-1} \begin{pmatrix} b_{011} & 0 & 0 \\ b_{021} & b_{022} & 0 \\ b_{031} & b_{032} & b_{033} \end{pmatrix}^{-1\prime}.
$$

Note that there are 6 equations in 6 unknowns, now allowing us to correctly estimate our model.

5.1.3 Impulse Response Functions and Variance Decomposition

We can now analyse the macroeconomic dynamics that are predicted by our VAR model. We do so through the study of the impulse response functions (IRFs) and the forecast error variance decomposition (FEVD) derived by the VAR.

Impulse response functions are used to track the dynamic impact of a "shock" to an input or a variable on a system. This is done by: i) estimating the VAR model; ii) implementing a one-unit (or standard deviation) increase in the error of one of the variables in the model, while holding the other errors equal to zero; iii) Predicting the impacts h-period-ahead of the error shock; iv) Plotting the forecasted impacts, along with the confidence intervals. A shock to our variable of interest, uncertainty in our case, will show us how the other variables included in the VAR model react to it in the h-periods-ahead.

Forecast error variance decomposition (FEVD) consists in "decomposing" the variance of the forecast error into the contributions from specific exogenous shocks. This is very useful since it shows us how relevant a shock is in explaining the variations of the variables in the model overtime.

5.2 VAR Model and Restrictions

After introducing the main concepts of the VAR models, we are now ready to investigate the macroeconomic dynamics of the different uncertainty proxies introduced. Significant dynamic correlations between real activity and numerous uncertainty proxies are a frequent result highlighted by existing empirical research on uncertainty. As also discussed above, existing studies show that uncertainty measures are countercyclical and VAR estimates imply that they have a significant impact on output and employment in the months following an innovation in these measures. A very important result that emerged by the study of these proxies (in particular Bloom (2009)) is that a positive shock to the stock market volatility measure initially cases a depression of real activity and then increases it, resulting in an overshoot of its long- run level, which is consistent with the predictions of the some of the theoretical models on uncertainty as a driver of macroeconomic fluctuations.

We employ VARs in order to compare the dynamic responses of the main Italian macroeconomic indicators to positive shocks in our estimates of uncertainty (for h=1 and h=4), to their responses to positive shocks in the commonly used proxies of uncertainty, namely Italian Stock Market Volatility, Economic Policy Uncertainty Index and World Uncertainty Index. As we have discussed in the previous sections, the choice of the identification scheme is crucial to obtain legitimate impulse responses (IRFs) and forecast error variance decompositions (FEVDs). As identification strategy we choose zero- short run effects restrictions (Cholesky identification). This identification scheme assumes that some shocks have no contemporaneous effect on one or more of the endogenous variables. We prefer it to zero long- run restrictions since we want to see how an innovation to our uncertainty measure affects the relevant variables overtime and we do not know what will happen in the long term. Therefore, imposing this type of restrictions would distort our results and would be based on pure speculation. We also avoid sign restrictions because we do not want to influence the impact of the shock to the uncertainty measure on the different variables, even if the theoretic framework well describes the general reactions these variables should have. Using the Cholesky identification scheme allows us to see the effects of a positive shock to macroeconomic uncertainty, leaving the variables free to move after the initial impact. The causal/ recursive ordering of the variables in our VAR model is extremely important.[57] This is because shocks to one equation contemporaneously affect variables below that equation but only affect variables above that equation with a lag. The variables are ordered with an exogeneity criterium, from the most exogenous to the least exogenous. In other words, the causal ordering defines the relationship among the variables of the VAR.

We will define shortly the ordering of the variables we choose, but first we need to determine which indicators to include in the VAR model. It is important that for our model we choose variables whose dynamic relationships have been studied deeply and proved by econometric research. Therefore, we start from a macroeconomic VAR model similar to the one presented in Christiano et al. (2005), namely CEE. Unfortunately, the data we are able to collect in our dataset does not permit the exact replication of their VAR-11 model, but we maintain the main framework and the main relationships within the model substituting the macroeconomic variables with similar ones. Also, the ordering of the variables follows their work built upon proven macroeconomic relationship, permitting us to approximately cover the same sources of variation in the economy. An important distinction between our model and CEE model is the inclusion of the macroeconomic uncertainty. However, we place our estimate (and the other

---

[57] This is a characteristic of the Cholesky identification scheme.

proxies) last in the VARs in order to maintain intact the proven macroeconomic relationships. In addition, as done by Jurado et al. (2015) in their study of U.S. macro uncertainty measure, we include in the model the stock price index. Since it is logical to expect the two variables to be dynamically associated, including the stock market index is critical for understanding the dynamics of macro uncertainty. Another aspect of our VAR models is that the uncertainty measures we use are all standardized to have a $\mu = 0$ and a $\sigma = 1$.

The variables we include in our VAR model are production of total industry; employment rate; unemployment rate; consumer price index of all items; value of total retail trade sales; hourly wage rate in industry; interest rates, government securities, government bonds; stock price index; uncertainty measure. All data for the VAR model, besides the uncertainty measures and the stock prices, are retrieved from FRED, Federal Reserve Bank of St. Louis.

Our VAR-9 presents the following structure:

$$(VAR - 9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (\ retail\ trade\ ) \\ log\ (\ wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ uncertainty\ measure \end{bmatrix} .$$

Before presenting our VAR results, we want to briefly discuss a few additional characteristics of our models. All the data in the model is quarterly. The necessary natural- logarithmic transformation is performed on industrial production, CPI, retail trade, wage and stock price variables to reduce the volatility of the time series where all the observations are positive (see Kirchgässner and Wolters (2007)). The number of lags we include for our variables are 2, meaning 2 quarters. When producing our estimates of IRFs and FEVDs, constant and trend of the variables are taken into account, we estimate our results for 20 steps, therefore for 5 years, and our confidence level is set at 68 percent. The size of the shock for the IRFs is one standard deviation, explaining our use of standardized uncertainty measures for better results comparison.

5.3 VAR-9 Uncertainty (1)

The first var we analyse is the VAR-9 containing our measure of macro uncertainty for h=1, hence $\bar{U}_t^y(1)$:

$$(VAR-9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (\ retail\ trade\ ) \\ log\ (\ wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ \bar{u}_t^y(1) \end{bmatrix}.$$

Figure 18 shows the dynamic responses of all our variables in VAR-9 of a positive shock to our macro uncertainty measure for $h = 1$.

Figure 188. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to $\bar{u}_t^y(1)$. The shadowed areas show 68 percent standard error bands. The data is quarterly.

An innovation in the uncertainty measure causes the output to significantly reduce, with the impacts lasting well beyond the 60- month horizon delineated. We can note a small volatility overshoot, meaning a rebound in production, following the initial decline. However, besides the rebound being small, the production goes back to suffering negative effects that, as said, protract over the 5 years of our study. A similar effect is observed by Bloom (2009) in his study around the VXO (U.S. stock market volatility index) as a measure of uncertainty in real activity variables. Employment shows a sharp decline, with the effects of the impact lasting well beyond the 60- month horizon delineated and not showing signs of quick recovery. In this instance, the variable does not show the overshoot effects seen in the output and found by Bloom (2009).

This is consistent with the findings of Jurado et al. (2015) and Bachmann et al. (2013). However, differently from the findings in Bachmann et al. (2013), the short- run (within a year) responses to our uncertainty measure shocks are significant. The Unemployment shows a slower but steady increase, underlining once again the negative effect of a positive innovation to $\bar{u}_t^y(1)$ on real economic activity. The CPI increases ever so slightly in the first few months, rapidly declining thereafter. This can be explained by the initial rigidity of prices to unexpected changes, also known as price stickiness. Price stickiness is defined as the resistance of market price(s) to change quickly, despite shifts in the broad economy suggesting a different price is optimal. Eventually prices react to the increase in macro uncertainty and inflation drops. A small rebound effect is observed after more than two years from the initial shock. Retail trade shows a quick drop as a reaction to the innovation in the uncertainty. This is to be expected since consumers will reduce their consumption in order to increase savings and cut spending during uncertain times. Also, in this case a rebound effect is observed after more or less two years. What we observe in the IRF of wage seems to be counterintuitive. As a reaction to the increase in uncertainty, wages appear to increase. In reality, since the wage variable represents the hourly wage rate, an increase in the measure could mean that businesses cut spending as we would expect, reducing first the number of less qualified workers or workers whose job is not vital to the company. This in turn will increase the hourly wage rate, hiding the real effect of the increase in uncertainty. In addition, this theory would also explain why the indicator seems not to follow the sticky wage theory, quickly reacting to the uncertainty innovation. Long term interest rates see a slow increase overtime for a considerable number of years (three). These findings are in accordance with what the economic theory predicts. As a recent article (2021) of the International Monetary Fund well explains, the yield of treasury bond rates, the main proxy of long- term interest rates, is the combination of real Treasury yield, based on the expectations on economic growth, and the inflation breakeven yield, based on investor's future inflation expectations. These two rates do not only represent current market expectations on inflation and growth. They also include the compensation that investors require for bearing the risks associated with both elements. An increase in the macroeconomic uncertainty automatically increases the risk premium asked by investors, increasing therefore the long- term interest rates on government securities and government bonds. As a reaction to the positive shock on our uncertainty measure, stock prices plumet rapidly, with the effects lasting for almost all the period considered. Megaritis et al. (2021) study how macro uncertainty affect the stock markets in the U.S. and find that the macroeconomic uncertainty factor explains the part of stock market volatility which cannot be attributed to changes in fundamentals. It is also intuitive that the prices of the stocks will decrease as a reaction to an increase in the uncertainty

due to the businesses performing poorly and people saving more, causing investment to decrease and disinvestment to increase, ultimately resulting in a rapid decrease of share prices. All the findings resulting from the VAR-9 to study the macroeconomic dynamics of a positive shock to our uncertainty measure are supported by countless research and studies on macroeconomic uncertainty theory. The last plot of the figure shows the persistence of the shock on uncertainty itself. After the initial increase, macroeconomic uncertainty slowly goes back to pre-shock levels after six quarters.

To summarize and provide a simplified representation of our results, an increase in the macroeconomic uncertainty depresses industrial production. Businesses cut down on costs reducing investments and employment, therefore increasing unemployment. As a result, hourly wage rate appears to be increasing, even though the fundamental cause is not positive. Consumers cut on spending, reducing prices and further deteriorating the industrial production, and increase precautionary saving therefore reducing investments. As a result of the reduced investments, financial instruments suffer heavily: stock prices plumet and investors require a higher yield as a compensation for the risk carried. Obviously, this simple representation of the world has to be taken with caution, but the important part is to get the idea behind every variable response to the innovation in macro uncertainty.

5.4 VAR-9 Uncertainty (4)

Next, we analyse the VAR-9 model containing our measure of macro uncertainty for h=4, hence $\bar{U}_t^y(4)$:

$$(VAR-9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (\ retail\ trade\ ) \\ log\ (\ wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ \bar{U}_t^y(4) \end{bmatrix}.$$

Figure 19 shows the dynamic responses of all our variables in VAR-9 of a positive shock to our macro uncertainty measure for h = 4.
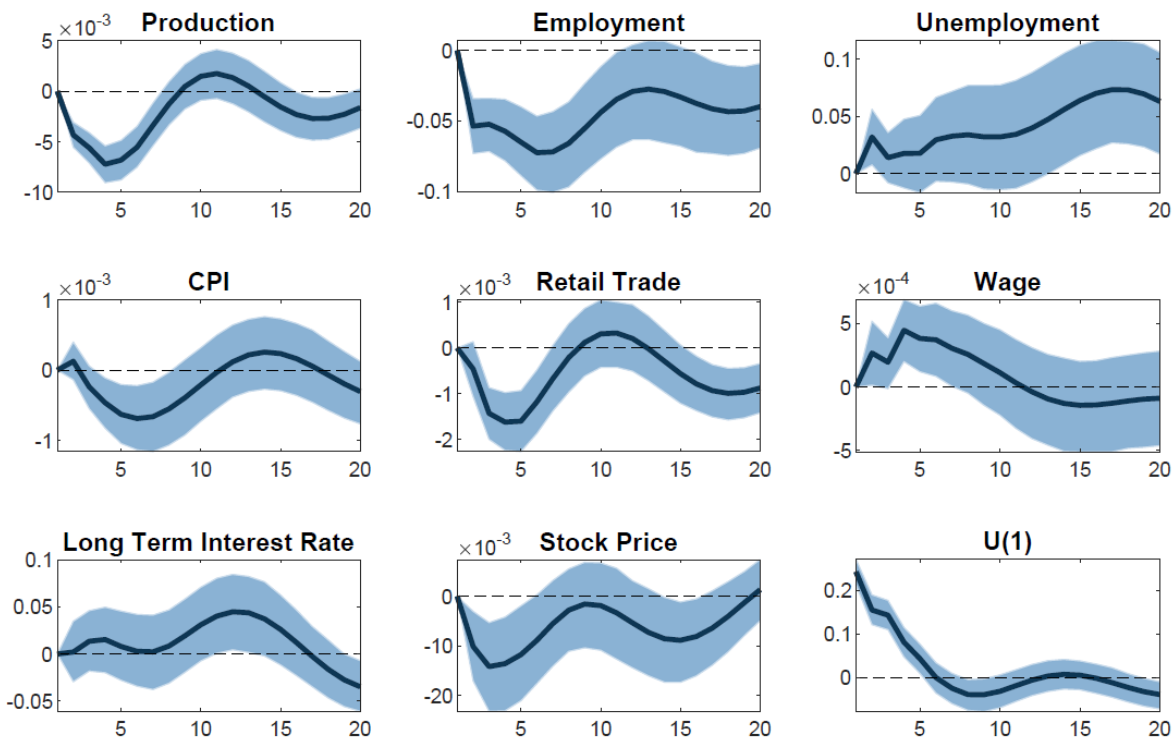
Figure 19. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to $\overline{\mathcal{U}}_t^y(4)$. The shadowed areas show 68 percent standard error bands. The data is quarterly.

The IRFs reported are very similar to the ones regarding the shock to the uncertainty for h=1, underlining the consistency of both our measures. A positive shock to the macroeconomic uncertainty causes the industrial production to decrease significantly, showing a slight overshoot around 9 quarters later. Employment sharply decreases while the unemployment increases slowly but steadily. No overshoot is shown by these measures. The dynamic responses of real activity variables show a persistence that protracts well over the five years horizon from us depicted. The CPI shows a steep decline, probably due to the reduction in consumption, after a quarter of relevant stability likely due to the price stickiness we discussed above. The retail trade plumets as well as a consequence of a decrease in consumer spending, among other reasons. Both CPI and retail trade show a small temporary rebound during the 5 years represented. Hourly wages increase probably as a result of the non-essential employee spending cut. Long interest rates show a substantial increase after a period of relative stability, while the stock prices' reaction is quick and significantly negative, showing persistence for well over 15 quarters. The last plot of the figure shows the persistence of the shock on uncertainty itself. Following the impact, macroeconomic uncertainty slowly goes back to pre-shock levels after more than six quarters. Again, all the IRFs, as in the case of a shock to $\overline{\mathcal{U}}_t^y(1)$, are in line with macro uncertainty theoretical models' predictions.

5.5 VAR-9 Italian Stock Market Volatility

The following analysis concerns the VAR-9 model containing the stock market volatility measure (ISV):

$$(VAR - 9) = \begin{bmatrix} log(\text{ industrial production }) \\ employment \\ unemployment \\ log(\text{ CPI }) \\ log(\text{ retail trade }) \\ log(\text{ wage }) \\ long\ term\ interest\ rate \\ log(\text{ stock price }) \\ ISV \end{bmatrix}.$$

Figure 20 shows the dynamic responses of all our variables in VAR-9 of a positive shock to ISV.
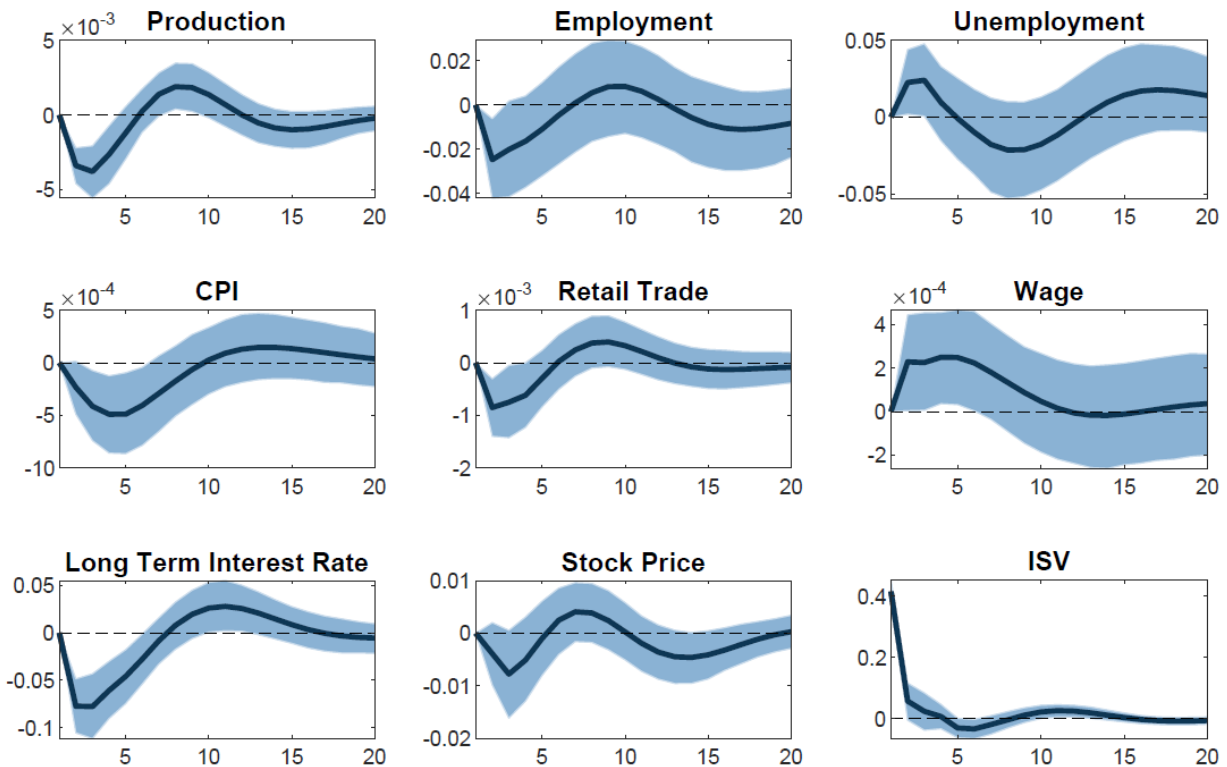
Figure 20. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to ISV. The shadowed areas show 68 percent standard error bands. The data is quarterly.

A positive innovation in the ISV measure immediately causes industrial production to decrease significantly. However, after the first three quarters, production quickly starts reverting the trend, consequently presenting an overshooting in the measure, much like the one reported in Bloom (2009). The employment also quickly falls as we expect, presenting again a rebound effect. Unemployment presents an immediate increase, reverting around the fourth quarter.

Although the real activity variables above described follow the general pattern we would expect as a reaction of the increased macro uncertainty, we can immediately notice that the economic recovery appears to be rather quick. More on this will be said when we will later compare all the IRFs of real activity indicators from a shock to our five uncertainty measures. The CPI decreases substantially before going back to pre- shock levels around the tenth quarter and does not show any trace of the stickiness of prices discussed above. Retail trade is also affected negatively from the increased uncertainty and the consequent reduction in consumers' spending. Also in this instance, the volatility overshoot is evident and the recovery period seems to be rapid. Hourly wage rates increase as in the case of our uncertainty measure, roughly presenting the same characteristics. The long- term interest rate shows a strange response to a shock to ISV, suggesting that a substantial decrease results from the shock. However, as reported before, the investors would require an increase in the yield compared to the one they receive in times of relative quiescence, in order to compensate for the additional risk they are subject to. Stock prices plumet initially, but fully recover after around 5 quarters, once again showing a marked overshooting effect. The last plot of the figure shows the persistence of the shock on ISV itself. After the impact, the ISV measure goes back to pre-shock levels very quickly, after roughly two quarters. This shows the lower persistency of the ISV with respect to our uncertainty measure. Although they generally follow the responses we expect according to the economic theory around macro uncertainty, all the variables (besides CPI and wage) present a small degree of persistence when compared to our uncertainty measures.

5.6 VAR-9 Economic Policy Uncertainty Index

The next two measures we will be analysing as proxies of macro uncertainty are economic policy uncertainty index and world uncertainty index, both news- based indexes.

Starting with the EPUI, the resulting VAR-9 through which we study its macroeconomic dynamics is the following:

$$(VAR - 9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (\ retail\ trade\ ) \\ log\ (\ wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ EPUI \end{bmatrix}.$$

Figure 21 plots the dynamic responses of all our variables in VAR-9 of a positive shock to EPUI.
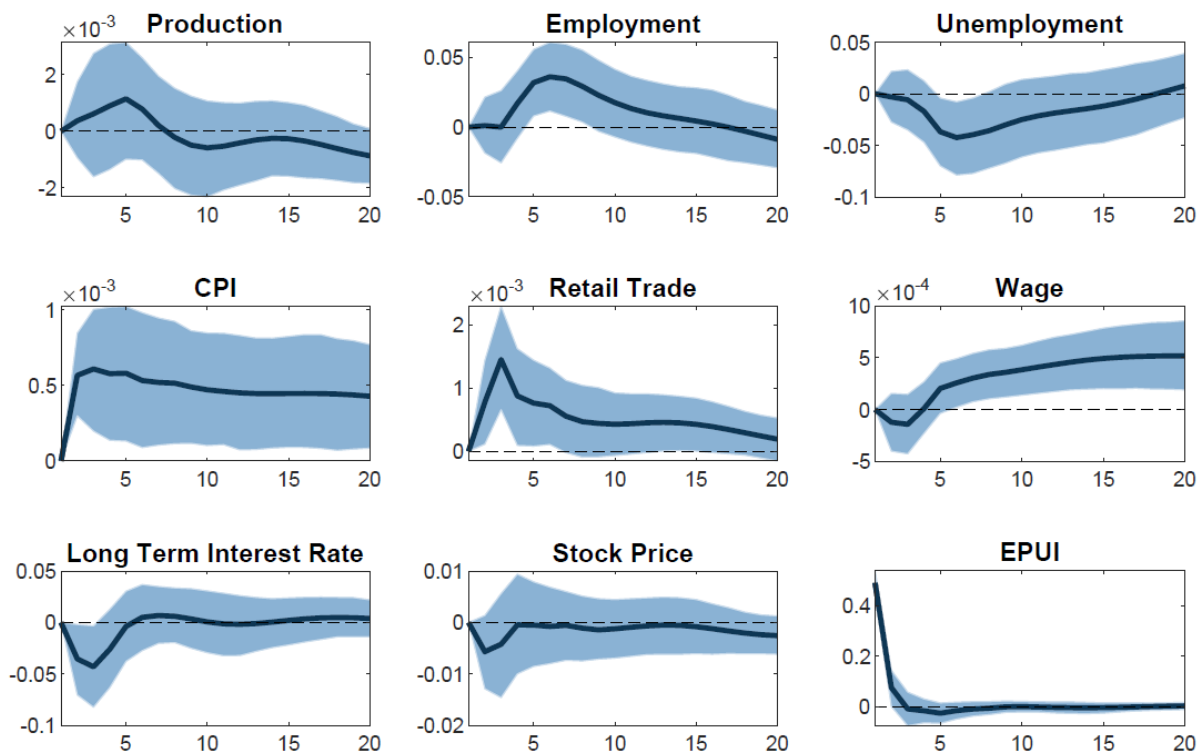
Figure 191. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to EPUI. The shadowed areas show 68 percent standard error bands. The data is quarterly.

We can immediately notice the contrast of the results here reported with the results we previously presented. As a response to a positive shock to the EPUI, the production increases slowly but steadily up to the fifth quarter, subsequently starting to decrease. The employment does not show a reaction to the shock if not almost one year later, after which it increases rapidly. Unemployment decreases very slowly for over 5 quarters. All the responses of real activity variables to a shock to the EPUI go against what the economic theory anticipates, thus heavily reducing the credibility of this news- based measure as a proxy of macroeconomic uncertainty. Continuing with the analysis, the CPI shows a marked rise in its levels as also retail trade does. Although the inflation rate response is ambiguous and not always straight forward as explained by countless research on the matter, an increase in retail trade indicator is typical of an expansionary period, in which the economy grows (as is in the cases of increased production and employment). The wages decrease for a few months, sharply increasing afterwards. Moreover, the long- term interest rate decreases in the first quarters, stabilizing at the starting rate after roughly one year. Stock prices contract for a brief period, going back to the initial level mimicking the flow of long- term interest rate. The last plot of the figure shows the persistence of the shock on EPUI itself. After the impact, the EPUI measure goes back to

80

pre-shock levels very quickly, after roughly two quarters. This shows the lower persistency of the EPUI, as the case of ISV, with respect to our uncertainty measure. The IRFs very rarely display overshooting. Despite the fact that some variables follow the general direction predicted by the economic theory, the vast majority does not. If the EPUI is used as a proxy of macroeconomic uncertainty, an increase in uncertainty would lead to economic growth, which is far from what countless empirical studies demonstrated and what economic theory predicts.

5.7 VAR-9 World Uncertainty Index

We now analyse the second news- based proxy as a measure of macro uncertainty. The VAR-9 through which we study its macroeconomic dynamics is the following:

$$(VAR - 9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (\ retail\ trade\ ) \\ log\ (\ wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ WUI \end{bmatrix}.$$

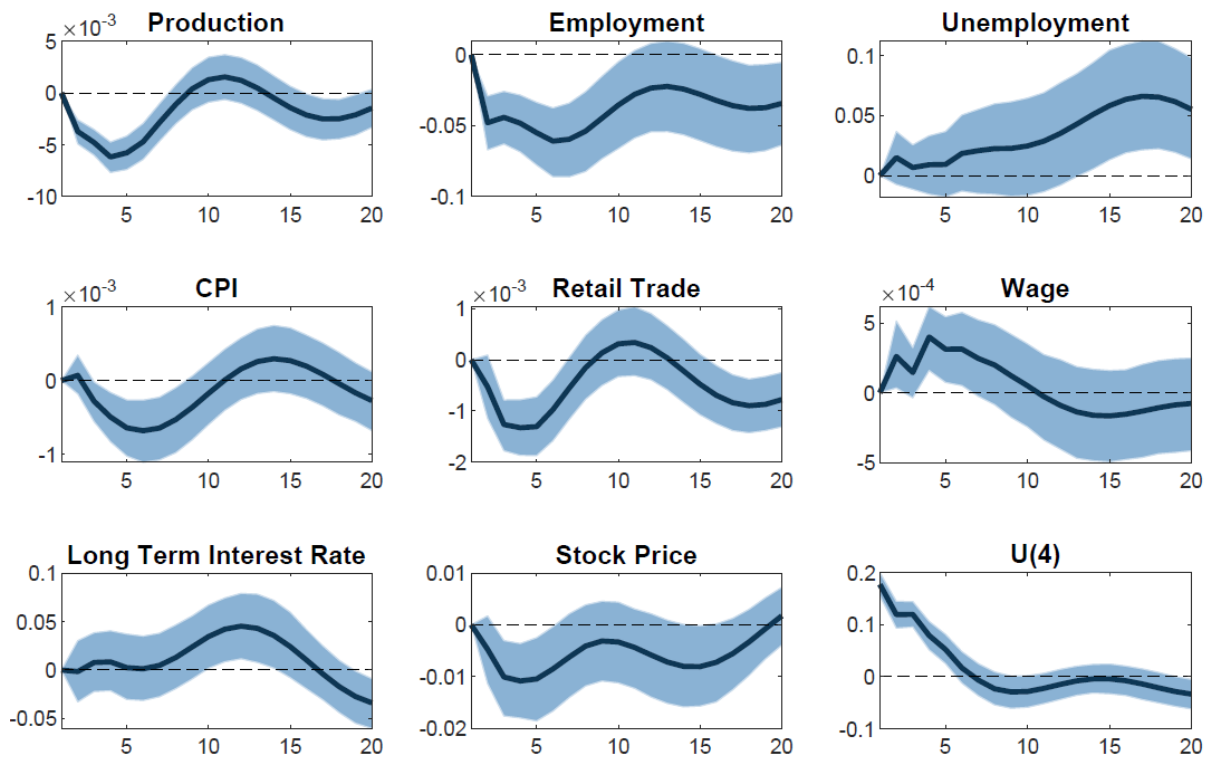Figure 22 plots the dynamic responses of all our variables in VAR-9 of a positive shock to WUI.
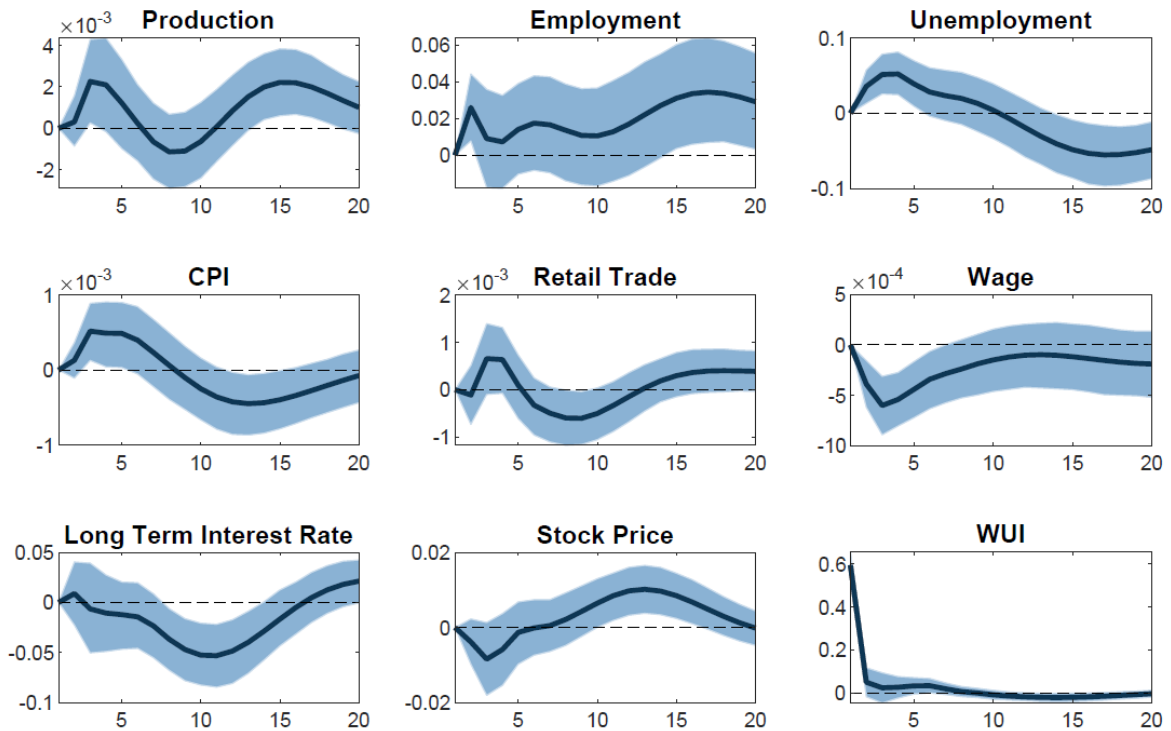
Figure 22. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to WUI. The shadowed areas show 68 percent standard error bands. The data is quarterly.

81

The similarities between the IRFs of the variables of a positive shock to the EPUI and of a positive shock to WUI immediately stand out. The industrial production shows a sharp increase after the shock, as does the employment. The production however shows a very pronounced rebound around the sixth quarter, becoming negative for roughly one year before surging above the initial level again. Differently from the EPUI case, the unemployment increases following the shock to the WUI, in line with the expectations. Again, CPI increases and this result that can be interpreted in different ways as we already explained.[58] Again, retail trade also presents an increment as in the previous analysis, hinting, as production and employment, to an economic growth. Hourly wage rate decreases immediately, while the long- term interest rate decreases after an initial small rise. The stock price decreases after the shock to the proxy, but the variable shows a speedy recovery, displaying a significant volatility overshooting. The last plot of the figure shows the persistence of the shock on WUI itself. After the impact, the WUI measure goes back to pre-shock levels very quickly, after roughly two quarters. This shows the lower persistency of the WUI, as in the case of EPUI and ISV, with respect to our uncertainty measures. As for the other news- based proxy, the WUI macroeconomic dynamics rarely follow what empirically demonstrated and what the economic models built around macroeconomic uncertainty predict. The legitimacy of the proxy as a measure of macro uncertainty is further put in doubt.

5.8 Real Economic Activity IRFs Comparison

Until now, we have presented and discussed the results of the different VARs individually. In this section we want to compare the macroeconomic dynamics of all the uncertainty measures used, concerning real economic activity. Therefore, we isolate the IRFs of a positive shock to the uncertainty measures for industrial production, employment and unemployment.

In figure 23 are plotted the IRFs that will allow us to investigate this aspect.

---

[58] The increase in inflation is coherent with the increase in industrial production and employment, however, we know that these results are not credible as a reaction to an increased macroeconomic uncertainty.
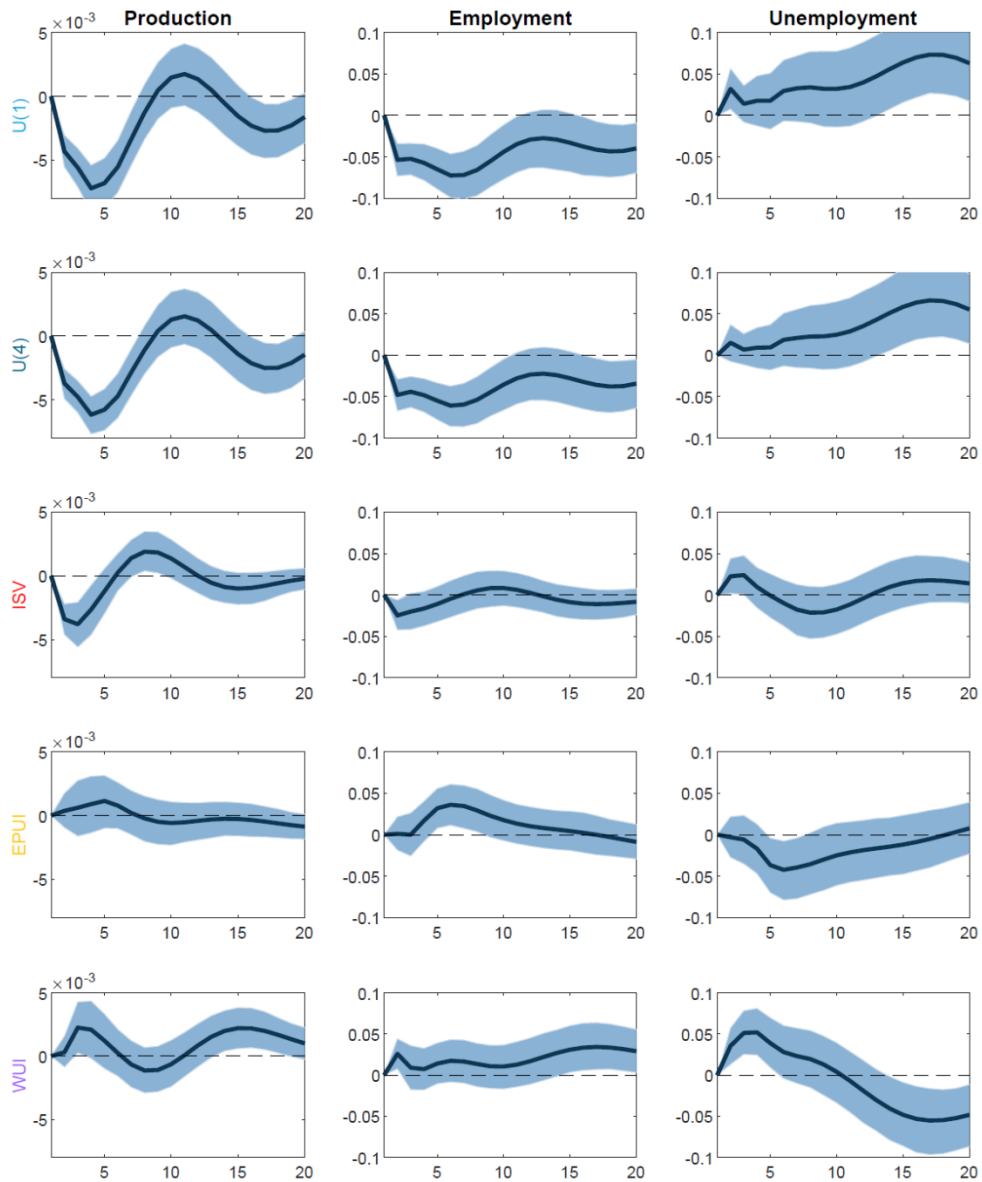
Figure 23. Impulse Response of real activity variables in VAR-9 to a one standard deviation shock to all of the uncertainty measures used. The shadowed areas show 68 percent standard error bands. The data is quarterly.

We report all the result in a visually easy to compare format.

The reduction in industrial production that the economic theory suggests, following the positive innovation in the uncertainty measures, is observed in three out of five cases, namely $\bar{\mathcal{U}}_t^y(1)$, $\bar{\mathcal{U}}_t^y(4)$ and ISV. However, although all three responses show a slight overshooting effect, both our measures of uncertainty are larger and more persistent than the stock market volatility index. Even more evident is the employment IRFs results. Again, the news- based measures do not follow the standard economic theory, and the ISV proxy result, even if it is consistent with the direction advocated by the theory, is not much large or very significant. On the other hand, our uncertainty measures, besides not showing any overshooting effects unlike the ISV case, show a considerable reduction in the employment, with the effects persisting well over the 5

years depicted. The IRFs of unemployment show realistic responses of the variable to a positive innovation in all the measures, besides the EPUI. Once again, both $\bar{\mathcal{U}}_t^y(1)$ and $\bar{\mathcal{U}}_t^y(4)$ show the results that are more consistent with what expected, with a relevant magnitude and persistency of the increase of unemployment as a response to the increase in the macro uncertainty level.

The results relative to real economic activity are in line with the results found by Jurado et al. (2015), in terms of persistency and magnitude of the dynamic responses of real activity to a shock to the uncertainty measure, although their research does not include the unemployment in the VARs.

5.9 FEVDs Analysis and Comparison

In this section we investigate the quantitative significance of the uncertainty measures' shocks for macroeconomic fluctuations. To do so, we study the forecast error variance decomposition for all our macroeconomic variables. Forecast error variance decomposition (FEVD) consists in "decomposing" the variance of the forecast error into the contributions from specific exogenous shocks, in our case we isolate the shock to the measures of uncertainty. This is very useful since it shows us how relevant a shock is in explaining the variations of the variables in the model overtime. First of all, we analyse the FEVDs of the real activity variables, namely industrial production, employment and unemployment, which are reported in figure 24.
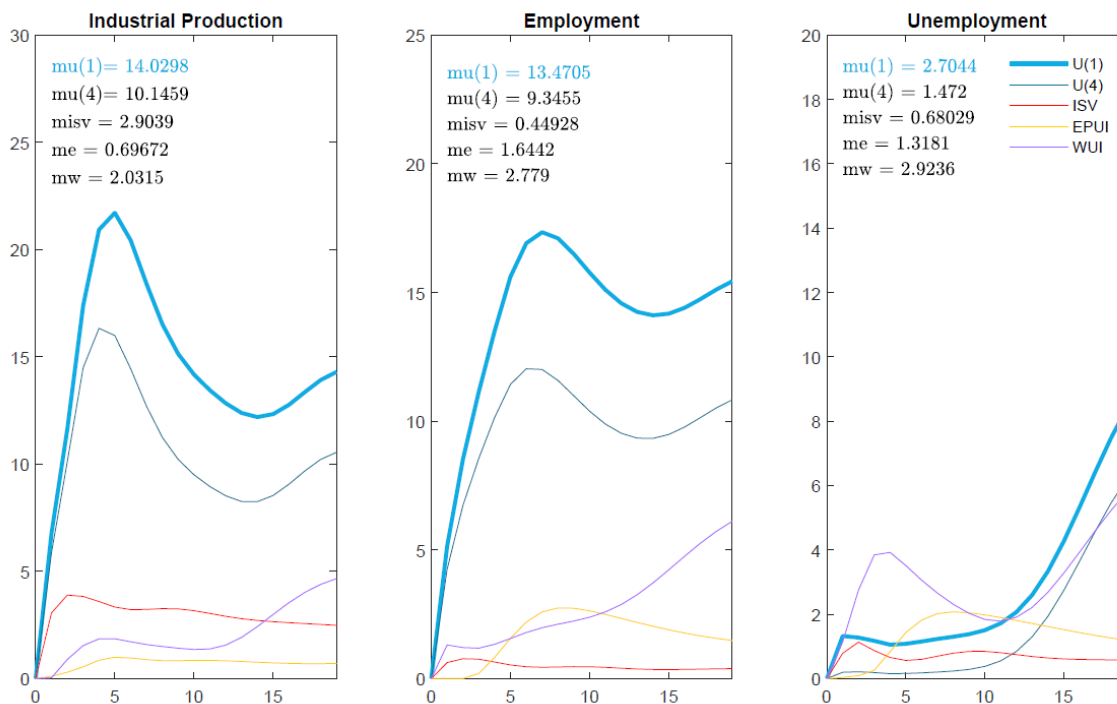
Figure 24. FEVDs of a shock to the uncertainty measures on industrial production, employment and unemployment. The "m" value reports the average forecast error explained by each uncertainty measure throughout the 20 periods horizon. The data is quarterly.

Industrial production. As we can see from the first plot, $\overline{\mathcal{U}}_t^y(1)$ shock is associated with the greatest fraction of VAR forecast error variance of industrial production, linked to up to 21.70 percent of the variation after 6 quarters and on average linked to 14.02 percent of the variation. The second- best results are those of the $\overline{\mathcal{U}}_t^y(4)$, linked to up to 16.32 percent of the variation after 5 quarters and on average linked to 10.14 percent of the variation. As it is clear from the plot, the other macro uncertainty proxies are associated with a much smaller part of the variation in production, not over 5 percent and averaging at max 2.9 percent in the case of the shock to the ISV.

Employment. Again, the shock of $\overline{\mathcal{U}}_t^y(1)$ is the one associated with the largest part of VAR forecast error variance of employment, linked to up to 17.33 percent of the variation after 8 quarters and on average linked to 13.47 percent of the variation. The second- best results are those of $\overline{\mathcal{U}}_t^y(4)$, linked to up to 12.03 percent of the variation after 7 quarters and on average linked to 9.34 percent of the variation. The other macro uncertainty proxies are again associated with a much smaller part of the variation in employment, at best slightly over 6 percent (in the case of WUI, 6.1 percent after 20 quarters), and averaging a mere 2.77 percent in the case of shocks to the WUI.

Unemployment. Once more, the shock of $\overline{\mathcal{U}}_t^y(1)$ is the one associated with the largest fraction of VAR forecast error variance of unemployment, linked to up to 8.4 percent of the variation after 20 quarters and on average linked to 2.70 percent of the variation. The second- best results are those of the $\overline{\mathcal{U}}_t^y(4)$, linked to up to 6.20 percent of the variation after 20 quarters and on average linked to 1.47 percent of the variation. This time, the WUI shocks are a close third, associated to up to 5.80 percent of the variation after 20 quarters and on average linked to 2.92 percent of the variation (slightly more than our uncertainty measure with h=1). ISV and EPUI report once more underwhelming results.

We now go quicky over the FEVDs of the remaining variables, represented in figure 25.

Figure 25. FEVDs of a shock to the uncertainty measures on CPI, retail trade, wage, long term interest rate and stock price. The data is quarterly.

The shock to EPUI is the one associated with the greatest fraction of FEV of consumer price index, the shock to WUI is the one associated with the largest part of FEV of wage, the shock to ISV is better linked to the FEV of long- term interest rates and shocks to our measures of uncertainty are the ones associated with the greatest part of FEV of retail trade and stock price. It is interesting to note that even when shocks to other proxies are associated with larger portions of the forecast error variances, shocks to $\bar{u}_t^y(1)$ and to $\bar{u}_t^y(4)$ are still relevantly associated to all the variables of our VAR models.

These variance decompositions are, of course, dependent on the order in which the variables in the analysis are arranged. Since uncertainty is the last variable in the VAR, the effects of uncertainty shocks on the other variables in the system are assessed after we have removed all the variation in every single variable due to shocks to the model's other endogenous variables. The fact that the impacts of uncertainty shocks are still significant supports the notion that macroeconomic uncertainty has significant implications for economic activity.

5.10 Remarks

We have analysed our uncertainty measure through a series of investigations: check of validity of our forecast method and the use of predictors in our estimation; time series comparison of our measure with the commonly used uncertainty proxies; proof of the countercyclicality of our estimate; economic interpretation of the time series of our measure, with historical events and recession dates; analysis of the macroeconomic dynamics of our estimates. Our measure of uncertainty is in accordance with the empirical research and the economic theory surrounding the macroeconomic uncertainty field. All our findings establish the legitimacy and the credibility of our uncertainty metrics as the best measure of macroeconomic uncertainty among all the analysed commonly used proxies for Italy.

Chapter 6

European Economic Policy and Italian Uncertainty Dynamics

Var Models Characteristics and Implementation, ECB Monetary Policy and Impact on Italian Macro Uncertainty

6.1 VAR Model and Restrictions

Monetary policy is a fundamental set of instruments that allow the policy makers to control macroeconomic fluctuations and to promote a sustainable economic growth. Particularly, monetary policy concerns the regulation of the quantity of money available in an economy and the channels by which new money is supplied. By managing the money supply, a central bank aims to influence macroeconomic factors including inflation, the rate of consumption, economic growth, and overall liquidity. [59]

In this chapter we want to investigate the dynamics between European monetary policy and Italian macroeconomic uncertainty. As we have previously mentioned, since the introduction of the euro, Italy is subject to the monetary policy imposed by the ECB.[60] In order to grasp the effects of an endogenous shock to monetary policy on our uncertainty measure, we use simple VAR models. We once again choose zero- short run effect restrictions (Cholesky identification), assuming that some shocks have no contemporaneous effects on one or more of the endogenous variables. The ordering of our variables matters since shocks to one equation contemporaneously affect variables below that equation but only affect variables above that equation with a lag. Therefore, the variables are ordered with an exogeneity criterium. The ordering of our variables and the structure of our VAR models is a very simplified version of the one we used in chapter 5. We will analyse the IRFs of a VAR-4 and of a VAR-6, discussing their variables in the relative sections. Before presenting our VARs and their results, we want to briefly discuss a few additional characteristics of our models. All the data in the model is quarterly. The necessary natural- logarithmic transformation is performed on industrial production and CPI, in order to reduce the volatility of the time series where all the observations

---

[59] Definition based on https://www.investopedia.com/terms/m/monetarypolicy.asp.
[60] The main objective of the European Central Bank is to keep prices stable in the euro area.

are positive (see Kirchgässner and Wolters (2007)). The number of lags we include for our variables are 2, hence 2 quarters. When producing our estimates of IRFs, constant and trend of the variables are taken into account, we estimate our results for 20 steps, therefore for 5 years, and our confidence level is set at 68 percent. The size of the shock for the IRFs is one standard deviation.

6.2 VAR-4 Analysis

The first VAR we analyse is the VAR-4 containing our measure of macroeconomic uncertainty for h=1, hence $\bar{\mathcal{U}}_t^y(1)$:

$$(VAR-4) = \begin{bmatrix} log \ (Euro \ Area \ industrial \ production \ ) \\ log \ (Euro \ Area \ CPI \ ) \\ ECB \ short \ term \ interest \ rate \\ Italian \ \bar{\mathcal{U}}_t^y(1) \end{bmatrix}.$$

To study the effect of the European monetary policy on our macroeconomic uncertainty measure, we choose, as proxy for the ECB short term interest rate, the Deposit Facility Rate. As explained on the ECB website, the deposit facility rate is one of the three interest rates the ECB sets every six weeks as part of its monetary policy. The rate defines the interest banks receive for depositing money with the central bank overnight. The necessary data is retrieved from the FRED, Federal Reserve Bank of St. Louis and are, in order, the total industry production excluding construction for the Euro Area (index 2015=100), harmonized index of consumer prices: all items for Euro Area (2015=100), the ECB Deposit Facility Rate, our Italian uncertainty measure $\bar{\mathcal{U}}_t^y(1)$.[61] The data implemented in our VAR goes from q1 of 1999 to q4 of 2019.

Figure 26 plots the dynamic responses of our variables of interest in VAR-4 to a positive shock to the monetary policy, hence the deposit facility rate.

---

[61] In the euro area, the Harmonised Index of Consumer Prices (HICP) is used to measure consumer price inflation. That means the change over time in the prices of consumer goods and services purchased by euro area households. It is "harmonised" because all the countries in the European Union follow the same methodology. Source:
https://www.ecb.europa.eu/stats/macroeconomic_and_sectoral/hicp/html/index.en.html#:~:text=In%20the%20euro%20area%2C%20the,Union%20follow%20the%20same%20methodology.
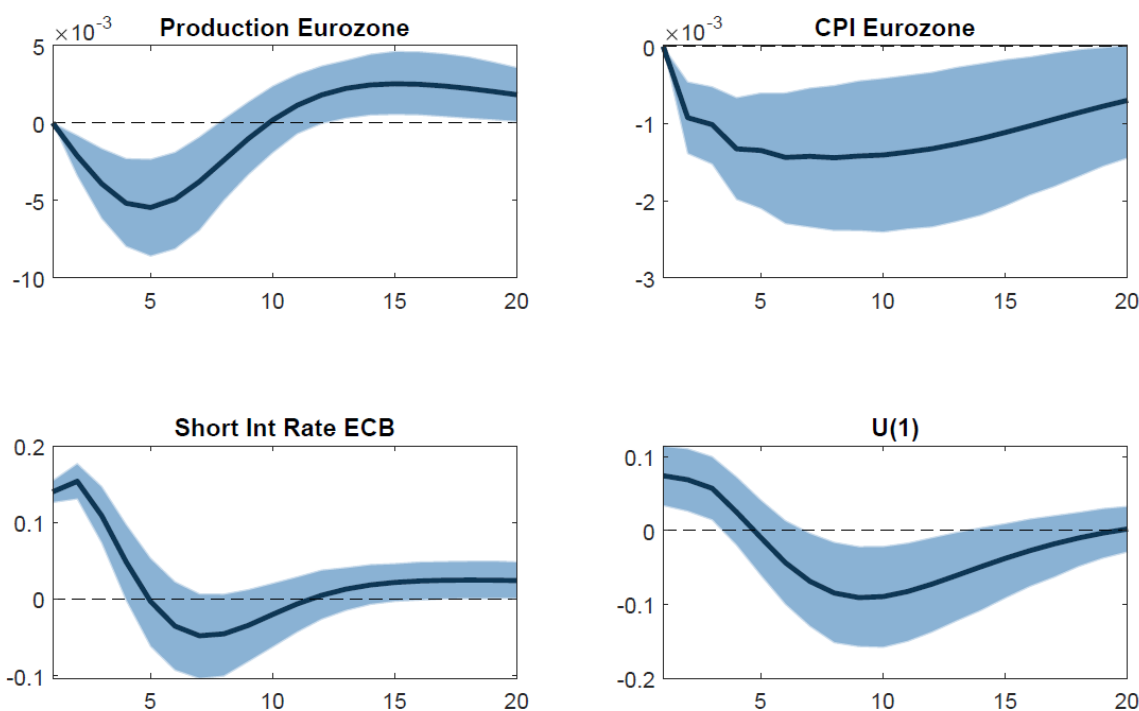
Figure 26. Impulse Response of the variables contained in VAR-4 to a one standard deviation shock to the ECB short-term interest rate. The shadowed areas show 68 percent standard error bands. The data is quarterly.

A positive innovation to the short-term interest rate of the European Central Bank causes the production of the Euro Area to sharply decrease for 5 quarters, showing signs of recovery after roughly two years. This result is in accordance with what the economic theory and empirical research predicts (see Arias et al. (2018)). A contractionary monetary policy is known to depress economic growth. The effect of the shock to the short-term interest rate on the Euro Area inflation is of the same type of the one on industrial production, showing a fall in the former which is much more persistent than the effect on the latter, protracting over the 5 years period horizon. Again, this is exactly what we expect from the economic theory. As a matter of fact, the increase of the interest rates is a monetary policy instrument used to reduce the rate of monetary expansion and fight inflation. Finally, a positive shock to the short-term interest rate leads to an immediate increase of the macroeconomic uncertainty. The relationship between the monetary policy and uncertainty has been a topic of extreme interest, especially after the Financial Crisis and subsequent Great Recession of 2007-2009. Our findings reported in the last IRF are again in line with empirical research on the subject. Bekaert et al. (2013) find that the VIX, the stock market option-based implied volatility, strongly co-moves with measures of the monetary policy. They find that a lax monetary policy decreases the uncertainty measure, implying that contractionary monetary polices should increase macroeconomic uncertainty.

6.3 VAR-6 Analysis

The second VAR we analyse is the VAR-6, also containing our measure of macroeconomic uncertainty for h=1, hence $\bar{\mathcal{U}}_t^y(1)$:

$$(VAR-6) = \begin{bmatrix} log(\text{ Euro Area industrial production }) \\ Euro\ Area\ employment \\ Euro\ Area\ unemployment \\ log\ (\text{ Euro Area CPI }) \\ ECB\ short\ term\ interest\ rate \\ Italian\ \bar{\mathcal{U}}_t^y(1) \end{bmatrix}.$$

The composition of VAR-6 is similar to the VAR-4, except the presence of two additional variables, namely employment and unemployment in the Euro area. The addition of relevant variables should generally increase the accuracy of the model, however, due to limited available data for the analysis, the dataset is constructed with data from the q1 of 2005 up to q4 of 2019, reducing the VAR-4 sample of 6 years.[62] Nonetheless, the analysis of VAR-6 can further confirm the results previously obtained.

Figure 27 plots the dynamic responses of the variables of interest in VAR-6 of a positive shock to the monetary policy, hence the deposit facility rate.
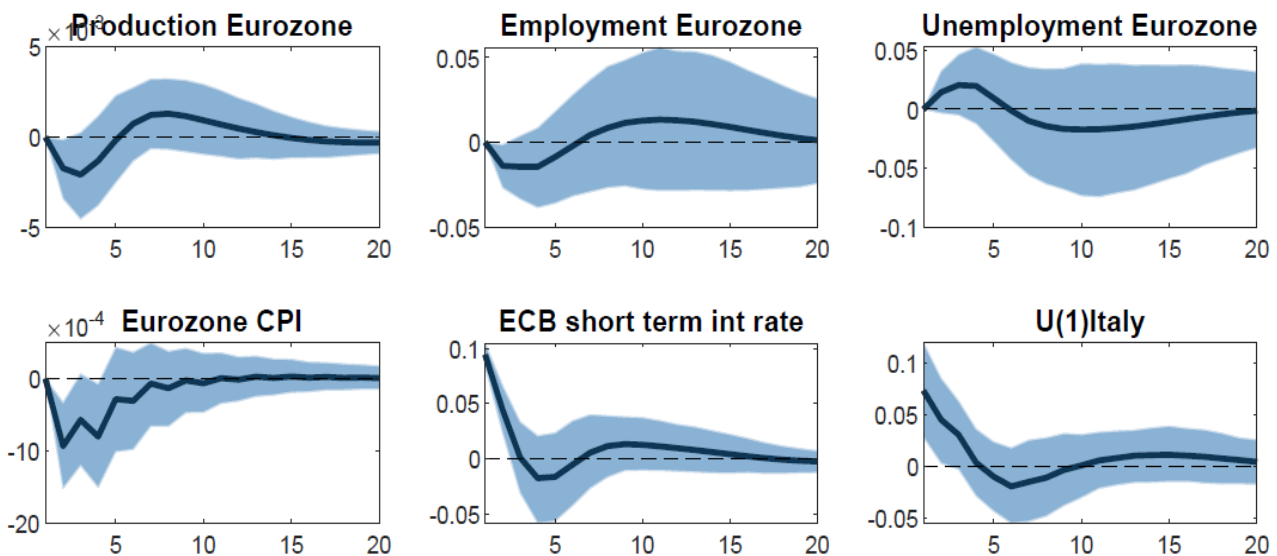
Figure 27. Impulse Response of the variables contained in VAR-6 to a one standard deviation shock to the ECB short- term interest rate. The shadowed areas show 68 percent standard error bands. The data is quarterly.

---

[62] Once again, we choose not to implement backtracking techniques in order to extend the dataset and artificially obtain the missing data. We prefer to conduct our analysis exclusively on real data. An artificial extension on the dataset could be an interesting topic of future research, particularly to implement during the estimation of our uncertainty measure.

Again, a positive innovation to the short- term interest rate of the European Central Bank causes the production of the Euro Area to decrease as in VAR-4, however, the magnitude of the decrease is in this case substantially lower. A shock to the ECB rate decreases employment and increases unemployment, both of which revert to the original level after more or less five quarters, showing a small overshooting effect. CPI decreases sharply at impact, going back at the initial level after two years. Finally, once more, macro uncertainty immediately increases as a result of the contractionary monetary policy, in accordance with the previous results. All the IRFs present results that clearly follow the economic theory and the empirical research around the macroeconomic uncertainty and monetary policy.[63]

6.4 Remarks

Given our findings from both VAR analysis, we can affirm with a high level of certainty that the policy makers play a fundamental role in combatting macroeconomic uncertainty. Through policy instruments, like the monetary policy, they can reduce (at least partially) the level of uncertainty in the economy. For instance, recessions are characterized by increased macroeconomic uncertainty and so an economic recovery may require management of expectations and assurance by policymakers. Basu and Bundick (2017), affirm that monetary policy plays a key role in offsetting the negative impact of uncertainty shocks during normal times. Higher uncertainty has even more negative effects if monetary policy can no longer perform its usual stabilizing function because of the zero- lower bound.[64] They also argue that increased uncertainty about the future likely played a role in worsening the Great Recession. Although policy makers dispose of instruments that help them contrasting macroeconomic uncertainty, their effectiveness during uncertain times is reduced (see Pellegrino (2021)). These findings further empathize the importance of developing an accurate measure of uncertainty for the purpose of realizing adequate policy responses.

---

[63] It is important to keep in mind that ECB monetary policy actions are based on the needs of whole Euro Area and not single member states.

[64] The Zero Lower Bound (ZLB) is a macroeconomic problem that happens when the short-term nominal interest rate is at or near zero, creating a liquidity trap and limiting the ability of the central bank to support economic growth.

Chapter 7

Combined Uncertainty Measure

Conceptualization, Initial Analysis, Var Analysis, European Policy Analysis

7.1 Conceptualization and Construction

The uncertainty measures we estimate, $\bar{\mathcal{U}}_t^y(1)$ and $\bar{\mathcal{U}}_t^y(4)$, bring us extremely satisfying results, behaving in accordance with the majority of the literature and the economic theory surrounding macroeconomic uncertainty. In this chapter we want to take an extra step towards the realization of an uncertainty measure as accurate as possible, trying to improve the already solid measure we estimated. To work towards this objective, we decide to try and aggregate our macroeconomic uncertainty measure with the other commonly used proxies for uncertainty. Of course, we do not want to simply combine the proxies we have because this would most likely worsen our measure.[65] Furthermore, simple combinations of the different measures (i.e., the simple weighting average) would be lacking a fundamental logic in the construction and would represent a guessing game at that point. Therefore, we exclude a priori methods like the ones described above. The objective of our combined uncertainty measure is to represent, as accurately as possible, all the macro uncertainty relevant events that we can. From now on we will be working with the $\bar{\mathcal{U}}_t^y(1)$ and standardized values of both our estimate and the other common proxies. As we have previously analysed, the ISV is highly correlated with our uncertainty measure, with a $\rho = 0.43359$, meaning that, in general, the two measures are capturing similar uncertainty events. For this reason, we exclude the ISV from our combined uncertainty measure. The EPUI is slightly negatively correlated with our uncertainty measure, with a $\rho = -0.15574$, suggesting that, sometimes, the two measures do not capture the same uncertainty events. However, the WUI is highly, negatively correlated with our uncertainty measure, with a $\rho = -0.47294$, hinting at the fact that the two measures capture different uncertainty events. For this reason, we decide to construct our new combined measure of uncertainty merging $\bar{\mathcal{U}}_t^y(1)$ and WUI.[66] We now need an aggregation method able to preserve

---

[65] Further investigation confirmed the worsening of the macroeconomic uncertainty measure when naively combining all the uncertainty proxies and our estimates.

[66] The correlation between WUI and EPUI is $\rho = 0.2762155$, therefore, combined with the low negative correlation with our measure, this leads us to exclude also the EPUI from the combined uncertainty measure.

one of the critical innovations introduced by our estimate, namely the persistence of macroeconomic uncertainty, while at the same time capturing the uncertainty events present in both measures. To accomplish this, we decide to aggregate the measures taking the max value between $\bar{\mathcal{U}}_t^y(1)$ and WUI, at each time t of the reference period. Formally:

$$C\bar{\mathcal{U}}_t^y(1) = MAX(\bar{\mathcal{U}}_t^y(1), WUI_t) .$$

Constructing the uncertainty series in this way, enables us to capture all the relevant uncertainty events (peaks), while maintain the fundamental persistency of our uncertainty measure, at least for the events captured by our estimate. If the events are captured only by the WUI, then we will not observe particular persistency, but we will at least capture the additional uncertainty phenomena.

7.2 Initial Analysis

Figure 28 plots the combined uncertainty measure and the recession dates for Italy used in chapter 4.
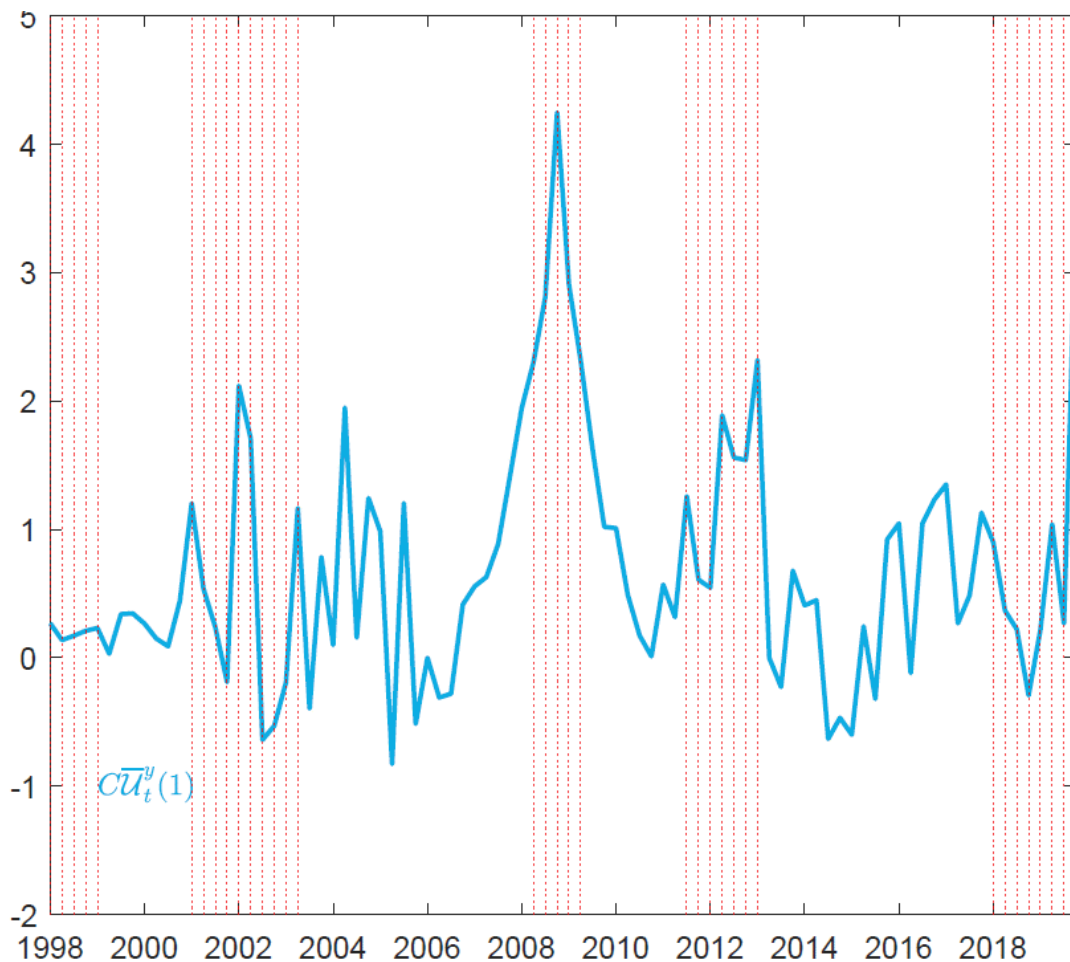
Figure 28. Combined Uncertainty Measure. The red dashed lines represent regression periods as defined by the OECD Composite Leading Indicators. The data are quarterly and span the period q1 1998- q4 2019.

We can immediately notice that the combined uncertainty measure presents many more uncertainty episodes than our baseline measure$\bar{\mathcal{U}}_t^y(1)$. The new measure continues to well capture all the most meaningful events that affected the Italian economy in the last two decades. In particular, as we can observe, there is still some residual trace of the 90ies crisis, the 2000-2001 Dotcom bubble burst and its effects, the 9/11 terroristic attack on the U.S., the effects of the Euro introduction, the Global Financial Crisis and the Great Recession of 2007-2009, the Sovereign Debt Crisis, the Italian Banks' Crisis, the Quantitative Easing introduction and its effects, and the Brexit effects. In addition, we can observe more accentuated crisis events with respect to our baseline case, in particular in the first half of the first decade of the 2000s, during the Sovereign Crisis, and the Banking Crisis. There is another, rather odd, uncertainty spike, at the end of 2019. 2019 has been a year of increased uncertainty for both the world economy, as well as for Italy. The International Monetary Fund alimented the beliefs of a world economy growth slowdown, caused mainly by new trade restrictions threats by big countries like the U.S. and China, and the increase of debt accumulation by different countries. Furthermore, Italy has been indicated by renowned press (i.e., the New York Times), to be the probable cause of a future crisis, due to the weak economic planning by the Italian government, the increase of the spread, the excessive exposure of Italian banks to Italian government bonds, and a possible liquidity crisis and credit crunch. Unfortunately, in August 2019, the Italian government fell, further increasing the uncertainty felt during the year up to that point. Even if the uncertainty level of the last year brought in by the WUI might be excessive, it is still important to capture the relevant events of 2019.

We now analyse the relationship between the combined uncertainty measure and real activity, namely industrial production, employment, and unemployment. As already explained, we expect our combined macro uncertainty measure to be countercyclical, as documented by Bloom (2009) and Jurado et al. (2015). The real variables are all expressed in yearly growth rate terms. All the data is quarterly and standardized to have $\mu = 0$ and $\sigma = 1$.

Figure 29 plots the combined uncertainty and the real activity variables.
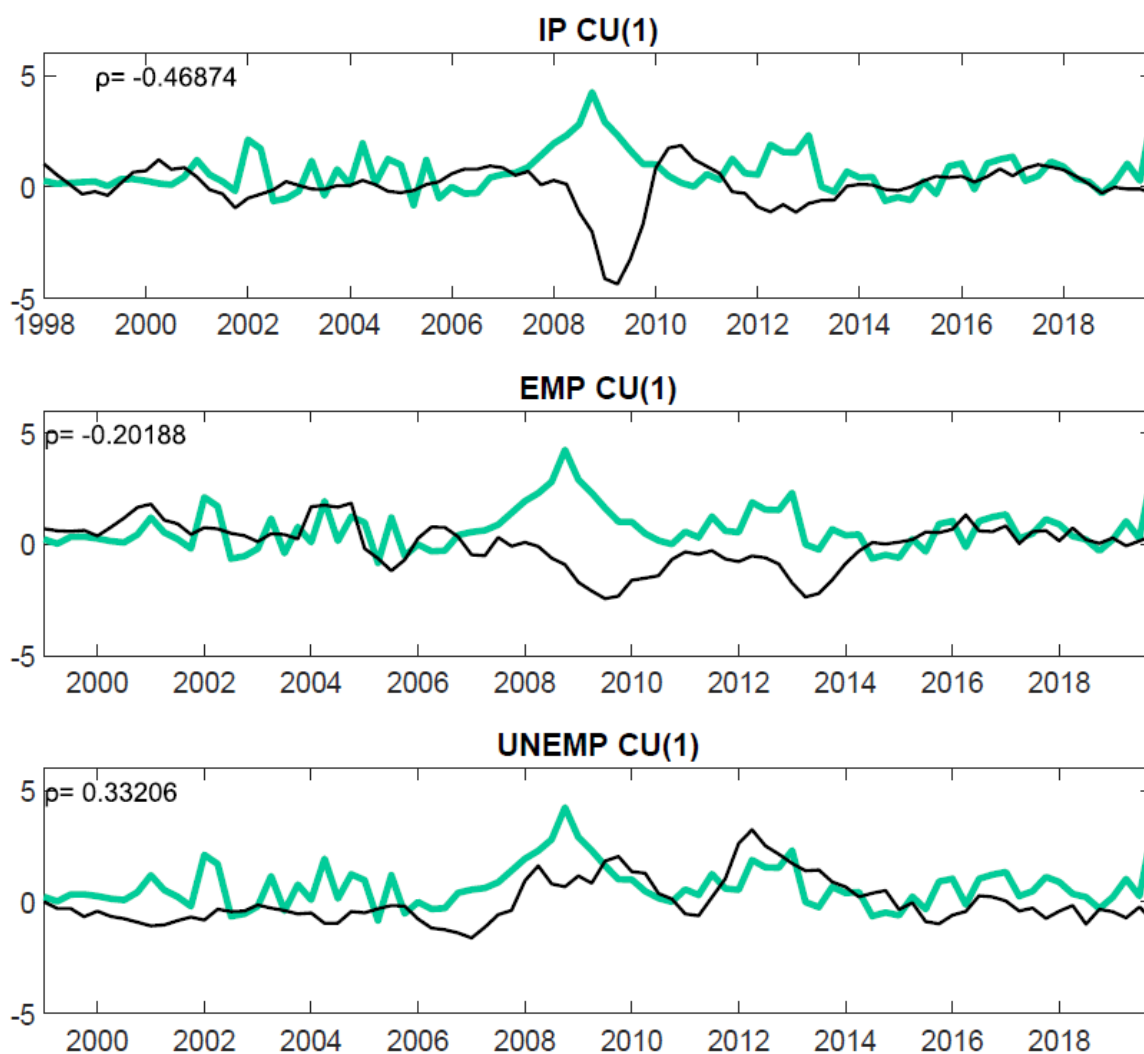
Figure 29. Combined uncertainty measure and real activity variables. All measures are expressed in standardized units with $\mu = 0$ and $\sigma = 1$. The correlation measures between the real variables and the combined uncertainty measure are reported in the top left of each graph. The data are quarterly and span the period q1 1998- q4 2019.

As the first plot shows, the combined uncertainty measure and the industrial production are highly, negatively correlated with ρ = -0.46874, just slightly lower than the case of $\bar{u}_t^y(1)$. The combined uncertainty measure is also negatively correlated with the employment ρ = -0.20188, but at a lower degree than our baseline uncertainty measure. $C\bar{U}_t^y(1)$ is countercyclical as the economic theory suggests. Lastly, the new measure is significantly, positively correlated with unemployment rate ρ = 0.33206. In this case the correlation is slightly higher than our base measure of uncertainty. All in all, the combined uncertainty measure follows what predicted by the aforementioned empirical studies and the expectations.

7.3 VAR, IRFs and FEVD

In this section, we study the macroeconomic dynamics of the combined uncertainty measure, and in particular, the effects that a positive shock of $C\overline{U}_t^y(1)$ has on the main macroeconomic variables. As for the previous analysis relative to the baseline uncertainty measure and the other uncertainty proxies, we use a VAR model to conduct the analysis. All the characteristics of the VAR model, as well as the identification scheme are the same as the ones used in chapter 5 in order to allow for a fair comparison. All the data in the model is quarterly. The necessary natural- logarithmic transformation is performed on the relative variables. The number of lags we include for our variables are 2, meaning 2 quarters. When producing our estimates of IRFs and FEVDs, constant and trend of the variables are taken into account, we estimate our results for 20 steps, therefore for 5 years, and our confidence level is set at 68 percent. The size of the shock for the IRFs is one standard deviation. The identification scheme is Cholesky identification, therefore ordering of the variables in the VAR model matters.

Our VAR-9 presents the following structure:

$$(VAR-9) = \begin{bmatrix} log(\ industrial\ production\ ) \\ employment \\ unemployment \\ log\ (\ CPI\ ) \\ log\ (retail\ trade\ ) \\ log\ (wage\ ) \\ long\ term\ interest\ rate \\ log\ (\ stock\ price\ ) \\ C\overline{U}_t^y(1) \end{bmatrix}.$$

Figure 30 shows the dynamic responses of all our macroeconomic variables in VAR-9 of a positive shock to our combined uncertainty measure.
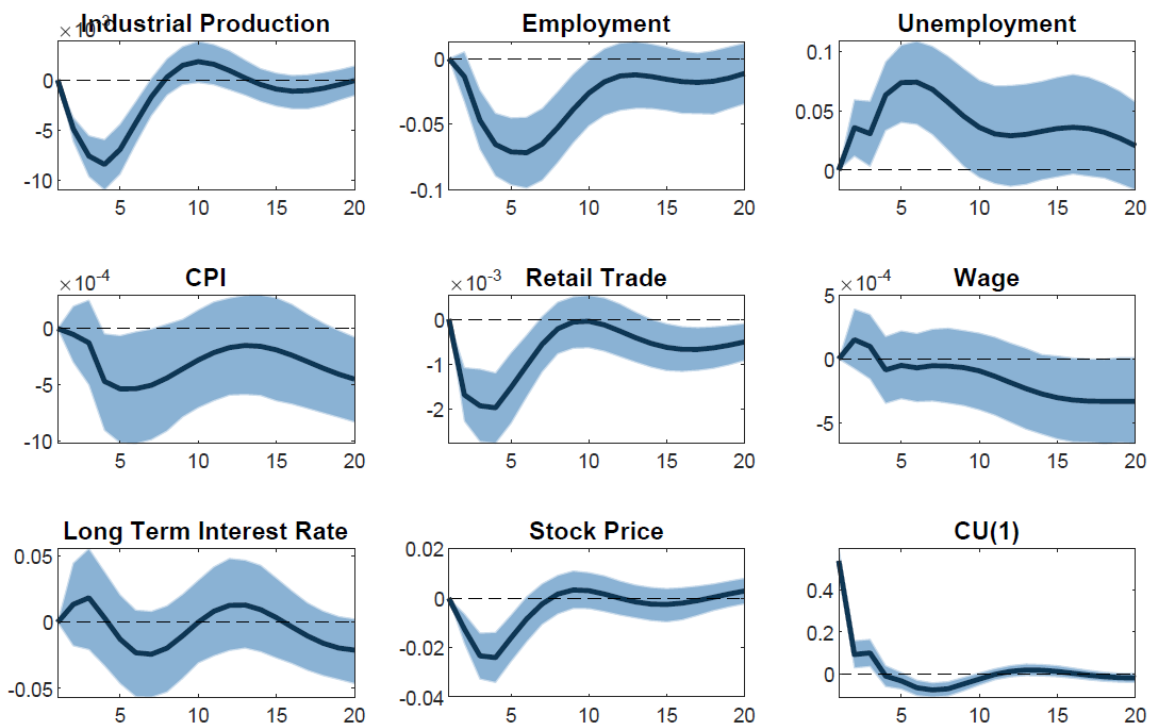
Figure 30. Impulse Response of all the variables contained in VAR-9 to a one standard deviation shock to $C\bar{u}_t^y(1)$. The shadowed areas show 68 percent standard error bands. The data is quarterly.

An innovation in the combined uncertainty measure causes the output to significantly reduce, with a small volatility overshoot after the initial decline and subsequent rebound. Employment shows a sharp decline, with the effects of the impact lasting well beyond the 60 months horizon delineated, and not showing signs of quick recovery. The unemployment rate presents a fast increase after the positive shock to the combined uncertainty, confirming once again the countercyclicality of our measure. Neither employment nor unemployment show the overshoot effects seen in the industrial production. The CPI decreases very slowly in the first few months, probably due to the price stickiness, followed by a sharp and persistent decrease that extends beyond the five years horizon delineated. Retail trade quickly decreases as we expect, going back to pre- shock levels after roughly two years before declining again. The hourly wage rate increases at the beginning, for the first year, probably following the same logic we explained in the analysis in chapter 5. However, this time the wages start falling quickly after the initial period. The long interest rate shows an initial increase as expected, but then decreases before increasing again. Lastly, the stock price variable decreases sharply after the shock, and goes back to initial levels after slightly less than two years, quickly with respect to what we observe for $\bar{u}_t^y(1)$. In this case the new measure could be representing better the behaviour of stock markets, which as we also saw for the ISV, seem to recover quicker than the real economy. The last plot of the figure shows the persistence of the shock on macroeconomic uncertainty itself.

After the impact, the combined uncertainty measure goes back to pre-shock levels rather quickly, after roughly four quarters. This shows the lower persistency of the $C\overline{U}_t^y(1)$ with respect to our baseline uncertainty measure, but a higher persistency with respect to all the other uncertainty proxies. In general, the combined uncertainty measure seems to be slightly less persistent than our baseline uncertainty measure. However, all the main economic variables behave accordingly to uncertainty theory.

Now we investigate the quantitative significance of the combined uncertainty measure shock for the macroeconomic fluctuations, through the forecast error variance decomposition. We plot the FEVDs of all the uncertainty measures in order to compare the new results with the results previously found. First of all, we analyse the FEVDs of real activity variables, namely industrial production, employment and unemployment, which are reported in figure 31.
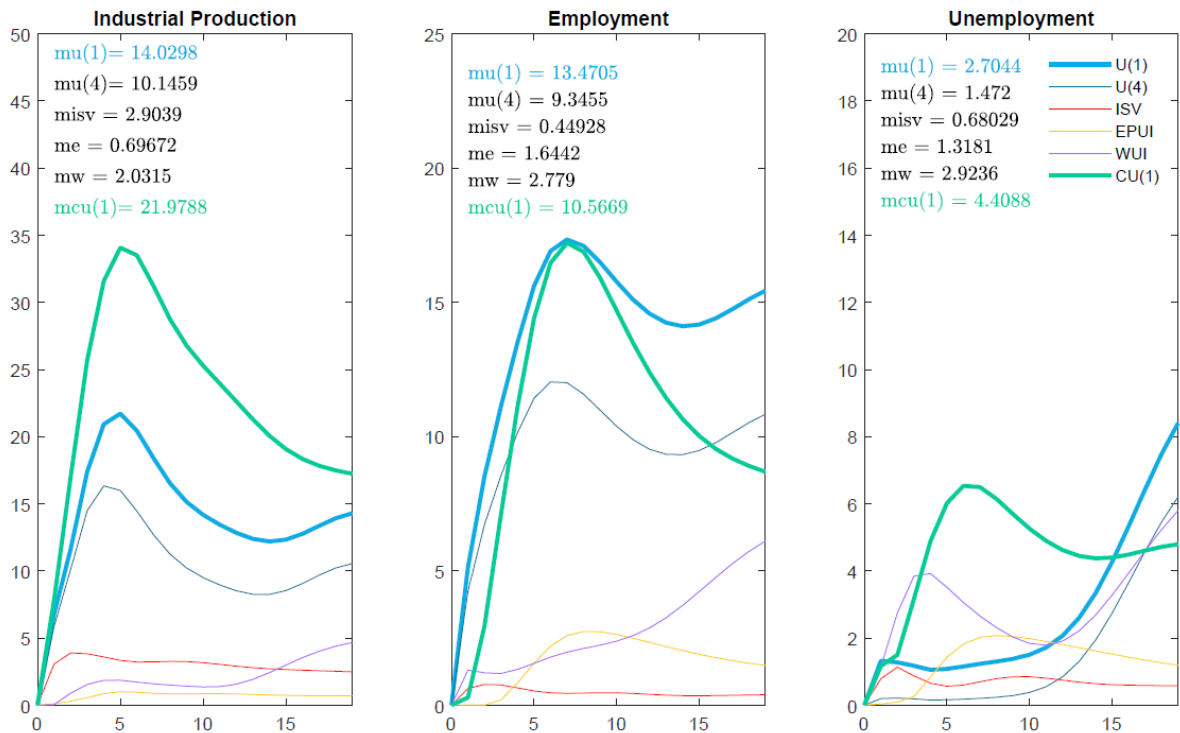
Figure 31. FEVDs of a shock to the uncertainty measures on industrial production, employment and unemployment. The "m" value reports the average forecast error explained by each uncertainty measure throughout the 20 periods horizon. The data is quarterly.

Industrial production. As we can see from the first plot, $C\overline{U}_t^y(1)$ shock is associated with the greatest fraction of VAR forecast error variance of industrial production, linked to up to 34.07 percent of the variation after 6 quarters and on average linked to 21.97 percent of the variation. The combined uncertainty measure shock explains the industrial production variation better than $\overline{U}_t^y(1)$ and $\overline{U}_t^y(4)$.

Employment. The shock of $\bar{\mathcal{U}}_t^y(1)$ is the one associated with the largest part of VAR forecast error variance of employment, closely followed by the combined uncertainty measure which is linked to up to 17.21 percent of the variation after 8 quarters and on average linked to 10.56 percent of the variation.

Unemployment. Again, the shock to the baseline uncertainty measure is the one associated with the largest fraction of VAR forecast error variance of unemployment, linked to up to 8.4 percent of the variation after 20 quarters and on average linked to 2.70 percent of the variation. However, the combined uncertainty measure shock is linked to up to 6.53 percent of the variation after 7 quarters and on average is linked to 4.40 percent of the variation, almost twice as much as the variation explained on average by a shock of $\bar{\mathcal{U}}_t^y(1)$.

We now go quickly over the FEVDs of the remaining macroeconomic variables, represented in figure 32.
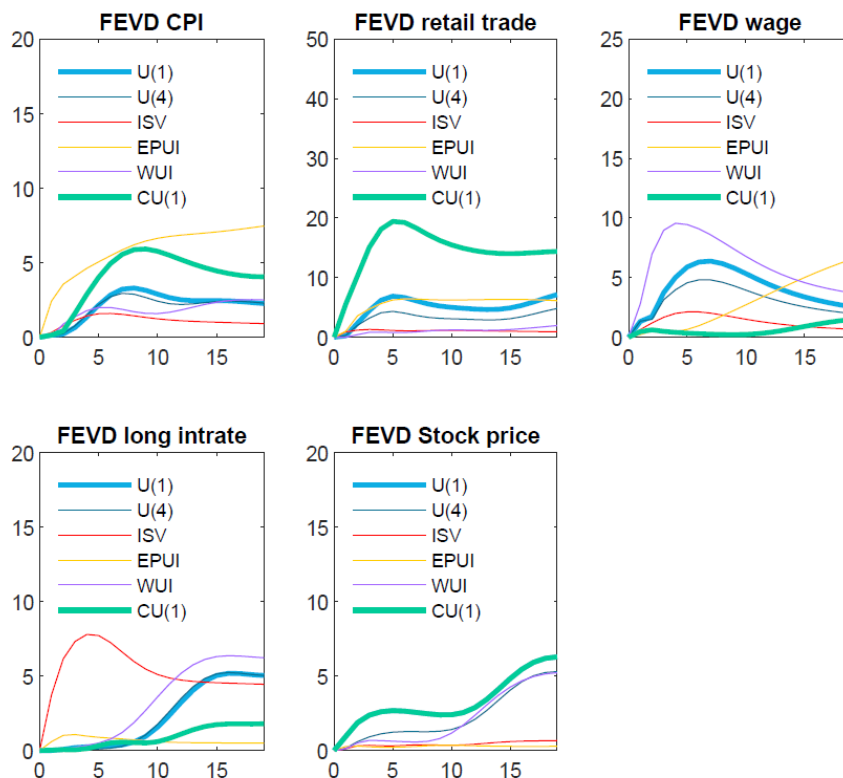
Figure 32. FEVDs of a shock to the uncertainty measures on CPI, retail trade, wage, long term interest rate and stock price. The data is quarterly.

The shock to the EPUI is still the one associated with the largest fraction of FEV of consumer price index, with the combined uncertainty measure being a close second. Furthermore, the shock to $C\bar{\mathcal{U}}_t^y(1)$ is the one associated with the greatest fraction of retail trade and stock prices, the shock to ISV is better linked to FEV of long- term interest rate and the shock to WUI is the one associated with the largest part of FEVD of wage.

7.4 European Economic Policy Analysis

We conclude the analysis of the combined uncertainty measure investigating the effect of a shock to a monetary policy of the European Central Bank on the combined measure and the economy.

In order to grasp the effects of an endogenous shock to monetary policy on the combined uncertainty measure, we use the same simple VAR models we used in chapter 6 for the analysis of $\bar{U}_t^y(1)$. We once again choose zero- short run effect restrictions (Cholesky identification), assuming that some shocks have no contemporaneous effects on one or more of the endogenous variables. The ordering of our variables matters. All the data in the model is quarterly. The necessary natural- logarithmic transformation is performed on the relative variables. The number of lags we include for our variables are 2, hence 2 quarters. When producing our estimates of IRFs, constant and trend of the variables are taken into account, we estimate our results for 20 steps, therefore for 5 years, and our confidence level is set at 68 percent. The size of the shock for the IRFs is one standard deviation.

The first VAR we analyse is the VAR-4 containing the combined measure of macroeconomic uncertainty, hence:

$$(VAR - 4) = \begin{bmatrix} log \ (Euro \ Area \ industrial \ production \ ) \\ log \ (Euro \ Area \ CPI \ ) \\ ECB \ short \ term \ interest \ rate \\ Italian \ C\bar{U}_t^y(1) \end{bmatrix}.$$

Figure 33 plots the dynamic responses of the variables of interest in VAR-4 of a positive shock to the monetary policy, hence the deposit facility rate.
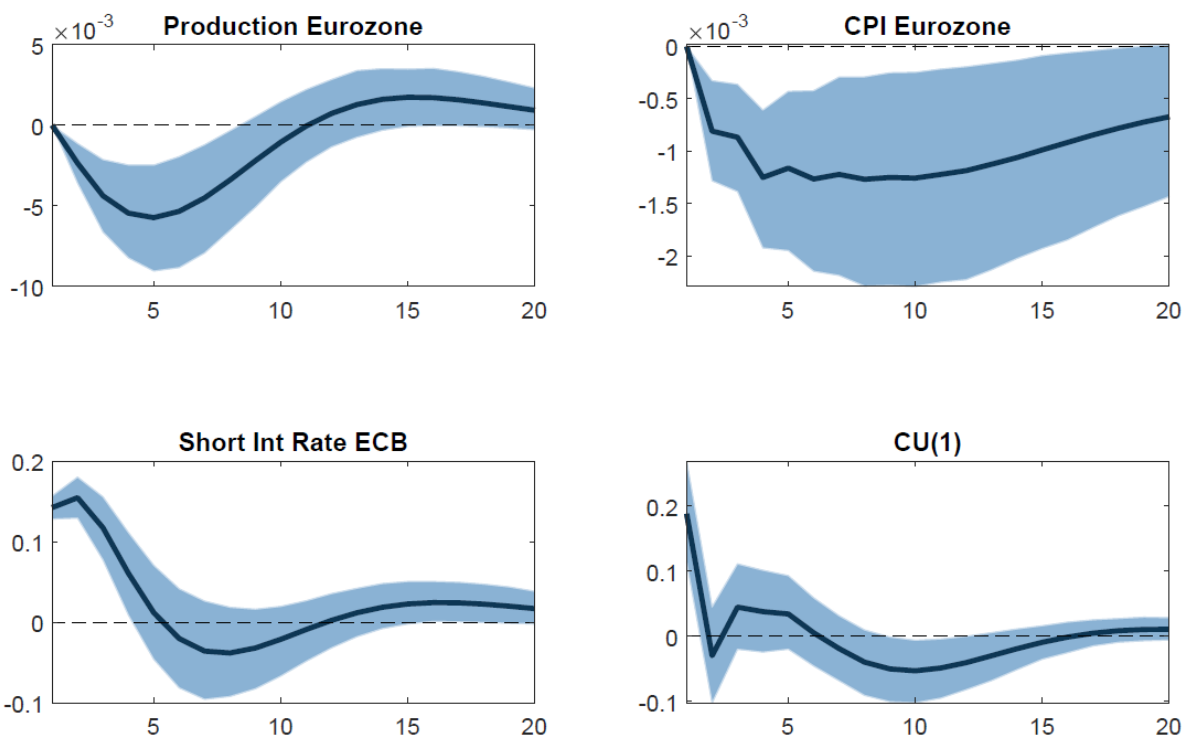
Figure 33. Impulse Response of the variables contained in VAR-4 to a one standard deviation shock to the ECB short-term interest rate. The shadowed areas show 68 percent standard error bands. The data is quarterly.

The effects of a positive innovation to the short-term interest rate of the European Central Bank is generally the same we observe in the analyses of chapter 6, hence the production of the Euro Area sharply decreases for 5 quarters, showing signs of recovery after more roughly two years, and the inflation falls with an effect that is much more persistent than the effect on the industrial production, protracting over the 5 years period horizon. However, at impact, the macroeconomic uncertainty level is higher than the one observed in the baseline case but shows a faster initial recovery in around two quarters before slightly increasing again. This effect is most definitively due to the WUI contribution to the combined measure. In general, the effects of a contractionary monetary policy are in accordance with the theoretical framework.

The second VAR we quickly analyse is the VAR-6, also containing the combined measure of macroeconomic uncertainty, hence:

$$(VAR-6) = \begin{bmatrix} log(\ Euro\ Area\ industrial\ production\ ) \\ Euro\ Area\ employment \\ Euro\ Area\ unemployment \\ log\ (\ Euro\ Area\ CPI\ ) \\ ECB\ short\ term\ interest\ rate \\ Italian\ C\bar{U}_t^y(1) \end{bmatrix}.$$

Figure 34 plots the dynamic responses of our variables of interest in VAR-6 of a positive shock to the monetary policy, hence the deposit facility rate.
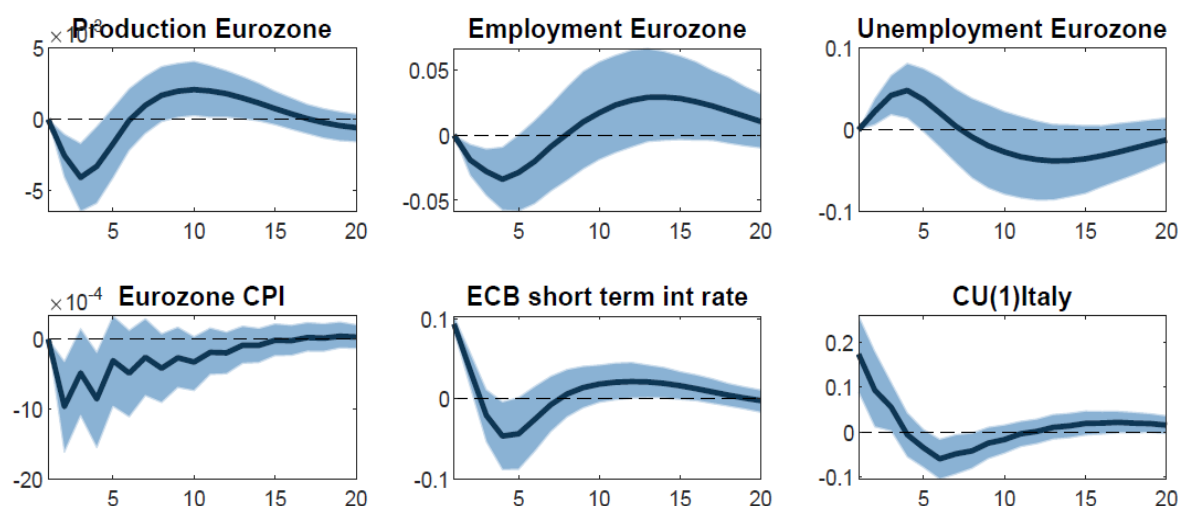
Figure 34. Impulse Response of the variables contained in VAR-6 to a one standard deviation shock to the ECB short-term interest rate. The shadowed areas show 68 percent standard error bands. The data is quarterly.

Again, a positive innovation to the short-term interest rate of the European Central Bank causes the production of the Euro Area to decrease as in VAR-4, however, the magnitude of the decrease is in this case higher than the one in the VAR-6 of the baseline case. This is also true for the employment and the unemployment, which respectively decrease and increase after the initial shock, showing an overshooting effect. CPI decreases sharply at impact, going back at the initial level after more than three years, as opposed of the two in the baseline case. Finally, once more, macro uncertainty immediately increases as a result of the contractionary monetary policy, with a reaction at impact twice more significant than the $\bar{u}_t^y(1)$. In this case, it looks that the combined uncertainty measure, presents both a higher persistence of the uncertainty and a higher magnitude of the effects with respect to the base case studied in chapter 6.

7.5 Remarks

We have shown how the combined uncertainty measure is definitively a good candidate as macroeconomic uncertainty measure. However, we want to clarify a few important points. First, our original macro uncertainty measure cannot be discarded by these results. On the contrary, it should be clear that our original estimate is the driving force of these findings. Second, the fact that the combined measure accounts for a larger portion of the forecast error variance decomposition of the industrial production or unemployment doesn't necessarily mean that it is a better representation of the real underlying uncertainty di per se. A combined measure of uncertainty proxies might be an interesting topic for future research as long as it has a real method supporting it and it's not a naïve combination of different measures.

Conclusions

This thesis introduces a new times series measure of macroeconomic uncertainty for Italy. We are interested in macroeconomic uncertainty, meaning uncertainty that is observed in many economic indicators at the same time. To be able to create an accurate estimate, we collect and process data for over 50 macroeconomic variables and complement the forecasting model with additional predictors retrieved from the same data. When compared to common uncertainty proxies (ISV, EPUI, WUI), our uncertainty measure displays significantly different characteristics. Our estimate suggests that quantitatively important uncertainty events occur far less frequently than what is indicated by conventional uncertainty proxies, but that, when they do occur, they display larger and more persistent correlations with real activity and, more in general, the economic activity. By contrast, common uncertainty proxies are less persistent and spike far more frequently, often in non-recession periods, or in periods of relative macroeconomic quiescence. Our measure well represents the uncertainty events that affected Italy in the last two decades. Furthermore, it exposes quantitatively important dynamic relationship between macroeconomic uncertainty and real activity, as also testified by Bloom (2009) and Jurado et al (2015). The strong countercyclicality of uncertainty suggested by the literature is appropriately represented by our metrics. In addition, using a VAR-9, we analyse the dynamic relationships between uncertainty and the most relevant Italian macroeconomic variables. Our measure of uncertainty is in accordance with the empirical research and the economic theory surrounding the field. We also find a relevant link between the ECB monetary policy and the Italian macroeconomic uncertainty, highlighting the crucial role of policy makers in trying to control uncertainty. All our findings establish the legitimacy and the credibility of our estimate as the best measure of macroeconomic uncertainty among the commonly used proxies for Italy. Our measure of uncertainty elegantly combines macroeconomic uncertainty from various sources into a single summary number. As a final step, we try to further improve the uncertainty measure, thoughtfully combining it to the other proxies. Although presenting some differences, the results of this new combined measure of macroeconomic uncertainty are largely consistent with our previous findings.

MATLAB and R codes

The structure of some of the MATLAB and R codes, for the uncertainty measure construction, are taken from Jurado et al (2015) and appropriately adjusted. The VAR analysis codes are constructed around the general structure of the VAR Toolbox 3.0 provided by Ambrogio Cesa- Bianchi, available at: *https://sites.google.com/site/ambropo/MatlabCodes*, with the appropriate adjustments and adaptation. Similar codes used for the different analysis, i.e., VARs, will be presented only once. Furthermore, we will include only the most important codes and functions.

Uncertainty Measures Estimation

Transformation of raw data and time series for our analysis (generate_ssdata.m)

```matlab
% ----------------------------------------------------
% Load raw macroeconomic data for Italy and generate transformed data for our analysis
% ----------------------------------------------------

% Load data
clear; clc;
mc=1;
[mdata,mtxt] = xlsread('ssrawdata.xlsx',1);

%%% windows users
vartype     = mdata(1,:);
mdata       = mdata(3:end,:); %start in 1996
mnames      = mtxt(1,:);
[yt,a,b,c]  = prepare(mdata,mnames,vartype);
yt          = yt(2:end,:); %remove NaNs
T           = length(yt);

% Save data to .mat file
data    = [yt];
names   = [mnames]';
vartype = [vartype];
dates   = 1900+(95:1/4:120-1/4)';
dates   = dates(end-T+1:end);
save ssdata data dates names vartype
```

Functions for generate_ssdata.m

```matlab
function [yt,yh1,yh3,yh12] = prepare(data,colheaders,vartype)

% ------------------------------------------------------------------------
% Transform raw data into stationary form
%  Input:  data       = raw data
%          colheaders = variable names
%          vartype    = variable type
%  Output: yt         = transformed data
% ------------------------------------------------------------------------

% Reformat data
series    = [];                        %initialize variables
rawdata   = [];
tcode     = [];
N         = size(data,2);              %number of series
for i = 1:N
   dum  = data(:,i);
   m    = mean(dum);
   if isnan(m) == 0;                   %check for non-numbers
      rawdata = [rawdata dum];         %keep numerical data
      series  = str2mat(series,colheaders{1,i});  %store series name
         tcode  = [tcode; vartype(i)];          %store series type code
   else
      disp([i m]);                     %else show the error
   end
end
series  = series(2:end,:);             %delete first name

% Transform data by group
group_id=[ones(2,1);ones(3,1)*4;ones(15,1); ...
      ones(30,1)*2;ones(10,1)*3;ones(10,1)*4;...
      ones(11,1)*5;ones(4,1)*8;ones(22,1)*6;...
      ones(21,1)*7; ones(3,1)*2; 4];
newtcode      = tcode;
newtcode(77)   = 7;  % compute percent change without taking logs
newtcode(51:60) = 5; % housing starts are differenced after logs
newtcode(46:49) = 2; % hours are differenced

y     = [];                           %initialize y
yh1   = [];
yh3   = [];
yh12  = [];
N     = size(rawdata,2);              %number of series kept
for i = 1:N
   % transxf.m is the new program that constructs the
   % h=1,3,12 step ahead variables to be forecasted
   [dum,dum1,dum3,dum12] = transxf(rawdata(:,i),newtcode(i));
   y    = [y dum];
   yh1  = [yh1 dum1];
   yh3  = [yh3 dum3];
   yh12 = [yh12 dum12];
```

```matlab
end
yt = y;

% Internal functions
 function [y,y1,y3,y12]=transxf(x,tcode)
 n=size(x,1);
 small=1e-6;
 y=NaN*ones(n,1);
 y1=NaN*ones(n,1);
 y3=NaN*ones(n,1);
 y12=NaN*ones(n,1);

switch(tcode);
  case 1,
  y=x;
  y1=lagn(x,-1);
  y3=lagn(x,-3);
  y12=lagn(x,-12);
 case 2,
  %y(1)=0;
  y(2:n)=x(2:n,1)-x(1:n-1,1);
  y1=(1200)*(lagn(x,-1)-x);
  y3=(1200/3)*(lagn(x,-3)-x);
  y12=(1200/12)*(lagn(x,-12)-x);
 case 3,
  %y(1)=0;y(2)=0;
  y(3:n)=x(3:n)-2*x(2:n-1)+x(1:n-2);
  y1=1200*(lagn(x,-h)-x)-1200*(x-lagn(x,1));
  y3=(1200/3)*(lagn(x,-3)-x)-1200*(x-lagn(x,1));
  y12=(1200/12)*(lagn(x,-12)-x)-1200*(x-lagn(x,1));
 case 4,
  if min(x) < small; y=NaN; else;
  y=log(x);
  y1=lagn(log(x),-1);
  y3=lagn(log(x),-3);
  y12=lagn(log(x),-12);
  end;
 case 5,
  if min(x) > small;
  x=log(x);
  %y(1)=0;
  y(2:n)=x(2:n)-x(1:n-1);
    y1=1200*(lagn(x,-1)-x);
  y3=(1200/3)*(lagn(x,-3)-x);
  y12=(1200/12)*(lagn(x,-12)-x);
  end;
 case 6,
  if min(x) > small;
  %y(1)=0;y(2)=0;
  x=log(x);
  y(3:n)=x(3:n)-2*x(2:n-1)+x(1:n-2);
  y1=1200*(lagn(x,-1)-x)-1200*(x-lagn(x,1));
```

```
  y3=(1200/3)*(lagn(x,-3)-x)-1200*(x-lagn(x,1));
  y12=(1200/12)*(lagn(x,-12)-x)-1200*(x-lagn(x,1));
  end;
case 7,
 %y1(1)=0;
 y1(2:n)=(x(2:n)-x(1:n-1))./x(1:n-1);
 %y(1)=0; y(2)=0;
 y(3:n)=y1(3:n)-y1(2:n-1);
 y1=1200*(lagn(x,-1)-x)./x-1200*(x-lagn(x,1))./lagn(x,1);
 y3=(1200/3)*(lagn(x,-3)-x)./x-1200*(x-lagn(x,1))./lagn(x,1);
 y12=(1200/12)*(lagn(x,-12)-x)./x-1200*(x-lagn(x,1))./lagn(x,1);
end;


y1(end-1+1,:) = NaN;
y3(end-3+1:end,:)=NaN;
y12(end-12+1:end,:)=NaN;
 end
end

function xx=trimr(x,a,b);
[nt,nc]=size(x);
if a >= 0 ;
xx=x(a+1:nt,:);
end;
if b >=0;
if a > 0; x=xx; end;
[nt,nc]=size(x);
xx=x(1:nt-b,1:nc);
end;
end

function y=lagn(x,n)
[nt,nc]=size(x);
if n> 0
x1=trimr(x,0,n);
 y=[zeros(n,nc); x1];
end
if n<0
x1=trimr(x,abs(n),0);
y=[x1;zeros(abs(n),nc)];
end
if n==0
 y=x;
end;
end
```

Generate Forecast Errors (generate_ferrors.m)

```matlab
% ----------------------------------------------------------------------
% Generate forecast errors
% ----------------------------------------------------------------------

% Load data
clear; clc;
load ssdata;
data= data(2:end,:);
dates= dates(2:end,:);
xt = data;

% Estimate factors
[e,fhat,lf,vf] = factors(xt,20,2,2);
[e,ghat,lg,vg] = factors(xt.^2,20,2,2);
outf    = 'mR2_fhat.out';
outg    = 'mR2_ghat.out';
[R2,mR2] = mrsq(fhat,lf,vf,names,vartype,outf);
[R2,mR2] = mrsq(ghat,lg,vg,names,vartype,outg);
ft      = [fhat,fhat(:,1).^2,ghat(:,1)]; %predictor set

% Generate forecast errors for yt
yt     = zscore(xt); % only the macro data
[T,N]  = size(yt);
py     = 4;
pz     = 2 ;
p      = max(py,pz);
q      = fix(4*(T/100)^(2/9));
ybetas = zeros(1+py+pz*size(ft,2),N);
for i = 1:N
   X    = [ones(T,1),mlags(yt(:,i),py),mlags(ft,pz)];
   reg  = nwest(yt(p+1:end,i),X(p+1:end,:),q);
   pass = abs(reg.tstat(py+2:end)) > 2.575; % hard threshold
   keep = [ones(1,py+1)==1,pass'];
   Xnew = X(:,keep);
   reg  = nwest(yt(p+1:end,i),Xnew(p+1:end,:),q);
   vyt(:,i)      = reg.resid; % forecast errors
   ybetas(keep,i) = reg.beta;
   fmodels(:,i)   = pass; %chosen predictors
end

% Generate AR(4) errors for ft
[T,R]  = size(ft);
pf     = 4;
q      = fix(4*(T/100)^(2/9));
fbetas = zeros(R,pf+1);
for i = 1:R
   X    = [ones(T,1),mlags(ft(:,i),pf)];
   reg = nwest(ft(pf+1:end,i),X(pf+1:end,:),q);
   vft(:,i)    = reg.resid;
   fbetas(i,:) = reg.beta';
end
```

```matlab
% Save data
[T,N]  = size(vyt);
ybetas = ybetas';
dates  = 1900+(95:1/4:120-1/4)';
dates  = dates(end-T+1:end);
save ferrors dates vyt vft names vartype ybetas fbetas py pz pf ft xt fmodels

% Also write to .txt file for R code
dlmwrite('vyt.txt',vyt,'delimiter','\t','precision',17);
dlmwrite('vft.txt',vft,'delimiter','\t','precision',17);
```

Functions for generate_ferrors.m

```matlab
function [ehat,Fhat,lamhat,ve2] = factors(X,kmax,jj,DEMEAN)
% ------------------------------------------------------------------------
% Estimate latent factors from observable data X using PCA
%  Input:  X     = observable data
%          kmax  = maximum number of factors to consider
%          jj    = information criterion from Bai and Ng (2002)
%          DEMEAN = 0 - no, 1 - yes, 2 - standardize
%  Output: ehat  = idiosyncratic errors
%          Fhat   = latent factor estimates
%          lamhat = factor loadings
%          ve2    = eigenvalues of data covariance matrix
% ------------------------------------------------------------------------

[ic1,chat,fhat,eigval]  = nbplog(X,kmax,jj,DEMEAN);
icstar    = ic1;
R2_static = sum(eigval(1:icstar))/sum(eigval);
if DEMEAN == 2;
[ehat,Fhat,lamhat,ve2]  = pc(standard(X),icstar);
end
if DEMEAN == 1;
[ehat,Fhat,lamhat,ve2]  = pc(X-repmat(mean(X),size(X,1),1),icstar);
end
if DEMEAN == 0;
[ehat,Fhat,lamhat,ve2]  = pc(X,icstar);
end
end


% Auxiliary functions
function [ic1, chat,Fhat,eigval]=nbplog(x,kmax,jj,DEMEAN);
%function [ic1, lambda,Fhat,IC1]=nbplog(x,kmax,jj,DEMEAN);
T=size(x,1);
N=size(x,2);
NT=N*T;
NT1=N+T;
CT=zeros(1,kmax);
ii=1:1:kmax;
if jj ==1;CT(1,:)=log(NT/NT1)*ii*NT1/NT;end;
if jj==2; CT(1,:)=(NT1/NT)*log(min([N;T]))*ii;end;
GCT=min([N;T]);
if jj==3; CT(1,:)=ii*log(GCT)/GCT; end;
if jj==4; CT(1,:)=2*ii/T; end;
if jj==5; CT(1,:)=log(T)*ii/T;end;
if jj==6; CT(1,:)=2*ii*NT1/NT; end;
if jj==7; CT(1,:)=log(NT)*ii*NT1/NT;end;
if jj==8; CT(1,:)= 2*ii*(sqrt(N)+sqrt(T))^2/(NT); end;% new modified CP


 if DEMEAN ==2;
 X=standard(x);
 end;
```

```
if DEMEAN ==1;
 X=x-repmat(mean(x),T,1);
 end;
if DEMEAN==0;
  X=x;;
  end;
IC1=zeros(size(CT,1),kmax+1);
Sigma=zeros(1,kmax+1);
if T< N;
[ev,eigval,ev1]=svd(X*X');
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Fhat0=sqrt(T)*ev;
Lambda0=X'*Fhat0/T;
else;
[ev,eigval,ev1]=svd(X'*X);
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Lambda0=sqrt(N)*ev;
Fhat0=X*Lambda0/N;
end;


if jj <= 8;
for i=kmax:-1:1;
Fhat=Fhat0(:,1:i);
%lambda=Fhat'*X;
lambda=Lambda0(:,1:i);
chat=Fhat*lambda';
%disp([i sumeigval(i) sum(sum(chat.*chat))/sum(sum(X.*X))]);
ehat=X-chat;
Sigma(i)=mean(sum(ehat.*ehat/T));
IC1(:,i)=log(Sigma(i))+CT(:,i);
end;
Sigma(kmax+1)=mean(sum(X.*X/T));
IC1(:,kmax+1)=log(Sigma(kmax+1));
ic1=minindc(IC1')';
ic1=ic1 .*(ic1 <= kmax);
end;
if jj==9;

  for j=1:rows(sumeigval);
    if sumeigval(j) >= .5; ic1=j; break; end;
  end;
 end;
Fhat=[];
Fhat=Fhat0(:,1:kmax);
Lambda=Lambda0(:,1:kmax);
chat=Fhat*Lambda';
eigval=diag(eigval);
end

function [ehat,fhat,lambda,ss]=pc(y,nfac);
```

116

```matlab
[bigt,bign]=size(y);
yy=y'*y;
[Fhat0,eigval,Fhat1]=svd(yy);
lambda=Fhat0(:,1:nfac)*sqrt(bign);
fhat=y*lambda/bign;
ehat=y-fhat*lambda';

ve2=sum(ehat'.*ehat')'/bign;
ss=diag(eigval);
end

function pos=minindc(x);
ncols=size(x,2);
nrows=size(x,1);
pos=zeros(ncols,1);
seq=seqa(1,1,nrows);
for i=1:ncols;
dum=min(x(:,i));
dum1= seq .* ( (x(:,i)-dum) ==0);
pos(i)=sum(dum1);
end;
end

function x=standard(y);
T=size(y,1);
N=size(y,2);
my=repmat(mean(y),T,1);
sy=repmat(std(y),T,1);
x=(y-my)./sy;

%x=(y-kron(mean(y),ones(rows(y),1)))./kron(std(y),ones(rows(y),1));
end

function seq=seqa(a,b,c);
seq=(a:b:(a+b*(c-1)))';
end

function [R2,mR2] = mrsq(Fhat,lamhat,ve2,colheaders,vartype,outfile)
% -----------------------------------------------------------------------
% Compute R2 and marginal R2 from estimated factors and factor loadings
%   Input:  Fhat      = estimated factor matrix
%           lamhat    = factor loadings
%           ve2       = eigenvalues
%           colheaders = variable names
%           vartype   = variable type
%           outfile   = name of output file
%   Output: R2        = R2 for each series
%           mR2       = marginal R2 for each group
% -----------------------------------------------------------------------

% Compute values
```

```matlab
[N ic]     = size(lamhat);
R2         = zeros(N,ic);
mR2        = zeros(N,ic);
tcode      = vartype;
for i = 1:ic
    R2(:,i)  = (var(Fhat(:,1:i)*lamhat(:,1:i)'))';
    mR2(:,i) = (var(Fhat(:,i:i)*lamhat(:,i:i)'))';
end

% Print to file
fp          = fopen(outfile,'w');
in.fid      = fp;
in.outwidth = N;
group_id    = [ones(2,1);ones(3,1)*4;ones(15,1);...    %group identifiers
               ones(30,1)*2;ones(10,1)*3;...
               ones(10,1)*4;ones(11,1)*5; ...
               ones(4,1)*8; ones(22,1)*6;...
               ones(21,1)*7;ones(3,1)*2;4;...
               ones(N-132,1)*9];
series      = [];
for i = 1:N
    series  = str2mat(series,colheaders{i});
end
series      = series(2:end,:);
fmt1        = ['\n                     ' repmat('%7d',1,ic)];
fmt         = ['\n' repmat('%4d',1,3)  ' %s' repmat('%7.3f',1,ic) ];
fprintf(fp,fmt1,(1:1:ic));

fprintf(fp,'\n R2\n');
for i = 1:N;
    fprintf(fp,fmt, i,group_id(i),tcode(i),series(i,:),R2(i,1:ic));
end;
fprintf(fp,'\n\n Marginal R2\n');
for i = 1:N;
    fprintf(fp,fmt,i,group_id(i),tcode(i),series(i,:),mR2(i,1:ic));
end;

[vals,ind] = sort(mR2,'descend');
Rsq        = ve2./sum(ve2);
fprintf(fp,'\n\n Highest Marginal R2''s');
for ii = 1:ic;
    fprintf(fp,'\n\n Factor %d: total contribution = %0.4f \n',ii,Rsq(ii));
    for j = 1:10;
        i = ind(j,ii);
        fprintf(fp,fmt,i,group_id(i),tcode(i),series(i,:),mR2(i,ii));
    end
end;
fclose(fp);
end
```

Estimate stochastic volatility in the forecast errors using 'stochvol'- R package (generate_svfdraws.r and generate_svydraws.r)

```
# -------------------------------------------------------------------------
# Estimate a first-order autoregressive stochastic volatility model on the
# forecast errors from an AR(4) model on each predictor (series by series)
# -------------------------------------------------------------------------

# Initialization
rm(list=ls())
library(stochvol)
library(coda)
set.seed(1000) # for replication
options(digits=17)

setwd('C:/Users/sukhanjeet/Desktop/New folder/Measuring uncertainty in Italy sensitivity
analysis/data/ss_macrodata')

infile='vft.txt'
outfile='svfmeans.txt'
vt   = read.table(infile,sep = '\t')
T    = dim(vt)[1]
N    = dim(vt)[2]

for (i in 1:N){
        if(min(log(vt[,i]^2))== -Inf){
                vt[,i] = vt[,i] + 0.00001 #offset to avoid taking log of zero
        }
}

# Run MCMC algorithm and store draws
S    = 50000
burn = 50000
m    = matrix(0,T+3,N)
g    = matrix(0,3,N)
for (i in 1:N){
 print(i)
 draws  = svsample(vt[,i],draws=S,burnin=burn,quiet=TRUE,thinpara=10,thinlatent=10)
 #      temp1=draws$para[[1]][,1:3]
 #      temp2=draws$latent[[1]]
 #      all=cbind(temp1,temp2)
 #      m[,i]=colMeans(all)
 latdraws = latent(draws)
 pardraws = para(draws)[, sampled_parameters(draws)]
 all      = cbind(pardraws,latdraws)
 m[,i]    = colMeans(all)
 g[,i]    = geweke.diag(pardraws)$z
 #name     = sprintf('svfdraws%d.txt',i)
 #write(t(all),file=name,ncolumn=dim(all)[2])
}
out = rbind(m,g) #include Geweke statistics
write(t(out),file="svfmeans.txt",ncolumn=dim(out)[2])
# -------------------------------------------------------------------------
```

```
# Estimate a first-order autoregressive stochastic volatility model on the
# forecast errors from the macroeconomic data (no conditional mean)
# -------------------------------------------------------------------------

# Initialization
rm(list=ls())
library(stochvol)
library(coda)
set.seed(0) # for replication
options(digits=17)

setwd('C:/Users/sukhanjeet/Desktop/New folder/Measuring uncertainty in Italy sensitivity
analysis/data/ss_macrodata')


infile='vyt.txt'
outfile='svymeans.txt'
vt   = read.table(infile,sep = '\t')


T    = dim(vt)[1]
N    = dim(vt)[2]
for (i in 1:N){
        if(min(log(vt[,i]^2))== -Inf){
                vt[,i] = vt[,i] + 0.00001 #offset to avoid taking log of zero
        }
}

# Run MCMC algorithm and store draws
S    = 50000
burn = 50000
m    = matrix(0,T+3,N)
g    = matrix(0,3,N)
for (i in 1:N){
  print(i)
  draws  = svsample(vt[,i],draws=S,burnin=burn,quiet=TRUE,thinpara=10,thinlatent=10)
  #      temp1=draws$para[[1]][,1:3]
  #      temp2=draws$latent[[1]]
  #      all=cbind(temp1,temp2)
  #      m[,i]=colMeans(all)
  latdraws = latent(draws)
  pardraws = para(draws)[, sampled_parameters(draws)]
  all      = cbind(pardraws,latdraws)
  m[,i]    = colMeans(all)
  g[,i]    = geweke.diag(pardraws)$z
  #name     = sprintf('svfdraws%d.txt',i)
  #write(t(all),file=name,ncolumn=dim(all)[2])
}
out = rbind(m,g) #include Geweke statistics
write(t(out),file="svymeans.txt",ncolumn=dim(out)[2])
```

Use svfmeans.txt and svymenas.txt, computed through R, as input to produce the 51 uncertainty estimates (generate_ut.m)

```matlab
% ------------------------------------------------------------------------
% Compute matrix of uncertainty estimates for horizons 1 through 4
% ------------------------------------------------------------------------

% Load data
clear; clc;
load ferrors;
svf = load('svfmeans.txt');
svy = load('svymeans.txt');

% Compute objects from predictors
h   = 4;
fb  = sparse(fbetas);
thf = [svf(1,:).*(1-svf(2,:));svf(2,:);svf(3,:).^2];
xf  = svf(4:end-3,:);
gf  = svf(end-3+1:end,:);
[evf,phif] = compute_uf(xf,thf,fb,h);

% Compute uncertainty
[T,N] = size(vyt);
ut    = zeros(T,N,h);
for i = 1:N
    tic;
    yb  = sparse(ybetas(i,:));
    thy = [svy(1,i).*(1-svy(2,i));svy(2,i);svy(3,i).^2];
    xy  = svy(4:end-3,i);
    ut(:,i,:) = compute_uy(xy,thy,yb,py,evf,phif);
    fprintf('Series %d, Elapsed Time = %0.4f \n',i,toc);
end
gy = svy(end-3+1:end,:);
save ut dates ut
save geweke dates gy gf names
```

Functions for generate_ut.m

```matlab
function [evf,phif] = compute_uf(xf,thf,fb,h)
% -------------------------------------------------------------------------
% Compute expected volatility of predictors up to horizon h,and construct
% coefficient matrix phiF
% -------------------------------------------------------------------------

% Initialize parameters
r   = size(xf,2);
pf  = size(fb,2)-1;

% Create phif matrix
phif_top = [];
for j = 2:pf+1
    phif_top = [phif_top,sparse(1:r,1:r,fb(:,j))];
end;
if pf > 1;
phif_bot = [sparse(1:r*(pf-1),1:r*(pf-1),1),sparse(r*(pf-1),r,0)];
phif    = [phif_top;phif_bot];
else
    phif = phif_top;
end;

% Compute evf
evf = cell(h,1);
for j = 1:h;
for i = 1:r
    alpha      = thf(1,i);
    beta       = thf(2,i);
    tau2       = thf(3,i);
    x          = xf(:,i);
    evf{j}(:,i) = expectedvar(alpha,beta,tau2,x,j); %Et[(v^f_t)^2]
end;
end;
end

% Auxiliary function
function [out] = expectedvar(a,b,t2,x,h)
% -------------------------------------------------------------------------
% Compute Et[exp{x(t+h)}] using the AR(1) law of motion for x(t)
% -------------------------------------------------------------------------
out = exp(a*(1-b^h)/(1-b)+t2/2*(1-b^(2*h))/(1-b^2)+ b^h*x);
end

function [U] = compute_uy(xy,thy,yb,py,evf,phif)
% -------------------------------------------------------------------------
% Compute expected volatility of predictors up to horizon h
% -------------------------------------------------------------------------

% Initialize parameters
h  = length(evf);
r  = size(evf{1},2);
```

```matlab
pf = size(phif,1)/r;
pz = (length(yb)-1-py)/r;
T  = length(xy);
% Preallocate variables
U = zeros(T,h);
if pf >1; evf0 = sparse(1,r*(pf-1),0); end;
if pf==1; evf0 = []; end;
if py >1; evy0 = sparse(1,py-1,0); end;
if py==1; evy0 = []; end;

% Construct the main phi matrix
if pf >pz; lambda_topright = sparse(1,(pf-pz)*r,0); end;
if pf==pz; lambda_topright = []; end;
if py >1;  lambda_bottom   = sparse(py-1,r*pf,0); end;
if py==1;  lambda_bottom   = []; end;
lambda   = [yb(py+2:end),lambda_topright;lambda_bottom];

phiy_top = yb(2:py+1);
if py >1; phiy_bottom = [sparse(1:py-1,1:py-1,1),sparse(py-1,1,0)]; end;
if py==1; phiy_bottom = []; end;
phiy        = [phiy_top;phiy_bottom];
phi_topright = sparse(r*pf,py,0);
phi         = [phif,phi_topright;lambda,phiy];

% Compute uncertainty using the recursion
alpha = thy(1);
beta  = thy(2);
tau2  = thy(3);
x     = xy;
for j = 1:h
    evy{j} = expectedvar(alpha,beta,tau2,x,j); %Et[(v^y_t)^2]
end;
for t = 1:T
    for j = 1:h
        ev = sparse(1:r*pf+py,1:r*pf+py,[evf{j}(t,:),evf0,evy{j}(t),evy0]);
        if j == 1; u = ev; end;
        if j  > 1; u = phi*u*phi' + ev; end;
        U(t,j) = u(r*pf+1,r*pf+1); % select relevant entry
    end
end
end

% Auxiliary function
function [out] = expectedvar(a,b,t2,x,h)
% ---------------------------------------------------------------------
% Compute Et[exp{x(t+h)}] using the AR(1) law of motion for x(t)
% ---------------------------------------------------------------------
out = exp(a*(1-b^h)/(1-b)+t2/2*(1-b^(2*h))/(1-b^2)+ b^h*x);
end
```

Aggregate individual ut into macro uncertainty (generate_aggu.m)

```matlab
% ------------------------------------------------------------------------
% Generate aggregate uncertainty estimates
% ------------------------------------------------------------------------

% Initialization
clear; clc;
load ut;
[T,N,h] = size(ut);

% Cross-sectional average
utcsa = squeeze(mean(sqrt(ut),2));

% Principal component analysis
utpca = zeros(T,h);
for j = 1:h
  logu    = log(sqrt(ut(:,:,j)));
  dlogu(:,:,j)  = logu(2:end,:) - logu(1:end-1,:);
  [de,du,dl,dv] = factors(dlogu(:,:,j),1,2,1);
  % Rotate estimate
  rho     = corr(cumsum([0;du(:,1)]),utcsa(:,j));
  if rho < 0;
     du  = -du;
     dl  = -dl;
  end;
  ufac    = cumsum([zeros(1,size(du,2));du]);
  dufac(:,:,j) = du;
  dlam(:,:,j)  = dl;
  deig(:,j)  = dv;
  % Calibrate to cross-section mean
  sd      = std(utcsa(:,j));
  mn      = mean(utcsa(:,j));
  p0      = [1,0.5];
  opt     = optimset('tolfun',1e-50,'display','off');
  [p,obj] = fminsearch(@(p)calibratef(p,ufac(:,1),sd,mn),p0,opt);
  utpca(:,j) = exp((p(1)*ufac(:,1)+p(2))./2);
end

% Save results
save aggu dates ut utpca utcsa dufac dlam deig dlogu
```

Functions for generate_aggu.m

```matlab
function [ehat,Fhat,lamhat,ve2] = factors(X,kmax,jj,DEMEAN)
% ------------------------------------------------------------------------
% Estimate latent factors from observable data X using PCA
%  Input: X     = observable data
%         kmax  = maximum number of factors to consider
%         jj    = information criterion from Bai and Ng (2002)
%         DEMEAN = 0 - no, 1 - yes, 2 - standardize
%  Output: ehat  = idiosyncratic errors
%          Fhat  = latent factor estimates
%          lamhat = factor loadings
%          ve2   = eigenvalues of data covariance matrix
% ------------------------------------------------------------------------

[ic1,chat,fhat,eigval]  = nbplog(X,kmax,jj,DEMEAN);
icstar    = ic1;
R2_static = sum(eigval(1:icstar))/sum(eigval);
if DEMEAN == 2;
[ehat,Fhat,lamhat,ve2]  = pc(standard(X),icstar);
end
if DEMEAN == 1;
[ehat,Fhat,lamhat,ve2]  = pc(X-repmat(mean(X),size(X,1),1),icstar);
end
if DEMEAN == 0;
[ehat,Fhat,lamhat,ve2]  = pc(X,icstar);
end
end

% Auxiliary functions
function [ic1, chat,Fhat,eigval]=nbplog(x,kmax,jj,DEMEAN);
%function [ic1, lambda,Fhat,IC1]=nbplog(x,kmax,jj,DEMEAN);
T=size(x,1);
N=size(x,2);
NT=N*T;
NT1=N+T;
CT=zeros(1,kmax);
ii=1:1:kmax;
if jj ==1;CT(1,:)=log(NT/NT1)*ii*NT1/NT;end;
if jj==2; CT(1,:)=(NT1/NT)*log(min([N;T]))*ii;end;
GCT=min([N;T]);
if jj==3; CT(1,:)=ii*log(GCT)/GCT; end;
if jj==4; CT(1,:)=2*ii/T; end;
if jj==5; CT(1,:)=log(T)*ii/T;end;
if jj==6; CT(1,:)=2*ii*NT1/NT; end;
if jj==7; CT(1,:)=log(NT)*ii*NT1/NT;end;
if jj==8; CT(1,:)= 2*ii*(sqrt(N)+sqrt(T))^2/(NT); end;% new modified CP


 if DEMEAN ==2;
 X=standard(x);
 end;
```

```
if DEMEAN ==1;
 X=x-repmat(mean(x),T,1);
 end;
if DEMEAN==0;
  X=x;;
  end;
IC1=zeros(size(CT,1),kmax+1);
Sigma=zeros(1,kmax+1);
if T< N;
[ev,eigval,ev1]=svd(X*X');
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Fhat0=sqrt(T)*ev;
Lambda0=X'*Fhat0/T;
else;
[ev,eigval,ev1]=svd(X'*X);
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Lambda0=sqrt(N)*ev;
Fhat0=X*Lambda0/N;
end;


if jj <= 8;
for i=kmax:-1:1;
Fhat=Fhat0(:,1:i);
%lambda=Fhat'*X;
lambda=Lambda0(:,1:i);
chat=Fhat*lambda';
%disp([i sumeigval(i) sum(sum(chat.*chat))/sum(sum(X.*X))]);
ehat=X-chat;
Sigma(i)=mean(sum(ehat.*ehat/T));
IC1(:,i)=log(Sigma(i))+CT(:,i);
end;
Sigma(kmax+1)=mean(sum(X.*X/T));
IC1(:,kmax+1)=log(Sigma(kmax+1));
ic1=minindc(IC1')';
ic1=ic1 .*(ic1 <= kmax);
end;
if jj==9;

  for j=1:rows(sumeigval);
    if sumeigval(j) >= .5; ic1=j; break; end;
  end;
 end;
Fhat=[];
Fhat=Fhat0(:,1:kmax);
Lambda=Lambda0(:,1:kmax);
chat=Fhat*Lambda';
eigval=diag(eigval);
end

function [ehat,fhat,lambda,ss]=pc(y,nfac);
```
126

```matlab
[bigt,bign]=size(y);
yy=y'*y;
[Fhat0,eigval,Fhat1]=svd(yy);
lambda=Fhat0(:,1:nfac)*sqrt(bign);
fhat=y*lambda/bign;
ehat=y-fhat*lambda';

ve2=sum(ehat'.*ehat')'/bign;
ss=diag(eigval);
end

function pos=minindc(x);
ncols=size(x,2);
nrows=size(x,1);
pos=zeros(ncols,1);
seq=seqa(1,1,nrows);
for i=1:ncols;
dum=min(x(:,i));
dum1= seq .* ( (x(:,i)-dum) ==0);
pos(i)=sum(dum1);
end;
end

function x=standard(y);
T=size(y,1);
N=size(y,2);
my=repmat(mean(y),T,1);
sy=repmat(std(y),T,1);
x=(y-my)./sy;

%x=(y-kron(mean(y),ones(rows(y),1)))./kron(std(y),ones(rows(y),1));
end

function seq=seqa(a,b,c);
seq=(a:b:(a+b*(c-1)))';
end
```

Generate No- predictors forecast errors (generate_npferrors.m)

```
% -----------------------------------------------------------------------
% Generate forecast errors with no predictors
% -----------------------------------------------------------------------

% Load data
clear; clc;
load ssdata;
data= data(2:end,:);
dates= dates(2:end,:);
xt= data;

% Generate forecast errors for yt
yt    = zscore(xt); % only the macro data
vyt   = yt;

% Save data
[T,N]  = size(vyt);
dates  = 1900+(95:1/4:120-1/4)';
dates  = dates(end-T+1:end);
save npferrors dates vyt names vartype xt

% Also write to .txt file for R code
dlmwrite('npvyt.txt',vyt,'delimiter','\t','precision',17);
```

Estimate stochastic volatility in the forecast errors using 'stochvol'- R package (generate_npsvdraws.r)

```
# -------------------------------------------------------------------------
# Estimate a first-order autoregressive stochastic volatility model on the
# forecast errors from the macroeconomic data (no predictors)
# -------------------------------------------------------------------------

# Initialization
rm(list=ls())
library(stochvol)
library(coda)
set.seed(0) # for replication
options(digits=17)

setwd('C:/Users/sukhanjeet/Desktop/New folder/Measuring uncertainty in Italy-
2/data/ss_macrodata')

infile='npvyt.txt'
outfile='npsvymeans.txt'
vt   = read.table(infile,sep = '\t')

T    = dim(vt)[1]
N    = dim(vt)[2]
for (i in 1:N){
  if(min(log(vt[,i]^2))== -Inf){
    vt[,i] = vt[,i] + 0.00001 #offset to avoid taking log of zero
  }
}

# Run MCMC algorithm and store draws
S    = 50000
burn = 50000
m    = matrix(0,T+3,N)
g    = matrix(0,3,N)
for (i in 1:N){
 print(i)
 draws  = svsample(vt[,i],draws=S,burnin=burn,quiet=TRUE,thinpara=10,thinlatent=10)
 #      temp1=draws$para[[1]][,1:3]
 #      temp2=draws$latent[[1]]
 #      all=cbind(temp1,temp2)
 #      m[,i]=colMeans(all)
 latdraws = latent(draws)
 pardraws = para(draws)[, sampled_parameters(draws)]
 all      = cbind(pardraws,latdraws)
 m[,i]    = colMeans(all)
 g[,i]    = geweke.diag(pardraws)$z
 #name     = sprintf('npsvfdraws%d.txt',i)
 #write(t(all),file=name,ncolumn=dim(all)[2])
}
out = rbind(m,g) #include Geweke statistics
write(t(out),file="npsvymeans.txt",ncolumn=dim(out)[2])
```

Use npsvmeans.txt, computed through R, as input to produce the 51 no predictors uncertainty estimates (generate_nput.m)

```matlab
% -------------------------------------------------------------------------
% Compute matrix of uncertainty estimates (no predictors)
% -------------------------------------------------------------------------

% Load data
clear; clc;
load npferrors;
svy = load('npsvymeans.txt');

% Compute uncertainty
h    = 4;
[T,N] = size(vyt);
thy  = [svy(1,:).*(1-svy(2,:));svy(2,:);svy(3,:).^2];
xy   = svy(4:end-3,:);
gy   = svy(end-3:1:end,:);
nput  = zeros(T,N,h);
for j = 1:h
    for i = 1:N
      t1 = thy(1,i)*(1-thy(2,i)^j)/(1-thy(2,i));
      t2 = thy(3,i)/2*(1-thy(2,i)^(2*j))/(1-thy(2,i)^2);
      nput(:,i,j) = exp(t1+t2+thy(2,i).*xy(:,i));
    end
end

% Save results
save nput dates nput
save npgeweke dates gy names
```

Aggregate individual nput into macro uncertainty (generate_npaggu.m)

```matlab
% ----------------------------------------------------------------------
% Generate no predictors aggregate uncertainty estimates
% ----------------------------------------------------------------------

% Initialization
clear; clc;
load nput;
[T,N,h] = size(nput);

% Cross-sectional average
utcsa = squeeze(mean(sqrt(nput),2));

% Principal component analysis
utpca = zeros(T,h);
for j = 1:h
  logu    = log(sqrt(nput(:,:,j)));
  dlogu(:,:,j)  = logu(2:end,:) - logu(1:end-1,:);
  [de,du,dl,dv] = factors(dlogu(:,:,j),1,2,1);
  % Rotate estimate
  rho     = corr(cumsum([0;du(:,1)]),utcsa(:,j));
  if rho < 0;
     du  = -du;
     dl  = -dl;
  end;
  ufac    = cumsum([zeros(1,size(du,2));du]);
  dufac(:,:,j) = du;
  dlam(:,:,j)  = dl;
  deig(:,j)  = dv;
  % Calibrate to cross-section mean
  sd      = std(utcsa(:,j));
  mn      = mean(utcsa(:,j));
  p0      = [1,0.5];
  opt     = optimset('tolfun',1e-50,'display','off');
  [p,obj] = fminsearch(@(p)calibratef(p,ufac(:,1),sd,mn),p0,opt);
  utpca(:,j) = exp((p(1)*ufac(:,1)+p(2))./2);
end

% Save results
save npaggu dates nput utpca utcsa dufac dlam deig dlogu
```

Functions for generate_npaggu.m

```matlab
function [ehat,Fhat,lamhat,ve2] = factors(X,kmax,jj,DEMEAN)
% ------------------------------------------------------------------------
% Estimate latent factors from observable data X using PCA
%  Input: X     = observable data
%         kmax  = maximum number of factors to consider
%         jj    = information criterion from Bai and Ng (2002)
%         DEMEAN = 0 - no, 1 - yes, 2 - standardize
%  Output: ehat   = idiosyncratic errors
%          Fhat   = latent factor estimates
%          lamhat = factor loadings
%          ve2    = eigenvalues of data covariance matrix
% ------------------------------------------------------------------------

[ic1,chat,fhat,eigval]  = nbplog(X,kmax,jj,DEMEAN);
icstar    = ic1;
R2_static = sum(eigval(1:icstar))/sum(eigval);
if DEMEAN == 2;
[ehat,Fhat,lamhat,ve2]  = pc(standard(X),icstar);
end
if DEMEAN == 1;
[ehat,Fhat,lamhat,ve2]  = pc(X-repmat(mean(X),size(X,1),1),icstar);
end
if DEMEAN == 0;
[ehat,Fhat,lamhat,ve2]  = pc(X,icstar);
end
end


% Auxiliary functions
function [ic1, chat,Fhat,eigval]=nbplog(x,kmax,jj,DEMEAN);
%function [ic1, lambda,Fhat,IC1]=nbplog(x,kmax,jj,DEMEAN);
T=size(x,1);
N=size(x,2);
NT=N*T;
NT1=N+T;
CT=zeros(1,kmax);
ii=1:1:kmax;
if jj ==1;CT(1,:)=log(NT/NT1)*ii*NT1/NT;end;
if jj==2; CT(1,:)=(NT1/NT)*log(min([N;T]))*ii;end;
GCT=min([N;T]);
if jj==3; CT(1,:)=ii*log(GCT)/GCT; end;
if jj==4; CT(1,:)=2*ii/T; end;
if jj==5; CT(1,:)=log(T)*ii/T;end;
if jj==6; CT(1,:)=2*ii*NT1/NT; end;
if jj==7; CT(1,:)=log(NT)*ii*NT1/NT;end;
if jj==8; CT(1,:)= 2*ii*(sqrt(N)+sqrt(T))^2/(NT); end;% new modified CP


 if DEMEAN ==2;
 X=standard(x);
 end;
```

```matlab
if DEMEAN ==1;
 X=x-repmat(mean(x),T,1);
 end;
if DEMEAN==0;
  X=x;;
  end;
IC1=zeros(size(CT,1),kmax+1);
Sigma=zeros(1,kmax+1);
if T< N;
[ev,eigval,ev1]=svd(X*X');
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Fhat0=sqrt(T)*ev;
Lambda0=X'*Fhat0/T;
else;
[ev,eigval,ev1]=svd(X'*X);
sumeigval=cumsum(diag(eigval))/sum(diag(eigval));
Lambda0=sqrt(N)*ev;
Fhat0=X*Lambda0/N;
end;


if jj <= 8;
for i=kmax:-1:1;
Fhat=Fhat0(:,1:i);
%lambda=Fhat'*X;
lambda=Lambda0(:,1:i);
chat=Fhat*lambda';
%disp([i sumeigval(i) sum(sum(chat.*chat))/sum(sum(X.*X))]);
ehat=X-chat;
Sigma(i)=mean(sum(ehat.*ehat/T));
IC1(:,i)=log(Sigma(i))+CT(:,i);
end;
Sigma(kmax+1)=mean(sum(X.*X/T));
IC1(:,kmax+1)=log(Sigma(kmax+1));
ic1=minindc(IC1')';
ic1=ic1 .*(ic1 <= kmax);
end;
if jj==9;

  for j=1:rows(sumeigval);
    if sumeigval(j) >= .5; ic1=j; break; end;
  end;
 end;
Fhat=[];
Fhat=Fhat0(:,1:kmax);
Lambda=Lambda0(:,1:kmax);
chat=Fhat*Lambda';
eigval=diag(eigval);
end

function [ehat,fhat,lambda,ss]=pc(y,nfac);
```

```
[bigt,bign]=size(y);
yy=y'*y;
[Fhat0,eigval,Fhat1]=svd(yy);
lambda=Fhat0(:,1:nfac)*sqrt(bign);
fhat=y*lambda/bign;
ehat=y-fhat*lambda';

ve2=sum(ehat'.*ehat')'/bign;
ss=diag(eigval);
end

function pos=minindc(x);
ncols=size(x,2);
nrows=size(x,1);
pos=zeros(ncols,1);
seq=seqa(1,1,nrows);
for i=1:ncols;
dum=min(x(:,i));
dum1= seq .* ( (x(:,i)-dum) ==0);
pos(i)=sum(dum1);
end;
end

function x=standard(y);
T=size(y,1);
N=size(y,2);
my=repmat(mean(y),T,1);
sy=repmat(std(y),T,1);
x=(y-my)./sy;

%x=(y-kron(mean(y),ones(rows(y),1)))./kron(std(y),ones(rows(y),1));
end

function seq=seqa(a,b,c);
seq=(a:b:(a+b*(c-1)))';
end
```

Italian Macroeconomic Dynamics VAR-9 models and FEVDs, U=1 sample case (generate_ss_VAR_u1.m).

```matlab
%%%-------------------------------------------------------------------
% Var 9 estimation utcsa
%%%-------------------------------------------------------------------
clear;clc;

[data,txt] = xlsread('VarDataSSUtcsa1.xlsx');
txt=txt(:,1:end);
load aggu;
pi      = log(data(:,1));
emp     =    (data(:,2));
unemp   =    (data(:,3));
cpi     = log(data(:,4));
tretailt = log(data(:,5));
wage    = log(data(:,6));
intrate =    (data(:,7));
stock   = log(data(:,8));
utcsa   =     data(:,9);


X= [pi, emp, unemp, cpi, tretailt, wage, intrate, stock, utcsa];


const_trend = 2;

% Choose number of lags
nbr_lags = 2;

% model
[VAR, VARopt] = VARmodel(X,nbr_lags,const_trend);

%%% OPTIONS

%Vnames
VARopt.vnames = {'Production' 'Employment' 'Unemployment' 'CPI' 'Retail Trade' 'Wage'
'Long Term Interest Rate' 'Stock Price' 'U(1)' };

% number of steps for computation of IRFs and FEVDs
VARopt.nsteps = 20;

% size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.impact = 0;

%frequency
VARopt.frequency = 'q';

% Recursive Identification with zero-short run/contemporaneous restriction
VARopt.ident = 'short';
```

```
%'bs' standard bootstrap, 'wild' wild bootstrap
VARopt.method = 'bs';

% method for computation of recursive stuff ('wold' form MA representation, 'comp' for
companion form)
VARopt.recurs    = 'wold';

% confidence level for bootstrap, default = 95
VARopt.pctg = 68;

% name of the shocks
VARopt.snames = VARopt.vnames;

%select on variable to plot, if=0 plot all
VARopt.pick = 0;

%printing
[TABLE_VAR, beta] = VARprint(VAR,VARopt);

%%% IR

% Apply the identification scheme and compute impulse responses
[IRF,VAR] = VARir(VAR,VARopt);

%BANDS
[IRF_lower,IRF_upper,IRF_median,IRF_mean] = VARirband(VAR,VARopt);

%%% Figures related options

VARopt.savefigs = true;

VARopt.quality  = 0;

VARopt.FigSize  = [12,8];

%%% Plot impulse response functions
VARirplot(IRF_mean,VARopt,IRF_lower,IRF_upper);


% Compute VD
[VD, VAR] = VARvd(VAR,VARopt);
% Compute VD error bands
[VDinf,VDsup,VDmed,VDbar] = VARvdband(VAR,VARopt);
% Plot VD
VARvdplot(VDbar,VARopt);

VDU1=VD;

save VDU1;

%save for plot_var_ss_irf
IRFu1=IRF;
```

```
IRFu1_lower=IRF_lower;
IRFu1_upper=IRF_upper;
IRFu1_mean=IRF_mean;
IRFu1_median=IRF_median;

save IRFu1;
```

Functions for generate_ss_VAR_u1.m

function [VAR, VARopt] = VARmodel(ENDO,nlag,const,EXOG,nlag_ex)
%===
=======
% Perform vector autogressive (VAR) estimation with OLS
%===
=======
% [VAR, VARopt] = VARmodel(ENDO,nlag,const,EXOG,nlag_ex)
% ---
% INPUT
%   - ENDO: an (nobs x nvar) matrix of y-vectors
%   - nlag: lag length
% ---
% OPTIONAL INPUT
%   - const: 0 no constant; 1 constant; 2 constant and trend; 3 constant
%   and trend^2 [dflt = 0]
%   - EXOG: optional matrix of variables (nobs x nvar_ex)
%   - nlag_ex: number of lags for exogeonus variables [dflt = 0]
% ---
% OUTPUT
%   - VAR: structure including VAR estimation results
%   - VARopt: structure including VAR options (see VARoption)
% ---
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
% ==
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% ---

%% Check inputs
% ---
[nobs, nvar] = size(ENDO);

% Create VARopt and update it
VARopt = VARoption;
VAR.ENDO = ENDO;
VAR.nlag = nlag;

% Check if ther are constant, trend, both, or none
if ~exist('const','var')
    const = 1;
end
VAR.const = const;

% Check if there are exogenous variables

```matlab
if exist('EXOG','var')
    [nobs2, nvar_ex] = size(EXOG);
    % Check that ENDO and EXOG are conformable
    if (nobs2 ~= nobs)
        error('var: nobs in EXOG-matrix not the same as y-matrix');
    end
    clear nobs2
    % Check if there is lag order of EXOG, otherwise set it to 0
    if ~exist('nlag_ex','var')
        nlag_ex = 0;
    end
    VAR.EXOG = EXOG;
else
    nvar_ex = 0;
    nlag_ex = 0;
    VAR.EXOG = [];
end


%%% Save some parameters and create data matrices
% -----------------------------------------------------------------
    nobse        = nobs - max(nlag,nlag_ex);
    VAR.nobs     = nobse;
    VAR.nvar     = nvar;
    VAR.nvar_ex  = nvar_ex;
    VAR.nlag     = nlag;
    VAR.nlag_ex  = nlag_ex;
    ncoeff       = nvar*nlag;
    VAR.ncoeff   = ncoeff;
    ncoeff_ex    = nvar_ex*(nlag_ex+1);
    ntotcoeff    = ncoeff + ncoeff_ex + const;
    VAR.ntotcoeff = ntotcoeff;
    VAR.const    = const;

% Create independent vector and lagged dependent matrix
[Y, X] = VARmakexy(ENDO,nlag,const);

% Create (lagged) exogenous matrix
if nvar_ex>0
    X_EX  = VARmakelags(EXOG,nlag_ex);
    if nlag == nlag_ex
        X = [X X_EX];
    elseif nlag > nlag_ex
        diff = nlag - nlag_ex;
        X_EX = X_EX(diff+1:end,:);
        X = [X X_EX];
    elseif nlag < nlag_ex
        diff = nlag_ex - nlag;
        Y = Y(diff+1:end,:);
        X = [X(diff+1:end,:) X_EX];
    end
end
```

```matlab
%% OLS estimation equation by equation
% ------------------------------------------------------------------------
for j=1:nvar
    Yvec = Y(:,j);
    OLSout = OLSmodel(Yvec,X,0);
    aux = ['eq' num2str(j)];
    eval( ['VAR.' aux '.beta  = OLSout.beta;'] );  % bhats
    eval( ['VAR.' aux '.tstat = OLSout.tstat;'] ); % t-stats
    eval( ['VAR.' aux '.bstd  = OLSout.bstd;'] );  % beta std error
    % compute t-probs
    tstat = zeros(ncoeff,1);
    tstat = OLSout.tstat;
    tout = tdis_prb(tstat,nobse-ncoeff);
    eval( ['VAR.' aux '.tprob = tout;'] );        % t-probs
    eval( ['VAR.' aux '.resid = OLSout.resid;'] );% resids
    eval( ['VAR.' aux '.yhat  = OLSout.yhat;'] ); % yhats
    eval( ['VAR.' aux '.y     = Yvec;'] );        % actual y
    eval( ['VAR.' aux '.rsqr  = OLSout.rsqr;'] ); % r-squared
    eval( ['VAR.' aux '.rbar  = OLSout.rbar;'] ); % r-adjusted
    eval( ['VAR.' aux '.sige  = OLSout.sige;'] ); % standard error
    eval( ['VAR.' aux '.dw    = OLSout.dw;'] );   % DW
end


%% Compute the matrix of coefficients & VCV
% ------------------------------------------------------------------------
Ft = (X'*X)\(X'*Y);
VAR.Ft = Ft;
F = Ft';
VAR.F = Ft';
SIGMA = (1/(nobse-ntotcoeff))*(Y-X*Ft)'*(Y-X*Ft); % adjusted for # of estimated coeff per equation
VAR.sigma = SIGMA;
VAR.resid = Y - X*Ft;
VAR.X = X;
VAR.Y = Y;
if nvar_ex > 0
    VAR.X_EX = X_EX;
end


%% Companion matrix of F and max eigenvalue
% ------------------------------------------------------------------------
Fcomp = [F(:,1+const:nvar*nlag+const); eye(nvar*(nlag-1)) zeros(nvar*(nlag-1),nvar)];
VAR.Fcomp = Fcomp;
VAR.maxEig = max(abs(eig(Fcomp)));


%% Initialize other results
% ------------------------------------------------------------------------
```

```matlab
VAR.B   = [];   % structural impact matrix (need identification: see VARir/VARfevd)
VAR.b   = [];   % first columns of structural impact matrix (need identification: see
VARir/VARfevd)
VAR.PSI = [];   % Wold multipliers (computed only with VARir/VARfevd)
VAR.Fp  = [];   % Recursive F by lag (useful to compute MA representation)
VAR.IV  = [];   % External instruments for identification


function VARopt = VARoption
%========================================================================
========
% Optional inputs for VAR analysis. This function is run automatically in
% the VARmodel function.
%========================================================================
========
% VARopt = VARoption
%
==========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------

VARopt.vnames    = [];      % endogenous variables names
VARopt.vnames_ex = [];      % exogenous variables names
VARopt.snames    = [];      % shocks names
VARopt.nsteps    = 20;      % number of steps for computation of IRFs and FEVDs
VARopt.impact    = 0;       % size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.shut      = 0;       % forces the IRF of one variable to zero
VARopt.ident     = 'short'; % identification method for IRFs ('short' zero short-run restr, 'long'
zero long-run restr, 'sign' sign restr, 'iv' external instrument)
VARopt.recurs    = 'wold';  % method for computation of recursive stuff ('wold' form MA
representation, 'comp' for companion form)
VARopt.ndraws    = 1000;    % number of draws for bootstrap or sign restrictions
VARopt.mult      = 10;      % multiple of draws to be printed at screen.
VARopt.pctg      = 68;      % confidence level for bootstrap
VARopt.method    = 'bs';    % methodology for error bands, 'bs' for standard bootstrap, 'wild'
wild bootstrap
VARopt.sr_hor    = 1;       % number of periods that sign restrcitions are imposed on
VARopt.sr_rot    = 500;     % max number of rotations for finding sign restrictions
VARopt.sr_draw   = 100000;  % max number of total draws for finding sign restrictions
VARopt.sr_mod    = 0;       % model uncertainty for sign restrictions (1=yes, 0=no)
VARopt.pick      = 0;       % selects one variable for IRFs and FEVDs plots (0 => plot all)
VARopt.quality   = 0;       % quality of exported figures: 1=high (ghostscript required), 0=low
VARopt.suptitle  = 1;       % title on top of figures
VARopt.datesnum  = [];      % numeric vector of dates in the VAR
VARopt.datestxt  = [];      % cell vector of dates in the VAR
VARopt.datestype = 1;       % 1 smart labels; 2 less smart labels
VARopt.firstdate = [];      % initial date of the sample in format 1999.75 => 1999Q4 (both for
annual and quarterly data)
VARopt.frequency = 'q';     % frequency of the data: 'm' monthly, 'q' quarterly, 'y' yearly
```

```matlab
VARopt.figname   = [];      % string for name of exported figure
VARopt.FigSize   = [26,24]; % size of window for plots

% In progress
%VARopt.maxvd_N   = 1;      % position of variable to maximize variance decomposition
%VARopt.maxvd_H   = 10;     % horizon over which to maximize variance decomposition
%VARopt.maxvd_rot = 1000;   % max number of rotations for maximization of variance
decomposition

function [TABLE, beta] = VARprint(VAR,VARopt,approx)
%
==========================================================================
====
% Prints the output of a VAR estimation
%
==========================================================================
====
% [TABLE, beta] = VARprint(VAR,VARopt,approx)
% -----------------------------------------------------------------------
% INPUT
%   - VAR: structure output of VARmodel function
%   - VARopt: options of the VAR (see VARopt from VARmodel)
% -----------------------------------------------------------------------
% OPTIONAL INPUT
%   - approx: number of decimal digits. Default = 4
%-----------------------------------------------------------------------
% OUPUT
%   - TABLE: table of estimated coefficients, std errors, t-stats, and p
%      values in in cell array
%   - beta: table of estimated coefficients only in cell array
% -----------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
==========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------


%% Check inputs
%===============================================
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end
% If there is VARopt get the vnames
vnames = VARopt.vnames;
vnames_ex = VARopt.vnames_ex;
% Check they are not empty
```

```matlab
if isempty(vnames)
    error('You need to add label for endogenous variables in VARopt');
end
if VAR.nvar_ex>0
    if isempty(vnames_ex)
        error('You need to add label for exogenous variables in VARopt');
    end
end
if ~exist('approx','var')
    approx = 4;
end


%%% Retrieve and initialize variables
%===============================================================
nlag = VAR.nlag;
nlag_ex = VAR.nlag_ex;
const = VAR.const;



%%% Additional checks
%===============================================================
% Check size of vnames (and change it if necessary)
htext = vnames;
if size(htext,2)==1
    htext = htext';
    nvars = size(htext,2);
else
    nvars = size(htext,2);
end

% Check size of vnames_ex (and change it if necessary)
if exist('vnames_ex','var')
    if size(vnames_ex,2)==1
        vnames_ex = vnames_ex';
        nvars_ex = size(vnames_ex,2);
    else
        nvars_ex = size(vnames_ex,2);
    end
end

%%% Labels of deterministic components
%=========================================================
switch const
    case 0
        aux = [];
    case 1
        aux = {'c'};
    case 2
        aux = {'c';'trend'};
    case 3
        aux = {'c';'trend';'trend2'};
end
```

```matlab
vtext = {' '};
vtext = [vtext; aux];
clear aux

%%% Labels of lagged variables
%================================================
for jj=1:nlag
    for ii=1:nvars
        aux(ii,1) = {[vnames{ii} '(-' num2str(jj) ')' ]};
    end
    vtext = [vtext ; aux];
end
clear aux

%%% Labels of exogenous variables
%================================================
if VAR.nvar_ex>0
    vtext = [vtext ; vnames_ex'];
    if nlag_ex > 0
        for jj=1:nlag_ex
            for ii=1:nvars_ex
                aux(ii,1) = {[vnames_ex{ii} '(-' num2str(jj) ')' ]};
            end
            vtext = [vtext ; aux];
        end
        clear aux
    end
end

%%% Save
%================================================
% Save a beta table
beta = roundnum2cell(VAR.Ft,approx);
beta = [htext; beta];
beta = [vtext beta];

% Save a standard error table
bstd = [];
for ii=1:nvars
    eval( ['aux = VAR.eq' num2str(ii) '.bstd;'] );
    bstd = [bstd aux];
end
bstd = roundnum2cell(bstd,approx);
bstd = [htext; bstd];
bstd = [vtext bstd];
clear aux

% Save a tstat table
tstat = [];
for ii=1:nvars
    eval( ['aux = VAR.eq' num2str(ii) '.tstat;'] );
    tstat = [tstat aux];
```

```matlab
end
tstat = roundnum2cell(tstat,2);
tstat = [htext; tstat];
tstat = [vtext tstat];
clear aux

% Save a p-value table
tprob = [];
for ii=1:nvars
    eval( ['aux = VAR.eq' num2str(ii) '.tprob;'] );
    tprob = [tprob aux];
end
tprob = roundnum2cell(tprob,approx);
tprob = [htext; tprob];
tprob = [vtext tprob];
clear aux

% Save a beta & tstat table
nn = size(beta,1)-1;
TABLE = {''};
index = 1;
for ii=1:nn
    for jj=1:nvars
        TABLE(index,jj) = beta(1+ii,1+jj);
        TABLE(index+1,jj) = bstd(1+ii,1+jj);
        aux1 = cell2mat(tstat(1+ii,1+jj)); % get the numeric value from cell
        aux2 = [ '[' num2str(aux1) ']' ];  % add parenthesis to t-stat value
        TABLE{index+2,jj} = aux2;
        TABLE(index+3,jj) = tprob(1+ii,1+jj);
    end
    index = index+4;
end
for jj=1:nvars
    eval( ['aux = VAR.eq' num2str(jj) '.rsqr;'] ); TABLE(index,jj) = num2cell(aux);
    eval( ['aux = VAR.eq' num2str(jj) '.rbar;'] ); TABLE(index+1,jj) = num2cell(aux);
    TABLE(index+2,jj) = num2cell(VAR.nobs);
end
clear aux
TABLE = [htext; TABLE];

% Create vertical label
TAB_v = {''};
index = 2;
for ii=1:nn
    TAB_v(index,1) = vtext(1+ii);
    TAB_v(index+1,1) = {['std(' vtext{1+ii} ')']};
    TAB_v(index+2,1) = {['t(' vtext{1+ii} ')']};
    TAB_v(index+3,1) = {['p(' vtext{1+ii} ')']};
    index = index + 4;
end
TAB_v(index,1) = {'R2'};
TAB_v(index+1,1) = {'R2bar'};
```

```matlab
TAB_v(index+2,1) = {'Obs'};
TABLE = [TAB_v TABLE];


%% Print the table on screen (only beta)
%================================================
info.cnames = char(htext);
info.rnames = char(vtext);
disp(' ')
%disp('----------------------------------------------------------------')
disp(' ')
disp('Reduced form VAR estimation:')
disp(' ')
mprint(VAR.Ft,info)
%disp('----------------------------------------------------------------')

function [IR, VAR] = VARir(VAR,VARopt)
%
=========================================================================
======
% Compute impulse responses (IRs) for a VAR model estimated with the
% VARmodel.m function. Four identification schemes can be specified:
% zero contemporaneous restrictions, zero long-run restrictions, sign
% restrictions, and external instrumenmts.
%
=========================================================================
======
% [IRF, VAR] = VARir(VAR,VARopt)
% -----------------------------------------------------------------------
% INPUT
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----------------------------------------------------------------------
% OUTPUT
%   - IR(:,:,:) : matrix with IRF (H horizons, N variables, N shocks)
%   - VAR: structure including VAR estimation results. Note here that the
%       structure VAR is an output of VARmodel tpp. This fucntion adds to
%       VAR some additional results, e.g. VAR.B is the structural impact
%       matrix
%
=========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------


%% Check inputs
%=========================================================================
=========
```

```matlab
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
IV = VAR.IV;
if strcmp(VARopt.ident,'iv')
    if isempty(IV)
        error('You need to provide the data for the instrument in VAR (IV)');
    end
end


%% Retrieve and initialize variables
%=========================================================================
%=========
nsteps = VARopt.nsteps;
impact = VARopt.impact;
shut   = VARopt.shut;
recurs = VARopt.recurs;
Fcomp  = VAR.Fcomp;
nvar   = VAR.nvar;
nlag   = VAR.nlag;
sigma  = VAR.sigma;
IR     = nan(nsteps,nvar,nvar);


%% Compute Wold representation
%=========================================================================
%=========
% Initialize Wold multipliers
PSI = zeros(nvar,nvar,nsteps);
% Re-write F matrix to compute multipliers
VAR.Fp = zeros(nvar,nvar,nlag);
I = VAR.const+1;
for ii=1:nsteps
    if ii<=nlag
        VAR.Fp(:,:,ii) = VAR.F(:,I:I+nvar-1);
    else
        VAR.Fp(:,:,ii) = zeros(nvar,nvar);
    end
    I = I + nvar;
end
% Compute multipliers
PSI(:,:,1) = eye(nvar);
for ii=2:nsteps
    jj=1;
    aux = 0;
    while jj<ii
        aux = aux + PSI(:,:,ii-jj)*VAR.Fp(:,:,jj);
        jj=jj+1;
    end
    PSI(:,:,ii) = aux;
end
```

```matlab
% Update VAR with Wold multipliers
VAR.PSI = PSI;


%% Identification: Recover B matrix
%=============================================================================
==========
% B matrix is recovered with Cholesky decomposition
if strcmp(VARopt.ident,'short')
    [out, chol_flag] = chol(sigma);
    if chol_flag~=0; error('VCV is not positive definite'); end
    B = out';
% B matrix is recovered with Cholesky on cumulative IR to infinity
elseif strcmp(VARopt.ident,'long')
    Finf_big = inv(eye(length(Fcomp))-Fcomp); % from the companion
    Finf = Finf_big(1:nvar,1:nvar);
    D  = chol(Finf*sigma*Finf')'; % identification: u2 has no effect on y1 in the long run
    B = Finf\D;
% B matrix is recovered with SR.m
elseif strcmp(VARopt.ident,'sign')
    if isempty(VAR.B)
        error('You need to provide the B matrix with SR.m and/or SignRestrictions.m')
    else
        B = VAR.B;
    end
% B matrix is recovered with external instrument IV
elseif strcmp(VARopt.ident,'iv')
    % Recover residuals (first variable is the one to be instrumented - order matters!)
    up = VAR.resid(:,1);     % residuals to be instrumented
    uq = VAR.resid(:,2:end); % residulas for second stage

    % Make sample of IV comparable with up and uq
    [aux, fo, lo] = CommonSample([up IV(VAR.nlag+1:end,:)]);
    p = aux(:,1);
    q = uq(end-length(p)+1:end,:); pq = [p q];
    Z = aux(:,2:end);

    % Run first stage regression and fitted
    FirstStage = OLSmodel(p,Z);
    p_hat = FirstStage.yhat;

    % Recover first column of B matrix with second stage regressions
    b(1,1) = 1;  % Start with impact IR normalized to 1
    sqsp = zeros(size(q,2),1);
    for ii=2:nvar
        SecondStage = OLSmodel(q(:,ii-1),p_hat);
        b(ii,1) = SecondStage.beta(2);
        sqsp(ii-1) = SecondStage.beta(2);
    end
    % Update size of the shock (ftn 4 of Gertler and Karadi (2015))
    sigma_b = (1/(length(pq)-VAR.ntotcoeff))*...
        (pq-repmat(mean(pq),size(pq,1),1))'*...
```

```matlab
        (pq-repmat(mean(pq),size(pq,1),1));
    s21s11 = sqsp;
    S11 = sigma_b(1,1);
    S21 = sigma_b(2:end,1);
    S22 = sigma_b(2:end,2:end);
    Q = s21s11*S11*s21s11'-(S21*s21s11'+s21s11*S21')+S22;
    sp = sqrt(S11-(S21-s21s11*S11)'*(Q\(S21-s21s11*S11)));
    % Rescale b vector
    b = b*sp;
    B = zeros(nvar,nvar);
    B(:,1) = b;
% If none of the above, you've done somerthing wrong :)
else
    disp('---------------------------------------------')
    disp('Identification incorrectly specified.')
    disp('Choose one of the following options:');
    disp('- short: zero contemporaneous restrictions');
    disp('- long:  zero long-run restrictions');
    disp('- sign:  sign restrictions');
    disp('- iv:  external instrument');
    disp('---------------------------------------------')
    error('ERROR. See details above');
end


%%% Compute the impulse response
%==================================================================
==========
for mm=1:nvar
    % Set to zero a row of the companion matrix if "shut" is selected
    if shut~=0
        Fcomp(shut,:) = 0;
    end
    % Initialize the impulse response vector
    response = zeros(nvar, nsteps);
    % Create the impulse vector
    impulse = zeros(nvar,1);
    % Set the size of the shock
    if impact==0
        impulse(mm,1) = 1; % one stdev shock
    elseif impact==1
        impulse(mm,1) = 1/B(mm,mm); % unitary shock
    else
        error('Impact must be either 0 or 1');
    end
    % First period impulse response (=impulse vector)
    response(:,1) = B*impulse;
    % Shut down the response if "shut" is selected
    if shut~=0
        response(shut,1) = 0;
    end
    % Recursive computation of impulse response
```

```matlab
        if strcmp(recurs,'wold')
            for kk = 2:nsteps
                response(:,kk) = PSI(:,:,kk)*B*impulse;
            end
        elseif strcmp(recurs,'comp')
            for kk = 2:nsteps
                FcompN = Fcomp^(kk-1);
                response(:,kk) = FcompN(1:nvar,1:nvar)*B*impulse;
            end
        end
    IR(:,:,mm) = response';
end
% Update VAR with structural impact matrix
VAR.B = B;
if strcmp(VARopt.ident,'iv')
    VAR.FirstStage = FirstStage;
    VAR.sigma_b = sigma_b;
    VAR.b = b;
end


function [INF,SUP,MED,BAR] = VARirband(VAR,VARopt)
%
%=========================================================================
====
% Calculate confidence intervals for impulse response functions computed
% with VARir
%
%=========================================================================
====
% [INF,SUP,MED,BAR] = VARirband(VAR,VARopt)
% -----------------------------------------------------------------------
% INPUTS
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----------------------------------------------------------------------
% OUTPUT
%   - INF(:,:,:): lower confidence band (H horizons, N variables, N shocks)
%   - SUP(:,:,:): upper confidence band (H horizons, N variables, N shocks)
%   - MED(:,:,:): median response (H horizons, N variables, N shocks)
%   - BAR(:,:,:): mean response (H horizons, N variables, N shocks)
% -----------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
%=========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------
```

```matlab
%%% Check inputs
%-------------------------------------------------------------------
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end


%%% Retrieve and initialize variables
%-------------------------------------------------------------------
nsteps = VARopt.nsteps;
ndraws = VARopt.ndraws;
pctg   = VARopt.pctg;
method = VARopt.method;

Ft     = VAR.Ft;  % this if \Phi' in the notes (rows are coeffs, columns are eqs)
nvar    = VAR.nvar;
nvar_ex = VAR.nvar_ex;
nlag    = VAR.nlag;
nlag_ex = VAR.nlag_ex;
const   = VAR.const;
nobs    = VAR.nobs;
resid   = VAR.resid;
ENDO    = VAR.ENDO;
EXOG    = VAR.EXOG;
IV      = VAR.IV;

INF = zeros(nsteps,nvar,nvar);
SUP = zeros(nsteps,nvar,nvar);
MED = zeros(nsteps,nvar,nvar);
BAR = zeros(nsteps,nvar,nvar);

%%% Create the matrices for the loop
%-------------------------------------------------------------------
y_artificial = zeros(nobs+nlag,nvar);


%%% Loop over the number of draws
%-------------------------------------------------------------------
tt = 1; % numbers of accepted draws
ww = 1; % index for printing on screen
while tt<=ndraws

    % Display number of loops
    if tt==VARopt.mult*ww
        disp(['Loop ' num2str(tt) ' / ' num2str(ndraws) ' draws'])
        ww=ww+1;
    end
```

```matlab
%% STEP 1: choose the method and generate the residuals
    if strcmp(method,'bs')
        % Use the residuals to bootstrap: generate a random number bounded
        % between 0 and # of residuals, then use the ceil function to select
        % that row of the residuals (this is equivalent to sampling with replacement)
        u = resid(ceil(size(resid,1)*rand(nobs,1)),:);
    elseif strcmp(method,'wild')
        % Wild bootstrap based on simple distribution (~Rademacher)
        if strcmp(VARopt.ident,'iv')
            rr = 1-2*(rand(nobs,size(IV,2))>0.5);
            u = resid.*(rr*ones(size(IV,2),nvar));
            Z = [IV(1:nlag,:); IV(nlag+1:end,:).*rr];
        else
            rr = 1-2*(rand(nobs,1)>0.5);
            u = resid.*(rr*ones(1,nvar));
        end
    else
        error(['The method ' method ' is not available'])
    end

%% STEP 2: generate the artificial data

    %% STEP 2.1: initial values for the artificial data
    % Intialize the first nlag observations with real data
    LAG=[];
    for jj = 1:nlag
        y_artificial(jj,:) = ENDO(jj,:);
        LAG = [y_artificial(jj,:) LAG];
    end
    % Initialize the artificial series and the LAGplus vector
    T = [1:nobs]';
    if const==0
        LAGplus = LAG;
    elseif const==1
        LAGplus = [1 LAG];
    elseif const==2
        LAGplus = [1 T(1) LAG];
    elseif const==3
        T = [1:nobs]';
        LAGplus = [1 T(1) T(1).^2 LAG];
    end
    if nvar_ex~=0
        LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
    end

    %% STEP 2.2: generate artificial series
    % From observation nlag+1 to nobs, compute the artificial data
    for jj = nlag+1:nobs+nlag
        for mm = 1:nvar
            % Compute the value for time=jj
            y_artificial(jj,mm) = LAGplus * Ft(1:end,mm) + u(jj-nlag,mm);
        end
    end
```

```matlab
        % now update the LAG matrix
        if jj<nobs+nlag
            LAG = [y_artificial(jj,:) LAG(1,1:(nlag-1)*nvar)];
            if const==0
                LAGplus = LAG;
            elseif const==1
                LAGplus = [1 LAG];
            elseif const==2
                LAGplus = [1 T(jj-nlag+1) LAG];
            elseif const==3
                LAGplus = [1 T(jj-nlag+1) T(jj-nlag+1).^2 LAG];
            end
            if nvar_ex~=0
                LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
            end
        end
    end

%% STEP 3: estimate VAR on artificial data.
    if nvar_ex~=0
        [VAR_draw, ~] = VARmodel(y_artificial,nlag,const,EXOG,nlag_ex);
    else
        [VAR_draw, ~] = VARmodel(y_artificial,nlag,const);
    end
    % If "iv" identification is selected, update VAR_draw with bootstrapped
    %instrument
    if exist('Z','var')
        VAR_draw.IV = Z;
    end

%% STEP 4: calculate "ndraws" impulse responses and store them
    % Uses options from VARopt and parameters from VAR_draw (from step 3)
    % to compute IRFs
    [IR_draw, VAR_draw] = VARir(VAR_draw,VARopt);
    if VAR_draw.maxEig<.9999
        IR(:,:,:,tt) = IR_draw;
        tt=tt+1;
    end
end
disp('-- Done!');
disp(' ');

%% Compute the error bands
%-------------------------------------------------------------------
pctg_inf = (100-pctg)/2;
pctg_sup = 100 - (100-pctg)/2;
INF(:,:,:) = prctile(IR(:,:,:,:),pctg_inf,4);
SUP(:,:,:) = prctile(IR(:,:,:,:),pctg_sup,4);
MED(:,:,:) = prctile(IR(:,:,:,:),50,4);
BAR(:,:,:) = mean(IR(:,:,:,:),4);
```

```matlab
function VARirplot(IR,VARopt,INF,SUP)
%
% =================================================================
====
% Plot the IRs computed with VARir
%
% =================================================================
====
% VARirplot(IR,VARopt,vnames,INF,SUP)
% -------------------------------------------------------------------
% INPUT
%   - IR(:,:,:) : matrix with IRF (H horizons, N variables, N shocks)
%   - VARopt: options of the VAR (see VARopt from VARmodel)
% -------------------------------------------------------------------
% OPTIONAL INPUT
%   - INF: lower error band
%   - SUP: upper error band
% -------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
% =================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated April 2021
% -------------------------------------------------------------------


%% Check inputs
%===============================================
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end
% If there is VARopt get the vnames
vnames = VARopt.vnames;
% Check they are not empty
if isempty(vnames)
    error('You need to add label for endogenous variables in VARopt');
end
% Define shock names
if isempty(VARopt.snames)
    snames = VARopt.vnames;
else
    snames = VARopt.snames;
end

%% Retrieve and initialize variables
%===============================================
filename = [VARopt.figname 'IR_'];
quality = VARopt.quality;
```

```matlab
suptitle = VARopt.suptitle;
pick = VARopt.pick;

% Initialize IR matrix
[nsteps, nvars, nshocks] = size(IR);

% If one shock is chosen, set the right value for nshocks
if pick<0 || pick>nvars
    error('The selected shock is non valid')
else
    if pick==0
        pick=1;
    else
        nshocks = pick;
    end
end

% Define the rows and columns for the subplots
row = 3;
col = 3;

% Define a timeline
steps = 1:1:nsteps;
x_axis = zeros(1,nsteps);


%% Plot
%=================================================
SwatheOpt = PlotSwatheOption;
SwatheOpt.trans = 1;
FigSize(VARopt.FigSize(1),VARopt.FigSize(2))
for jj=pick:nshocks
    for ii=1:nvars
        subplot(row,col,ii);
        plot(steps,IR(:,ii,jj),'LineStyle','-','Color','k','LineWidth',2); hold on
        if exist('INF','var') && exist('SUP','var')
            PlotSwathe(IR(:,ii,jj),[INF(:,ii,jj) SUP(:,ii,jj)],SwatheOpt); hold on;
        end
        plot(x_axis,'--k','LineWidth',0.5); hold on
        xlim([1 nsteps]);
        pbaspect([2 1 1])
        title([vnames{ii}], 'FontWeight','bold','FontSize',10);
        set(gca, 'Layer', 'top');
    end
    % Save
    FigName = [filename num2str(jj)];
    SupTitle(['IR of a shock to '  vnames{jj}])
    if quality
        set(gcf, 'Color', 'b');
        export_fig(FigName,'-pdf','-painters')
    else
        print('-bestfit','-dpdf','-r100',FigName);
```

```matlab
    end
    clf('reset');
end

close all

function [VD, VAR] = VARvd(VAR,VARopt)
%
==========================================================================
====
% Compute forecast error variance decompositions (VDs) for a VAR model
% estimated with the VARmodel.m function. Three identification schemes can
% be specified: zero contemporaneous restrictions, zero long-run
% restrictions, and sign restrictions
%
==========================================================================
====
% [VD, VAR] = VARvd(VAR,VARopt)
% -----------------------------------------------------------------------
% INPUT
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----------------------------------------------------------------------
% OUTPUT
%   - VD(:,:,:): matrix with FEVDs (H horizons, N shocks, N variables)
%   - VAR: structure including VAR estimation results
%      * VAR.B: strcutral impact matrix
% -----------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
==========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------


%% Check inputs
%=========================================================================
=========
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
IV = VAR.IV;
if strcmp(VARopt.ident,'iv')
    disp('-------------------------------------------')
    disp('Forecast error variance decomposition not available with')
    disp('external instruments identification (iv)');
    disp('-------------------------------------------')
```
156

```matlab
    error('ERROR. See details above');
end


%% Retrieve and initialize variables
%=========================================================================
=========
nsteps = VARopt.nsteps;
ident  = VARopt.ident;
Fcomp  = VAR.Fcomp;
nlag   = VAR.nlag;
nvar   = VAR.nvar;
sigma  = VAR.sigma;
VD     = zeros(nsteps,nvar,nvar);
SE     = zeros(nsteps,nvar);
MSE    = zeros(nvar,nvar,nsteps);
MSE_shock = zeros(nvar,nvar,nsteps);

%% Compute Wold representation
%=========================================================================
=========
% Initialize Wold multipliers
PSI = zeros(nvar,nvar,nsteps);
% Re-write F matrix to compute multipliers
VAR.Fp = zeros(nvar,nvar,nlag);
I = VAR.const+1;
for kk=1:nsteps
    if kk<=nlag
        VAR.Fp(:,:,kk) = VAR.F(:,I:I+nvar-1);
    else
        VAR.Fp(:,:,kk) = zeros(nvar,nvar);
    end
    I = I + nvar;
end
% Compute multipliers
PSI(:,:,1) = eye(nvar);
for kk=2:nsteps
    jj=1;
    aux = 0;
    while jj<kk
        aux = aux + PSI(:,:,kk-jj)*VAR.Fp(:,:,jj);
        jj=jj+1;
    end
    PSI(:,:,kk) = aux;
end
% Update VAR with Wold multipliers
VAR.PSI = PSI;


%% Identification: Recover B matrix
%=========================================================================
=========
```

```matlab
% B matrix is recovered with Cholesky decomposition
if strcmp(ident,'short')
    [out, chol_flag] = chol(sigma);
    if chol_flag~=0; error('VCV is not positive definite'); end
    B = out';
% B matrix is recovered with Cholesky on cumulative IR to infinity
elseif strcmp(ident,'long')
    Finf_big = inv(eye(length(Fcomp))-Fcomp); % from the companion
    Finf = Finf_big(1:nvar,1:nvar);
    D  = chol(Finf*sigma*Finf')'; % identification: u2 has no effect on y1 in the long run
    B = Finf\D;
% B matrix is recovered with SR.m
elseif strcmp(ident,'sign')
    if isempty(VAR.B)
        error('You need to provide the B matrix with SR.m and/or SignRestrictions.m')
    else
        B = VAR.B;
    end
% B matrix is recovered with external instrument IV
elseif strcmp(ident,'iv')
    disp('-------------------------------------------')
    disp('Forecast error variance decomposition not available yet ')
    disp('with external instruments identification (iv)');
    disp('-------------------------------------------')
    error('ERROR. See details above');
% If none of the above, you've done somerthing wrong :)
else
    disp('-------------------------------------------')
    disp('Identification incorrectly specified.')
    disp('Choose one of the following options:');
    disp('- short: zero contemporaneous restrictions');
    disp('- long:  zero long-run restrictions');
    disp('- sign:  sign restrictions');
    disp('- iv:    external instrument');
    disp('-------------------------------------------')
    error('ERROR. See details above');
end


%% Calculate the contribution to the MSE for each shock (i.e, VD)
%=================================================================
=========
for ii = 1:nvar % loop for the shocks

    % The 1-step ahead variance of the forecast error is the variance of
    % the residulas (sigma).
    MSE(:,:,1) = sigma;
    for nn = 2:nsteps
        MSE(:,:,nn) = MSE(:,:,nn-1) + PSI(:,:,nn)*sigma*PSI(:,:,nn)';
    end
    % The 1-step ahead variance of the mm^th structural forecast error is
    % the square of the mm^th column of the structural impact matrix (B)
```

```matlab
        MSE_shock(:,:,1) = B(:,ii)*B(:,ii)';
        for nn = 2:nsteps
            MSE_shock(:,:,nn) = MSE_shock(:,:,nn-1) + PSI(:,:,nn)*MSE_shock(:,:,1)*PSI(:,:,nn)';
        end

        % Compute the Forecast Error Covariance Decomposition
        FECD = MSE_shock(1:nvar,1:nvar,:)./MSE(1:nvar,1:nvar,:);

        % Select only the variance terms
        for nn = 1:nsteps
            for kk = 1:nvar
                VD(nn,ii,kk) = 100*FECD(kk,kk,nn);
                SE(nn,:) = sqrt(diag(MSE(1:nvar,1:nvar,nn))' );
            end
        end
end

% Update VAR with structural impact matrix
VAR.B = B;



function [INF,SUP,MED,BAR] = VARvdband(VAR,VARopt)
%
%========================================================================
====
% Calculate confidence intervals for forecast error variance decomposition
% computed with VARvd
%
%========================================================================
====
% [INF,SUP,MED,BAR] = VARvdband(VAR,VARopt)
% -----------------------------------------------------------------------
% INPUTS
%   - VAR: structure, result of VARmodel.m
%   - VARopt: options of the VAR (result of VARmodel.m)
% -----------------------------------------------------------------------
% OUTPUT
%   - INF(:,:,:): lower confidence band (H horizons, N shocks, N variables)
%   - SUP(:,:,:): upper confidence band (H horizons, N shocks, N variables)
%   - MED(:,:,:): median response (H horizons, N shocks, N variables)
%   - BAR(:,:,:): mean response (H horizons, N shocks, N variables)
% -----------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
%========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated November 2020
% -----------------------------------------------------------------------
```

```matlab
%%% Check inputs
%-------------------------------------------------------------------------
if ~exist('VAR','var')
    error('You need to provide VAR structure, result of VARmodel');
end
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end


%%% Retrieve and initialize variables
%-------------------------------------------------------------------------
nsteps  = VARopt.nsteps;
ndraws  = VARopt.ndraws;
pctg    = VARopt.pctg;
method  = VARopt.method;
Ft      = VAR.Ft; % rows are coefficients, columns are equations
nvar    = VAR.nvar;
nvar_ex = VAR.nvar_ex;
nlag    = VAR.nlag;
nlag_ex = VAR.nlag_ex;
const   = VAR.const;
nobs    = VAR.nobs;
resid   = VAR.resid;
ENDO    = VAR.ENDO;
EXOG    = VAR.EXOG;

INF = zeros(nsteps,nvar,nvar);
SUP = zeros(nsteps,nvar,nvar);
MED = zeros(nsteps,nvar,nvar);
BAR = zeros(nsteps,nvar,nvar);

%%% Create the matrices for the loop
%-------------------------------------------------------------------------
y_artificial = zeros(nobs+nlag,nvar);

%%% Loop over the number of draws
%-------------------------------------------------------------------------

tt = 1; % numbers of accepted draws
ww = 1; % index for printing on screen
while tt<=ndraws

    % Display number of loops
    if tt==10*ww
        disp(['Loop ' num2str(tt) ' / ' num2str(ndraws) ' draws'])
        ww=ww+1;
    end

%%% STEP 1: choose the method and generate the residuals
```

```matlab
    if strcmp(method,'bs')
        % Sampling with replacement
        u = resid(ceil(size(resid,1)*rand(nobs,1)),:);
    elseif strcmp(method,'wild')
        % Wild bootstrap based on simple distribution (~Rademacher)
        rr = 1-2*(rand(nobs,1)>0.5);
        u = resid.*(rr*ones(1,nvar));
    else
        error(['The method ' method ' is not available'])
    end

%% STEP 2: generate the artificial data

    %% STEP 2.1: generate initial values for the artificial data
    % Intialize the first nlag observations with real data
    LAG=[];
    for jj = 1:nlag
        y_artificial(jj,:) = ENDO(jj,:);
        LAG = [y_artificial(jj,:) LAG];
    end
    % Initialize the artificial series and the LAGplus vector
    T = [1:nobs]';
    if const==0
        LAGplus = LAG;
    elseif const==1
        LAGplus = [1 LAG];
    elseif const==2
        LAGplus = [1 T(1) LAG];
    elseif const==3
        T = [1:nobs]';
        LAGplus = [1 T(1) T(1).^2 LAG];
    end
    if nvar_ex~=0
        LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
    end

    %% STEP 2.2: generate artificial series
    % From observation nlag+1 to nobs, compute the artificial data
    for jj = nlag+1:nobs+nlag
        for mm = 1:nvar
            % Compute the value for time=jj
            y_artificial(jj,mm) = LAGplus * Ft(1:end,mm) + u(jj-nlag,mm);
        end
        % now update the LAG matrix
        if jj<nobs+nlag
            LAG = [y_artificial(jj,:) LAG(1,1:(nlag-1)*nvar)];
            if const==0
                LAGplus = LAG;
            elseif const==1
                LAGplus = [1 LAG];
            elseif const==2
                LAGplus = [1 T(jj-nlag+1) LAG];
```

161

```
            elseif const==3
                LAGplus = [1 T(jj-nlag+1) T(jj-nlag+1).^2 LAG];
            end
            if nvar_ex~=0
                LAGplus = [LAGplus VAR.X_EX(jj-nlag+1,:)];
            end
        end
    end
```

%%% STEP 3: estimate VAR on artificial data
```
    if nvar_ex~=0
        [VAR_draw, ~] = VARmodel(y_artificial,nlag,const,EXOG,nlag_ex);
    else
        [VAR_draw, ~] = VARmodel(y_artificial,nlag,const);
    end
```

%%% STEP 4: calculate "ndraws" vd and store them

```
    [vd_draw, VAR_draw_opt] = VARvd(VAR_draw,VARopt); % uses options from VARopt,
```
but parameters etc. from VAR_draw

```
    if VAR_draw_opt.maxEig<.9999
        VD(:,:,:,tt) = vd_draw;
        tt=tt+1;
    end
end
disp('-- Done!');
disp(' ');
```

%%% Compute the error bands
```
%-------------------------------------------------------------------------
pctg_inf = (100-pctg)/2;
pctg_sup = 100 - (100-pctg)/2;
INF(:,:,:) = prctile(VD(:,:,:,:),pctg_inf,4);
SUP(:,:,:) = prctile(VD(:,:,:,:),pctg_sup,4);
MED(:,:,:) = prctile(VD(:,:,:,:),50,4);
BAR(:,:,:) = mean(VD(:,:,:,:),4);
```

```
function VARvdplot(VD,VARopt)
%
%=========================================================================
====
% Plot the VDs computed with VARvd
%
%=========================================================================
====
% VARvdplot(VD,VARopt)
% -----------------------------------------------------------------------
% INPUT
%   - VD(:,:,:): matrix with 't' steps, the VD due to 'j' shock for
%      'k' variable
%   - VARopt: options of the VDs (see VARoption)
```
162

```matlab
% -----------------------------------------------------------------------
% OPTIONAL INPUT
%   - INF: lower error band
%   - SUP: upper error band
% -----------------------------------------------------------------------
% EXAMPLE
%   - See VARToolbox_Code.m in "../Primer/"
%
% =========================================================================
====
% VAR Toolbox 3.0
% Ambrogio Cesa-Bianchi
% ambrogiocesabianchi@gmail.com
% March 2012. Updated April 2021
% -----------------------------------------------------------------------


%% Check inputs
%=========================================================================
=========
if ~exist('VARopt','var')
    error('You need to provide VAR options (VARopt from VARmodel)');
end
% If there is VARopt check that vnames is not empty
vnames = VARopt.vnames;
if isempty(vnames)
    error('You need to add label for endogenous variables in VARopt');
end
% Define shock names
if isempty(VARopt.snames)
    snames = VARopt.vnames;
else
    snames = VARopt.snames;
end


%% Retrieve and initialize variables
%=========================================================================
=========
filename = [VARopt.figname 'VD'];
quality = VARopt.quality;
suptitle = VARopt.suptitle;
pick = VARopt.pick;

% Initialize VD matrix
[nsteps, nvars, nshocks] = size(VD);

% If one variable is chosen, set the right value for nvars
if pick<0 || pick>nvars
    error('The selected variable is non valid')
else
    if pick==0
```

```matlab
        pick=1;
    else
        nvars = pick;
    end
end

% Define the rows and columns for the subplots
row = 2;
col = 2;

% Define a timeline
steps = 1:1:nsteps;
x_axis = zeros(1,nsteps);



%%% Plot
%===========================================================================
=========
% Area plot
FigSize(VARopt.FigSize(1),VARopt.FigSize(2))
for ii=1:nvars
    subplot(row,col,ii);
    H = AreaPlot(VD(:,:,ii));
    xlim([1 nsteps]); ylim([0 100]);
    title(vnames{ii}, 'FontWeight','bold','FontSize',10);
    set(gca, 'Layer', 'top');
end
% Save
FigName = [filename];
if quality
    if suptitle==1
        Alphabet = char('a'+(1:nshocks)-1);
        SupTitle([Alphabet(ii) ') VD of '  vnames{ii}])
    end
    opt = LegOption; opt.handle = H(1,:);
    LegSubplot(snames,opt);
    set(gcf, 'Color', 'w');
    export_fig(FigName,'-pdf','-painters')
else
    legend(H(1,:),snames)
    print('-fillpage','-dpdf','-r100',FigName);
end

close all
```

European Policy Macroeconomic Dynamics VAR-4 models and FEVDs, U=1 sample case (generate_ss_VAR_European_Policy_4.m).

```matlab
%%------------------------------------------------------------------
% Var 4 for European policy analysis
%%------------------------------------------------------------------
clear;clc;

[data,txt] = xlsread('VarDataSSEuropeanIntRateu.xlsx');
txt=txt(:,1:end);
load aggu;

shortrate  =   (data(:,3));
piez       = log(data(:,1));
cpiez      = log(data(:,2));
utcsa      =   (data(:,4));


X= [ piez, cpiez, shortrate, utcsa];


const_trend = 2;

% Choose number of lags
nbr_lags = 2;

% model
[VAR, VARopt] = VARmodel(X,nbr_lags,const_trend);

%%% OPTIONS

%Vnames
VARopt.vnames = { 'Production Eurozone' 'CPI Eurozone' 'Short Int Rate ECB'  'U(1)' };

% number of steps for computation of IRFs and FEVDs
VARopt.nsteps = 20;

% size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.impact = 0;

%frequency
VARopt.frequency = 'q';

% Recursive Identification with zero-short run/contemporaneous restriction
VARopt.ident = 'short';

%'bs' standard bootstrap, 'wild' wild bootstrap
VARopt.method = 'bs';

% method for computation of recursive stuff ('wold' form MA representation, 'comp' for
companion form)
```

```matlab
VARopt.recurs   = 'wold';

% confidence level for bootstrap, default = 95
VARopt.pctg = 68;

% name of the shocks
VARopt.snames = VARopt.vnames;

%select on variable to plot, if=0 plot all
VARopt.pick = 0;

%printing
[TABLE_VAR, beta] = VARprint(VAR,VARopt);

%%% IR

% Apply the identification scheme and compute impulse responses
[IRF,VAR] = VARir(VAR,VARopt);

%BANDS
[IRF_lower,IRF_upper,IRF_median,IRF_mean] = VARirband(VAR,VARopt);

%%% Figures related options

VARopt.savefigs = true;

VARopt.quality  = 0;

VARopt.FigSize  = [12,8];

%%% Plot impulse response functions
VARirplot(IRF_mean,VARopt,IRF_lower,IRF_upper);
```

European Policy Macroeconomic Dynamics VAR-6 models and FEVDs, U=1 sample case (generate_ss_VAR_European_Policy_6.m).

```
%%------------------------------------------------------------------
% Var 6 for European policy analysis
%%------------------------------------------------------------------
clear;clc;

[data,txt] = xlsread('VarDataSSEuropeanPolicy6_U.xlsx');
txt=txt(:,1:end);
load aggu;

piez     = log(data(:,1));
empez   =    (data(:,2));
unempez =    (data(:,3));
cpiez    = log(data(:,4));
intrate  =    (data(:,5));
u     =       (data(:,6));


X= [ piez,empez, unempez, cpiez, intrate, u];


const_trend = 2;

% Choose number of lags
nbr_lags = 2;

% model
[VAR, VARopt] = VARmodel(X,nbr_lags,const_trend);

%%% OPTIONS

%Vnames
VARopt.vnames = {'Production Eurozone' 'Employment Eurozone' 'Unemployment
Eurozone' 'Eurozone CPI' 'ECB short term int rate' 'U(1)Italy' };

% number of steps for computation of IRFs and FEVDs
VARopt.nsteps = 20;

% size of the shock for IRFs: 0=1stdev, 1=unit shock
VARopt.impact = 0;

%frequency
VARopt.frequency = 'q';

% Recursive Identification with zero-short run/contemporaneous restriction
VARopt.ident = 'short';

%'bs' standard bootstrap, 'wild' wild bootstrap
VARopt.method = 'bs';
```

```matlab
% method for computation of recursive stuff ('wold' form MA representation, 'comp' for
companion form)
VARopt.recurs    = 'wold';

% confidence level for bootstrap, default = 95
VARopt.pctg = 68;

% name of the shocks
VARopt.snames = VARopt.vnames;

%select on variable to plot, if=0 plot all
VARopt.pick = 0;

%printing
%[TABLE_VAR, beta] = VARprint(VAR,VARopt);

%% IR

% Apply the identification scheme and compute impulse responses
[IRF,VAR] = VARir(VAR,VARopt);

%BANDS
[IRF_lower,IRF_upper,IRF_median,IRF_mean] = VARirband(VAR,VARopt);

%% Figures related options

VARopt.savefigs = true;

VARopt.quality  = 0;

VARopt.FigSize  = [12,8];

%% Plot impulse response functions
VARirplot(IRF_mean,VARopt,IRF_lower,IRF_upper);
```

Matlab Codes for Figures

Figure 18- 19- 20- 21- 22- 26- 27- 29- 30- 33- 34 already represented in previous codes.

Figure 1-2 Uncertainty Measures CSA and PCA

```matlab
% -------------------------------------------------------------------------
% Plot aggregate uncertainty estimates CSA and PCA
% -------------------------------------------------------------------------

% Load estimates
clear; clc; close all;
load aggu;
T = length(dates);

% Plot csa estimates
fig1 = figure(1);
u1  = utcsa(:,1);
u4 = utcsa(:,4);
plot(dates,u1,'color','#0dade3','linewidth',2); hold on;
plot(dates,u4,'color','#086f91','linewidth',2);
plot([dates(1),dates(end)],(mean(u1)+1.65*std(u1)).*[1,1],'--k');
plot([dates(1),dates(end)],(mean(u4)+1.65*std(u4)).*[1,1],'--k');
txt4 = '$\overline{\mathcal{U}}^y_t(4)$';
txt1  = '$\overline{\mathcal{U}}^y_t(1)$';
text(2002,0.75,txt4,'interpreter','latex','color','#086f91');
text(2002,0.57,txt1,'interpreter','latex','color','#0dade3');
xlim([dates(1),dates(end)]);
ylim([0.55,1]);

title('Uncertainty Measure csa');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','aggu_csa');

% Plot pca estimates
fig2 = figure(2);
u1  = utpca(:,1);
u4 = utpca(:,4);
plot(dates,u1,'color','#0dade3','linewidth',2); hold on;
plot(dates,u4,'color','#086f91','linewidth',2);
plot([dates(1),dates(end)],(mean(u1)+1.65*std(u1)).*[1,1],'--k');
plot([dates(1),dates(end)],(mean(u4)+1.65*std(u4)).*[1,1],'--k');
txt4 = '$\widehat{\mathcal{U}}^y_t(4)$';
txt1  = '$\widehat{\mathcal{U}}^y_t(1)$';
text(2002,0.74,txt4,'interpreter','latex','color','#086f91');
text(2002,0.57,txt1,'interpreter','latex','color','#0dade3');
xlim([dates(1),dates(end)]);
```

```matlab
ylim([0.55,1]);

title('Uncertainty Measure pca');

% Print figure
dim = [6,6];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig2,'-dpdf','aggu_pca');
```

Figure 3-4 Uncertainty Measures Comparison CSA vs. PCA

```matlab
% ----------------------------------------------------------------------
% Plot aggregate uncertainty estimates to compare
% ----------------------------------------------------------------------

% Load estimates
clear; clc; close all;
load aggu;
T = length(dates);

% Plot csa and pca estimates together u=1
fig1 = figure(1);
ucsa1  = utcsa(:,1);
upca1 = utpca(:,1);
plot(dates,ucsa1,'color','#0dade3','linewidth',2); hold on;
plot(dates,upca1,'color','#6ed5f7','linewidth',1);
txt4 = '$\widehat{\mathcal{U}}^y_t(1)pca$';
txt1  = '$\overline{\mathcal{U}}^y_t(1)csa$';
text(1999,0.57,txt4,'interpreter','latex','color','#6ed5f7');
text(1999,0.675,txt1,'interpreter','latex','color','#0dade3');
xlim([dates(1),dates(end)]);
ylim([0.55,0.85]);

title('Uncertainty Measure (1) csa vs pca');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','aggu_csa_pca_comparisonu1');

% Plot csa and pca estimates together u=4
fig2 = figure(2);
ucsa4  = utcsa(:,4);
upca4 = utpca(:,4);
plot(dates,ucsa4,'color','#0dade3','linewidth',2); hold on;
plot(dates,upca4,'color','#6ed5f7','linewidth',1);
txt4 = '$\widehat{\mathcal{U}}^y_t(4)pca$';
txt1  = '$\overline{\mathcal{U}}^y_t(4)csa$';
text(1999,0.76,txt4,'interpreter','latex','color','#6ed5f7');
text(1999,0.83,txt1,'interpreter','latex','color','#0dade3');
xlim([dates(1),dates(end)]);
ylim([0.7,0.95]);

title('Uncertainty Measure (4) csa vs pca');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig2,'-dpdf','aggu_csa_pca_comparisonu4');
```

Figure 5 Italian Macro Uncertainty vs. U.S. Macro Uncertainty

```
% -----------------------------------------------------------------------
% Plot aggregate uncertainty estimates for italy and USA
% -----------------------------------------------------------------------

% Load estimates for italy
clear; clc; close all;
load aggu;
dates=dates(1:56,:);
utcsa=utcsa(1:56,1);
utpca=utpca(1:56,1);
T = length(dates);

%Load estimates for US
[mdata,mtxt] = xlsread('USdataUncertainty.xlsx',1);
mdata        = mdata(1:end,:);
usutcsa=mdata(:,1);
usutpca=mdata(:,2);

% Plot csa estimates
fig1 = figure(1);
u1  = utcsa(:,1);
u2 = usutcsa(:,1);
plot(dates,u1,'color','#0dade3','linewidth',2); hold on;
plot(dates,u2,'color','#000000','linewidth',1);
txt4 = '${\mathcal{US}}$';
txt1  = '${\mathcal{IT}}$';
text(2001,0.75,txt4,'interpreter','latex','color','#000000');
text(2001,0.58,txt1,'interpreter','latex','color','#0dade3');
xlim([dates(1),dates(end)]);
ylim([0.55,1.3]);

title('Uncertainty Measure csa Italy vs USA');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','aggu_csa_comparison_Italy_USA');

% Plot pca estimates
% Plot csa estimates
fig2 = figure(2);
u1  = utpca(:,1);
u2 = usutpca(:,1);
plot(dates,u1,'color','#0dade3','linewidth',2); hold on;
plot(dates,u2,'color','#000000','linewidth',1);
txt4 = '${\mathcal{US}}$';
txt1  = '${\mathcal{IT}}$';
text(2001,0.75,txt4,'interpreter','latex','color','#3366ff');
text(2001,0.57,txt1,'interpreter','latex','color','#000000');
xlim([dates(1),dates(end)]);
```

```matlab
ylim([0.55,1.3]);

title('Uncertainty Measure pca Italy vs USA');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig2,'-dpdf','aggu_pca_comparison_Italy_USA');
```

Figure 6. Predictors' Uncertainty

```matlab
% -----------------------------------------------------------------------
% Plot uncertainty of predictor variables (h = 1 only)
% -----------------------------------------------------------------------

% Load data
clear; clc; close all;
load ferrors;
svf = load('svfmeans.txt');

% Compute uncertainty
thf   = [svf(1,:).*(1-svf(2,:));svf(2,:);svf(3,:).^2];
xf    = svf(4:end-3,:);
[T,r] = size(xf);
uf    = zeros(T,r);
for i = 1:r
    uf(:,i) = exp(thf(1,i)+thf(3,i)/2 + thf(2,i).*xf(:,i));
end

% Plot results
fig = figure(1);
set(gcf,'defaultlinelinewidth',1.5);

subplot(2,2,1); plot(dates,uf(:,1));
xlim([dates(1),dates(end)]);ylim([0,0.1]);
title('$F_{1t}:$ P1','interpreter','latex');

subplot(2,2,2); plot(dates,uf(:,2));
xlim([dates(1),dates(end)]);ylim([0,0.25]);
title('$F_{2t}:$ P2','interpreter','latex');

subplot(2,2,3); plot(dates,uf(:,3));
xlim([dates(1),dates(end)]);ylim([0,0.1]);
title('$F_{1t}^2:$ P3','interpreter','latex');

subplot(2,2,4); plot(dates,uf(:,4));
xlim([dates(1),dates(end)]);ylim([0,0.7]);
title('$G_{1t}:$ P4','interpreter','latex');


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig,'-dpdf','utpredictor');
```

Figure 7. Keyseries

```matlab
% ---------------------------------------------------------------------
% Compare uncertainty estimates (np vs. p) for key series
% ---------------------------------------------------------------------

% Load data
clear; clc;
load ferrors; % for variable names
load npaggu;
h      = 1; % horizon to consider
ut0    = nput(:,:,h);
load aggu;
ut1    = ut(:,:,h);
[T,N,h] = size(ut);
ut0    = ut0(end-T+1:end,:);
individualspreads=(ut0-ut1);
totalspreads=sum(individualspreads);

% Select series to compare
ind    = [32,40,1,20,45,46,47,49];

% Plot results
fig = figure(1);
for i = 1:length(ind);
  subplot(4,2,i);
  plot(dates,sqrt(ut1(:,ind(i))),'color','#0dade3'); hold on;
  plot(dates,sqrt(ut0(:,ind(i))),'k','linewidth',1.5); hold off;
  title(names(ind(i)));
  xlim([dates(1),dates(end)]);
  if i==1; ylim([0,2]); spread=totalspreads(1,32); txt1=['s= ',num2str(spread)];
text(1999,1.5,txt1,'interpreter','latex','color','r'); end;
  if i==2; ylim([0,2]); spread=totalspreads(1,40); txt1=['s= ',num2str(spread)];
text(1999,0.2,txt1,'interpreter','latex','color','r'); end;
  if i==3; ylim([0,1.5]); spread=totalspreads(1,1); txt1=['s= ',num2str(spread)];
text(1999,1.3,txt1,'interpreter','latex','color','r'); end;
  if i==4; ylim([0,1.5]); spread=totalspreads(1,20); txt1=['s= ',num2str(spread)];
text(1999,1.3,txt1,'interpreter','latex','color','r'); end;
  if i==5; ylim([0,1.5]); spread=totalspreads(1,45); txt1=['s= ',num2str(spread)];
text(1999,1.3,txt1,'interpreter','latex','color','r'); end;
  if i==6; ylim([0,2.5]); spread=totalspreads(1,46); txt1=['s= ',num2str(spread)];
text(1999,2,txt1,'interpreter','latex','color','r'); end;
  if i==7; ylim([0,1.5]); spread=totalspreads(1,47); txt1=['s= ',num2str(spread)];
text(1999,1.4,txt1,'interpreter','latex','color','r'); end;
  if i==8; ylim([0,1.5]); spread=totalspreads(1,49); txt1=['s= ',num2str(spread)];
text(1999,1.4,txt1,'interpreter','latex','color','r'); end;
  if i==8;
    leg = legend('Baseline','No predictors');
    set(leg,'location','southeast','box','off');
    SupTitle('Keyseries');
  end
end
```

```matlab
% Print figure
dim = [6,7];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig,'-dpdf','keyseries');
```

Figure 8 Macro Uncertainty Measure vs. No- Predictors Macro Uncertainty

```matlab
% -----------------------------------------------------------------------
% Compare Macro uncertainty estimates (np vs. p)
% -----------------------------------------------------------------------

% Load estimates
clear; clc; close all;
load aggu;
putcsa=utcsa(:,1);
load npaggu;
nputcsa=utcsa(5:end,1);
dates=dates(5:end,:);
T = length(dates);


% Plot csa estimates for both aggu and npaggu for h=1
fig1 = figure(1);
up  = putcsa(:,1);
unp = nputcsa(:,1);
spread= trapz(unp)-trapz(up);

plot(dates,up,'color','#0dade3','linewidth',2); hold on;
plot(dates,unp,'color','#6ed5f7','linewidth',1);

txt1  = ['spread  = ',num2str(spread)];
text(1999,1.3,txt1,'interpreter','latex','color','#000000');

lab1 = sprintf('Uncertainty measure(1) with predictors');
lab3 = sprintf('Uncertainty measure(1) without predictors');
leg = legend(lab1,lab3);
set(leg,'location','northwest','box','off');

xlim([dates(1),dates(end)]);
ylim([0.5,1.5]);

title('aggu vs npaggu (1)');

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','aggu_vs_npaggu');
```

Figure 9- 10- 11 Macro Uncertainty vs Common Uncertainty Proxies

```matlab
% ----------------------------------------------------------------------
% Plot aggregate uncertainty estimates and other uncertainty measures
% ----------------------------------------------------------------------

% Load uncertainty measures
clear; clc; close all;
[utcsa1]=xlsread('UTCSA1.xlsx',2);
[wuii]=xlsread('WUII.xlsx',2);
[epuii]=xlsread('EPUII.xlsx',2);
[isv]=xlsread('ISV.xlsx',3);
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (13:end,:);

% Plot u-wuii
fig1= figure(1);
subplot(3,1,3);
U  = utcsa1(:,1);
WUII  = wuii(:,1);
plot(dates,U,'color','#0dade3','linewidth',2); hold on;
plot(dates,WUII,'color','#a366ff','linewidth',1);
plot([dates(1),dates(end)],(mean(WUII)+1.65*std(WUII)).*[1,1],'--k');
lab1 = sprintf('UNCERTAINTY MEASURE (1)');
lab2 = sprintf('WORLD UNCERTAINTY INDEX');
leg = legend(lab1,lab2);
leg.FontSize= 5;
set(leg,'location','northwest','box','off');
xlim([dates(1),dates(end)]);
ylim([-3,5]);

% Plot u-epuii
subplot(3,1,2);
U  = utcsa1(:,1);
EPUII = epuii(:,1);
plot(dates,U,'color','#0dade3','linewidth',2); hold on;
plot(dates,EPUII,'color','#ffcc00','linewidth',1);
plot([dates(1),dates(end)],(mean(EPUII)+1.65*std(EPUII)).*[1,1],'--k');
lab1 = sprintf('UNCERTAINTY MEASURE (1)');
lab3 = sprintf('ECONOMIC POLICY UNCERTAINTY INDEX');
leg = legend(lab1,lab3);
leg.FontSize= 5;
set(leg,'location','northwest','box','off');
xlim([dates(1),dates(end)]);
ylim([-3,5]);

% Plot u-isv
subplot(3,1,1);
U  = utcsa1(:,1);
ISV = isv(:,1);
plot(dates,U,'color','#0dade3','linewidth',2); hold on;
plot(dates,ISV,'color','r','linewidth',1);
plot([dates(1),dates(end)],(mean(ISV)+1.65*std(ISV)).*[1,1],'--k');
```

```matlab
lab1 = sprintf('UNCERTAINTY MEASURE (1)');
lab4 = sprintf('ITALIAN STOCK VOLATILITY');
leg = legend(lab1,lab4);
leg.FontSize= 5;
set(leg,'location','northwest','box','off');
xlim([dates(1),dates(end)]);
ylim([-3,5]);

% Print figure
dim = [6,5];
SupTitle('Uncertainty Measure vs other Uncertainty proxies');
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','UTCSA_vs_other_uncertainty_measures');
```

Figure 12 Uncertainty measures and IP growth rate

```matlab
% ------------------------------------------------------------------------
% Plot uncertainty estimates and IP growht
% ------------------------------------------------------------------------

% Load uncertainty measures
clear; clc; close all;
[utcsa1]=xlsread('UTCSA1.xlsx',2);
[wuii]=xlsread('WUII.xlsx',2);
[epuii]=xlsread('EPUII.xlsx',2);
[isv]=xlsread('ISV.xlsx',3);
[ipgrowth]=xlsread('ProductionIndexGrowth',2);
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (13:end,:);

% Plot u
subplot(2,2,1);
U1 = utcsa1(:,1);
ucorrip=corr(utcsa1,ipgrowth);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on
plot(dates,ipgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ucorrip)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('U(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot isv
subplot(2,2,2);
ISV = isv(:,1);
isvcorrip=corr(isv,ipgrowth);
plot(dates,ISV,'r','linewidth',1); hold on
plot(dates,ipgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(isvcorrip)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('ISV');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot epuii
subplot(2,2,3);
EPUII = epuii(:,1);
ecorrip=corr(epuii,ipgrowth);
plot(dates,EPUII,'color','#ffcc00','linewidth',1); hold on
plot(dates,ipgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ecorrip)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('EPUI');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot wuii
```

```matlab
fig1= figure(1);
subplot(2,2,4);
WUII  = wuii(:,1);
wcorrip=corr(wuii,ipgrowth);
plot(dates,ipgrowth,'k','linewidth',1); hold on
plot(dates,WUII,'color','#a366ff','linewidth',1);
txt1  = ['?= ', num2str(wcorrip)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
lab1 = 'IP growth';
leg = legend(lab1);
set(leg,'location','northeast','box','off','FontSize', 6);
title('WUI');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Print figure
dim = [6,5];
SupTitle('Uncertainty Measures and Industrial Production growth');
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','Uncertainty Measures and IP growth');
```

Figure 13 Uncertainty Measures and Employment Growth Rate

```matlab
% ----------------------------------------------------------------------
% Plot uncertainty estimates and EMP growht
% ----------------------------------------------------------------------

% Load uncertainty measures
clear; clc; close all;
[utcsa1]=xlsread('UTCSA1.xlsx',2);
[wuii]=xlsread('WUII.xlsx',2);
[epuii]=xlsread('EPUII.xlsx',2);
[isv]=xlsread('ISV.xlsx',3);
[empgrowth]=xlsread('EmploymentRateGrowth',2);
utcsa1=utcsa1(5:end,1);
isv=isv(5:end,1);
epuii=epuii(5:end,1);
wuii=wuii(5:end,1);
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (17:end,:);

% Plot u
subplot(2,2,1);
U1 = utcsa1(:,1);
ucorremp=corr(utcsa1,empgrowth);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on
plot(dates,empgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ucorremp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('U(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot isv
subplot(2,2,2);
ISV = isv(:,1);
isvcorremp=corr(isv,empgrowth);
plot(dates,ISV,'r','linewidth',1); hold on
plot(dates,empgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(isvcorremp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('ISV');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot epuii
subplot(2,2,3);
EPUII = epuii(:,1);
ecorremp=corr(epuii,empgrowth);
plot(dates,EPUII,'color','#ffcc00','linewidth',1); hold on
plot(dates,empgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ecorremp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('EPUI');
```

```matlab
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot wuii
fig1= figure(1);
subplot(2,2,4);
WUII  = wuii(:,1);
wcorremp=corr(wuii,empgrowth);
plot(dates,empgrowth,'k','linewidth',1);hold on
plot(dates,WUII,'color','#a366ff','linewidth',1);
txt1  = ['?= ', num2str(wcorremp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
lab1 = 'EMP growth';
leg = legend(lab1);
set(leg,'location','northeast','box','off','FontSize', 6);
title('WUI');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Print figure
dim = [6,5];
SupTitle('Uncertainty Measures and Employment growth');
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','Uncertainty Measures and EMP growth');
```

Figure 14 Uncertainty Measures and Unemployment Growth Rate

```
% ------------------------------------------------------------------------
% Plot uncertainty estimates and UNEMP growht
% ------------------------------------------------------------------------

% Load uncertainty measures
clear; clc; close all;
[utcsa1]=xlsread('UTCSA1.xlsx',2);
[wuii]=xlsread('WUII.xlsx',2);
[epuii]=xlsread('EPUII.xlsx',2);
[isv]=xlsread('ISV.xlsx',3);
[unempgrowth]=xlsread('UnemploymentRateGrowth',2);
utcsa1=utcsa1(5:end,1);
isv=isv(5:end,1);
epuii=epuii(5:end,1);
wuii=wuii(5:end,1);
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (17:end,:);

% Plot u
subplot(2,2,1);
U1 = utcsa1(:,1);
ucorrunemp=corr(utcsa1,unempgrowth);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on
plot(dates,unempgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ucorrunemp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('U(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot isv
subplot(2,2,2);
ISV = isv(:,1);
isvcorrunemp=corr(isv,unempgrowth);
plot(dates,ISV,'r','linewidth',1); hold on
plot(dates,unempgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(isvcorrunemp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('ISV');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot epuii
subplot(2,2,3);
EPUII = epuii(:,1);
ecorrunemp=corr(epuii,unempgrowth);
plot(dates,EPUII,'color','#ffcc00','linewidth',1); hold on
plot(dates,unempgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(ecorrunemp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('EPUI');
```

```matlab
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Plot wuii
fig1= figure(1);
subplot(2,2,4);
WUII  = wuii(:,1);
wcorrunemp=corr(wuii,unempgrowth);
plot(dates,unempgrowth,'k','linewidth',1); hold on
plot(dates,WUII,'color','#a366ff','linewidth',1);
txt1  = ['?= ', num2str(wcorrunemp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
lab1 = 'UNEMP growth';
leg = legend(lab1);
set(leg,'location','northeast','box','off','FontSize', 6);
title('WUI');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Print figure
dim = [6,5];
SupTitle('Uncertainty Measures and Unemployment growth');
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','Uncertainty Measures and UNEMP growth');
```

Figure 15 Macro Uncertainty Measure and Interpretation

```matlab
% -----------------------------------------------------------------------
% Plot aggregate uncertainty estimates + comments
% -----------------------------------------------------------------------

% Load estimates
clear; clc; close all;
load aggu;
T = length(dates);

%shades options
SwatheOpt = PlotSwatheOption;
SwatheOpt.trans = 1;

%load recession dates
[rdata,rtxt] = xlsread('rdatesitaly.xlsx',1);


% Load raw industrial production
[data,txt] = xlsread('ssrawdata.xlsx',1);
ipg = data(:,33);
ipg = [NaN;log(ipg(2:end)./ipg(1:end-1))];
ipg = tsmovavg(ipg,'s',4,1);
ipg = ipg(end-T+1:end)*100;


% Plot csa estimates
fig1 = figure(1);
u1  = utcsa(:,1);
plot(dates,u1,'color','#0dade3','linewidth',1.5); hold on;

for i=1:88
    if rdata(i)==1
      xline(dates(i),':r');
    end
end

txt1  = '$\overline{\mathcal{U}}^y_t(1)$';
text(1999.4,0.57,txt1,'interpreter','latex','color','#0dade3');

txt2  = '9/11';
text(2000,0.670,txt2,'interpreter','latex','color','k','FontSize',7);

txt3  = 'Dotcom bubble burst';
text(2000,0.677,txt3,'interpreter','latex','color','k','FontSize',7);

txt4  = 'Euro introduction';
text(2002,0.62,txt4,'interpreter','latex','color','k','FontSize',7);

txt5  = 'Global financial crisis';
text(2007,0.785,txt5,'interpreter','latex','color','k','FontSize',7);
```

```matlab
txt6  = 'Sovereign debt crisis';
text(2010.5,0.651,txt6,'interpreter','latex','color','k','FontSize',7);

txt7  = 'QE';
text(2015,0.61,txt7,'interpreter','latex','color','k','FontSize',7);

txt9  = 'Italian Banks' Crisis';
text(2015,0.619,txt9,'interpreter','latex','color','k','FontSize',7);

txt8  = 'Brexit';
text(2017.5,0.61,txt8,'interpreter','latex','color','k','FontSize',7);

xlim([dates(1),dates(end)]);
ylim([0.55,0.85]);


title('Uncertainty Measure(1) and its main causes');


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','aggu_csa_commented');
```

Figure 17 Sensitivity Analysis of our Uncertainty Measure

```matlab
% ---------------------------------------------------------------------
% Generate and save data for sensitivity analysis
% ---------------------------------------------------------------------

clear;clc;close all;

load aggu

load ulessCPI

load ulessPPI

load ulessLAB

load ulessIP

load ulessGDP

load ulessINTERN

load ulessINTRATE

load ulessHOUSING

load ulessSTOCK


dates   = 1900+(95:1/4:120-1/4)';
dates = dates (13:end,:);

%plot the data

fig= figure(1);

%U1
subplot(5,2,1);
U1  = utcsa(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1)');

%lessCPI
subplot(5,2,2);
U1  = utcsa(:,1);
u1lesscpi  = ulessCPI(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lesscpi,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less CPI');
```

```
%lessPPI
subplot(5,2,3);
U1  = utcsa(:,1);
u1lessppi  = ulessPPI(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lessppi,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less PPI');

%lessLAB
subplot(5,2,4);
U1  = utcsa(:,1);
u1lesslab  = ulessLAB(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lesslab,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less LAB');

%lessIP
subplot(5,2,5);
U1  = utcsa(:,1);
u1lessip  = ulessIP(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lessip,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less IP');

%less GDP
subplot(5,2,6);
U1  = utcsa(:,1);
u1lessgdp  = ulessGDP(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lessgdp,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less GDP');

%less INTERN
subplot(5,2,7);
U1  = utcsa(:,1);
u1lessintern  = ulessINTERN(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lessintern,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less INTERN');

%less INTRATE
```

```matlab
subplot(5,2,8);
U1   = utcsa(:,1);
u1lessintrate  = ulessINTRATE(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lessintrate,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less INTRATE');

%less HOUSING
subplot(5,2,9);
U1   = utcsa(:,1);
u1lesshousing  = ulessHOUSING(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1); hold on;
plot(dates,u1lesshousing,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less HOUSING');

%less STOCK
subplot(5,2,10);
U1   = utcsa(:,1);
u1lessstock  = ulessSTOCK(:,1);
plot(dates,U1,'color','#0dade3','linewidth',1.5); hold on;

plot(dates,u1lessstock,':k','linewidth',1);
xlim([dates(1),dates(end)]);
ylim([0.50,0.9]);
title('U(1) less STOCK');

% Print figure
VARopt.savefigs = true;

VARopt.quality  = 0;

SupTitle(['SENSITIVITY ANALYSIS OF UNCERTAINTY MEASURE(1)'])
dim = [8,10];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig,'-dpdf','Uncertainty sensitivity analysis');
```

Figure 23. Impulse Response of real activity variables in VAR-9

```matlab
%%-------------------------------------------------------------------
% PLOT IRFs ss
%%-------------------------------------------------------------------

clear;clc;close all;

load IRFu1;
load IRFu4;
load IRFisv;
load IRFe;
load IRFw;

%shadows of irf upper and lower
SwatheOpt = PlotSwatheOption;
SwatheOpt.trans = 1;

%set up n of steps and x axis
n_steps=20;
steps = 1:1:n_steps;
x_axis = zeros(1,n_steps);

fig=figure(1);

%%-------------------------------------------------------------------
% PLOT Production for u1, u4, isv, epuii, wuii
%%-------------------------------------------------------------------

%irf of ip to u1
IRFu1_mean=IRFu1_mean(:,:,9);
IRFu1_lower=IRFu1_lower(:,:,9);
IRFu1_upper=IRFu1_upper(:,:,9);

ipIRFu1_mean=IRFu1_mean(:,1);
ipIRFu1_lower=IRFu1_lower(:,1);
ipIRFu1_upper=IRFu1_upper(:,1);

subplot(5,3,1);
plot(steps,ipIRFu1_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(ipIRFu1_mean, [ipIRFu1_lower ipIRFu1_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.008, 0.005]);
ylabel('U(1)','color','#0dade3');
title('Production','FontWeight','bold','FontSize',10);


%irf of ip to u4
IRFu4_mean=IRFu4_mean(:,:,9);
IRFu4_lower=IRFu4_lower(:,:,9);
IRFu4_upper=IRFu4_upper(:,:,9);
```

```matlab
ipIRFu4_mean=IRFu4_mean(:,1);
ipIRFu4_lower=IRFu4_lower(:,1);
ipIRFu4_upper=IRFu4_upper(:,1);

subplot(5,3,4);
plot(steps,ipIRFu4_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(ipIRFu4_mean, [ipIRFu4_lower ipIRFu4_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.008, 0.005]);
ylabel('U(4)','color','#086f91');


%irf of ip to isv
IRFisv_mean=IRFisv_mean(:,:,9);
IRFisv_lower=IRFisv_lower(:,:,9);
IRFisv_upper=IRFisv_upper(:,:,9);

ipIRFisv_mean=IRFisv_mean(:,1);
ipIRFisv_lower=IRFisv_lower(:,1);
ipIRFisv_upper=IRFisv_upper(:,1);

subplot(5,3,7);
plot(steps,ipIRFisv_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(ipIRFisv_mean, [ipIRFisv_lower ipIRFisv_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.008, 0.005]);
ylabel('ISV','color','r');


%irf of ip to epuii
IRFe_mean=IRFe_mean(:,:,9);
IRFe_lower=IRFe_lower(:,:,9);
IRFe_upper=IRFe_upper(:,:,9);

ipIRFe_mean=IRFe_mean(:,1);
ipIRFe_lower=IRFe_lower(:,1);
ipIRFe_upper=IRFe_upper(:,1);

subplot(5,3,10);
plot(steps,ipIRFe_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(ipIRFe_mean, [ipIRFe_lower ipIRFe_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.008, 0.005]);
ylabel('EPUI','color','#ffcc00');


%irf of ip to wuii
IRFw_mean=IRFw_mean(:,:,9);
IRFw_lower=IRFw_lower(:,:,9);
```

```matlab
IRFw_upper=IRFw_upper(:,:,9);

ipIRFw_mean=IRFw_mean(:,1);
ipIRFw_lower=IRFw_lower(:,1);
ipIRFw_upper=IRFw_upper(:,1);

subplot(5,3,13);
plot(steps,ipIRFw_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(ipIRFw_mean, [ipIRFw_lower ipIRFw_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.008, 0.005]);
ylabel('WUI','color','#a366ff');


%%-----------------------------------------------------------------
% PLOT Employment for u1, u4, isv, epuii, wuii
%%-----------------------------------------------------------------

%irf of emp to u1
empIRFu1_mean=IRFu1_mean(:,2);
empIRFu1_lower=IRFu1_lower(:,2);
empIRFu1_upper=IRFu1_upper(:,2);

subplot(5,3,2);
plot(steps,empIRFu1_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(empIRFu1_mean, [empIRFu1_lower empIRFu1_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);
title('Employment','FontWeight','bold','FontSize',10);


%irf of emp to u4
empIRFu4_mean=IRFu4_mean(:,2);
empIRFu4_lower=IRFu4_lower(:,2);
empIRFu4_upper=IRFu4_upper(:,2);

subplot(5,3,5);
plot(steps,empIRFu4_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(empIRFu4_mean, [empIRFu4_lower empIRFu4_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of emp to isv
empIRFisv_mean=IRFisv_mean(:,2);
empIRFisv_lower=IRFisv_lower(:,2);
empIRFisv_upper=IRFisv_upper(:,2);

subplot(5,3,8);
```

```matlab
plot(steps,empIRFisv_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(empIRFisv_mean, [empIRFisv_lower empIRFisv_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of ip to epuii
empIRFe_mean=IRFe_mean(:,2);
empIRFe_lower=IRFe_lower(:,2);
empIRFe_upper=IRFe_upper(:,2);

subplot(5,3,11);
plot(steps,empIRFe_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(empIRFe_mean, [empIRFe_lower empIRFe_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of ip to wuii
empIRFw_mean=IRFw_mean(:,2);
empIRFw_lower=IRFw_lower(:,2);
empIRFw_upper=IRFw_upper(:,2);

subplot(5,3,14);
plot(steps,empIRFw_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(empIRFw_mean, [empIRFw_lower empIRFw_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%%%-----------------------------------------------------------------------
% PLOT Unemployment for u1, u4, isv, epuii, wuii
%%%-----------------------------------------------------------------------

%irf of emp to u1
unempIRFu1_mean=IRFu1_mean(:,3);
unempIRFu1_lower=IRFu1_lower(:,3);
unempIRFu1_upper=IRFu1_upper(:,3);

subplot(5,3,3);
plot(steps,unempIRFu1_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(unempIRFu1_mean, [unempIRFu1_lower unempIRFu1_upper],SwatheOpt); hold
on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);
title('Unemployment','FontWeight','bold','FontSize',10);
```

```matlab
%irf of emp to u4
unempIRFu4_mean=IRFu4_mean(:,3);
unempIRFu4_lower=IRFu4_lower(:,3);
unempIRFu4_upper=IRFu4_upper(:,3);

subplot(5,3,6);
plot(steps,unempIRFu4_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(unempIRFu4_mean, [unempIRFu4_lower unempIRFu4_upper],SwatheOpt); hold
on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of emp to isv
unempIRFisv_mean=IRFisv_mean(:,3);
unempIRFisv_lower=IRFisv_lower(:,3);
unempIRFisv_upper=IRFisv_upper(:,3);

subplot(5,3,9);
plot(steps,unempIRFisv_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(unempIRFisv_mean, [unempIRFisv_lower unempIRFisv_upper],SwatheOpt);
hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of ip to epuii
unempIRFe_mean=IRFe_mean(:,3);
unempIRFe_lower=IRFe_lower(:,3);
unempIRFe_upper=IRFe_upper(:,3);

subplot(5,3,12);
plot(steps,unempIRFe_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(unempIRFe_mean, [unempIRFe_lower unempIRFe_upper],SwatheOpt); hold on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
ylim([-0.1, 0.1]);


%irf of ip to wuii
unempIRFw_mean=IRFw_mean(:,3);
unempIRFw_lower=IRFw_lower(:,3);
unempIRFw_upper=IRFw_upper(:,3);

subplot(5,3,15);
plot(steps,unempIRFw_mean,'LineStyle','-','Color','k','LineWidth',2); hold on
PlotSwathe(unempIRFw_mean, [unempIRFw_lower unempIRFw_upper],SwatheOpt); hold
on;
plot(x_axis,'--k','LineWidth',0.5); hold on
xlim([1 n_steps]);
```

```matlab
ylim([-0.1, 0.1]);


%%-------------------------------------------------------------------
% PRINT THE FIGURE
%%-------------------------------------------------------------------

% Print figure
VARopt.savefigs = true;

VARopt.quality  = 0;

SupTitle(['IRF of Variables to different Uncertainty Measures'])
dim = [8,10];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig,'-dpdf','IRFs_comparison');
```

Figure 24 FEVDs real variables (figure 31 similar)

```
%%------------------------------------------------------------------
% PLOT VARIANCE DECOMPOSITION ANALYSIS VAR
%%------------------------------------------------------------------

close all;clc;clear;

load VDU1
load VDU4
load VDISV
load VDE
load VDW

%take vatiables for the variance decomposition analysis
VDU1ip=squeeze(VDU1(:,:,1));
VDU1emp=squeeze(VDU1(:,:,2));
VDU1unemp=squeeze(VDU1(:,:,3));
VDU1cpi=squeeze(VDU1(:,:,4));
VDU1tretailt=squeeze(VDU1(:,:,5));
VDU1wage=squeeze(VDU1(:,:,6));
VDU1intrate=squeeze(VDU1(:,:,7));
VDU1stock=squeeze(VDU1(:,:,8));

VDU4ip=squeeze(VDU4(:,:,1));
VDU4emp=squeeze(VDU4(:,:,2));
VDU4unemp=squeeze(VDU4(:,:,3));
VDU4cpi=squeeze(VDU4(:,:,4));
VDU4tretailt=squeeze(VDU4(:,:,5));
VDU4wage=squeeze(VDU4(:,:,6));
VDU4intrate=squeeze(VDU4(:,:,7));
VDU4stock=squeeze(VDU4(:,:,8));

VDISVip=squeeze(VDISV(:,:,1));
VDISVemp=squeeze(VDISV(:,:,2));
VDISVunemp=squeeze(VDISV(:,:,3));
VDISVcpi=squeeze(VDISV(:,:,4));
VDISVtretailt=squeeze(VDISV(:,:,5));
VDISVwage=squeeze(VDISV(:,:,6));
VDISVintrate=squeeze(VDISV(:,:,7));
VDISVstock=squeeze(VDISV(:,:,8));

VDEip=squeeze(VDE(:,:,1));
VDEemp=squeeze(VDE(:,:,2));
VDEunemp=squeeze(VDE(:,:,3));
VDEcpi=squeeze(VDE(:,:,4));
VDEtretailt=squeeze(VDE(:,:,5));
VDEwage=squeeze(VDE(:,:,6));
VDEintrate=squeeze(VDE(:,:,7));
VDEstock=squeeze(VDE(:,:,8));

VDWip=squeeze(VDW(:,:,1));
VDWemp=squeeze(VDW(:,:,2));
```

```matlab
VDWunemp=squeeze(VDW(:,:,3));
VDWcpi=squeeze(VDW(:,:,4));
VDWtretailt=squeeze(VDW(:,:,5));
VDWwage=squeeze(VDW(:,:,6));
VDWintrate=squeeze(VDW(:,:,7));
VDWstock=squeeze(VDW(:,:,8));

%compute mean of FE explained during the forecasting horizon =20
%IP



horizon=[0:19]';
T=length(horizon);

%%%-----------------------------------------------------------------------
%Plot the variance decomposition IP
%%%-----------------------------------------------------------------------
fig1 = figure(1);
title('FE variance explained by different Uncertainty Proxies');

subplot(1,3,1);
ipVDU1=VDU1ip(:,9);
ipVDU4=VDU4ip(:,9);
ipVDISV=VDISVip(:,9);
ipVDE=VDEip(:,9);
ipVDW=VDWip(:,9);
%means
ipmeanvdu1=mean(ipVDU1);
ipmeanvdu4=mean(ipVDU4);
ipmeanvdisv=mean(ipVDISV);
ipmeanvde=mean(ipVDE);
ipmeanvdw=mean(ipVDW);
%plot
plot(horizon,ipVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,ipVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,ipVDISV,'color','r','linewidth',0.5);
plot(horizon,ipVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,ipVDW,'color','#a366ff','linewidth',0.5);
txt1  = ['mu(1)= ',num2str(ipmeanvdu1)];
txt2  = ['mu(4)= ',num2str(ipmeanvdu4)];
txt3  = ['misv = ',num2str(ipmeanvdisv)];
txt4  = ['me   = ',num2str(ipmeanvde)];
txt5  = ['mw   = ',num2str(ipmeanvdw)];
text(1,28.5,txt1,'interpreter','latex','color','k','color','#0dade3');
text(1,27.2,txt2,'interpreter','latex','color','k');
text(1,25.9,txt3,'interpreter','latex','color','k');
text(1,24.6,txt4,'interpreter','latex','color','k');
text(1,23.3,txt5,'interpreter','latex','color','k');
title('Industrial Production');
xlim([horizon(1),horizon(end)]);
ylim([0,30]);
```

```matlab
%%%-----------------------------------------------------------------
%Plot the variance decomposition EMP
%%%-----------------------------------------------------------------
subplot(1,3,2);
empVDU1=VDU1emp(:,9);
empVDU4=VDU4emp(:,9);
empVDISV=VDISVemp(:,9);
empVDE=VDEemp(:,9);
empVDW=VDWemp(:,9);
%means
empmeanvdu1=mean(empVDU1);
empmeanvdu4=mean(empVDU4);
empmeanvdisv=mean(empVDISV);
empmeanvde=mean(empVDE);
empmeanvdw=mean(empVDW);
%plot
plot(horizon,empVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,empVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,empVDISV,'color','r','linewidth',0.5);
plot(horizon,empVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,empVDW,'color','#a366ff','linewidth',0.5);
txt1  = ['mu(1)  = ',num2str(empmeanvdu1)];
txt2  = ['mu(4)  = ',num2str(empmeanvdu4)];
txt3  = ['misv = ',num2str(empmeanvdisv)];
txt4  = ['me   = ',num2str(empmeanvde)];
txt5  = ['mw   = ',num2str(empmeanvdw)];
text(1,23.5,txt1,'interpreter','latex','color','k','color','#0dade3');
text(1,22.5,txt2,'interpreter','latex','color','k');
text(1,21.5,txt3,'interpreter','latex','color','k');
text(1,20.5,txt4,'interpreter','latex','color','k');
text(1,19.5,txt5,'interpreter','latex','color','k');
title('Employment');
xlim([horizon(1),horizon(end)]);
ylim([0,25]);

%%%-----------------------------------------------------------------
%Plot the variance decomposition UNEMP
%%%-----------------------------------------------------------------
subplot(1,3,3);
unempVDU1=VDU1unemp(:,9);
unempVDU4=VDU4unemp(:,9);
unempVDISV=VDISVunemp(:,9);
unempVDE=VDEunemp(:,9);
unempVDW=VDWunemp(:,9);
%means
unempmeanvdu1=mean(unempVDU1);
unempmeanvdu4=mean(unempVDU4);
unempmeanvdisv=mean(unempVDISV);
unempmeanvde=mean(unempVDE);
unempmeanvdw=mean(unempVDW);
```

```matlab
%plot
plot(horizon,unempVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,unempVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,unempVDISV,'color','r','linewidth',0.5);
plot(horizon,unempVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,unempVDW,'color','#a366ff','linewidth',0.5);
txt1  = ['mu(1)  = ',num2str(unempmeanvdu1)];
txt2  = ['mu(4)  = ',num2str(unempmeanvdu4)];
txt3  = ['misv = ',num2str(unempmeanvdisv)];
txt4  = ['me   = ',num2str(unempmeanvde)];
txt5  = ['mw   = ',num2str(unempmeanvdw)];
text(1,19,txt1,'interpreter','latex','color','k','color','#0dade3');
text(1,18.2,txt2,'interpreter','latex','color','k');
text(1,17.4,txt3,'interpreter','latex','color','k');
text(1,16.6,txt4,'interpreter','latex','color','k');
text(1,15.8,txt5,'interpreter','latex','color','k');
title('Unemployment');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
leg.FontSize=8;
set(leg,'location','northeast','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);


% Print figure
SupTitle(['FE variance explained by different Uncertainty Proxies'])
dim = [10,6];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','FE variance of IP, EMP amd UNEMP explained by different Uncertainty
Proxies');
```

Figure 25 FEVDs all variables (figure 32 similar)

```
%%------------------------------------------------------------------
% VARIANCE DECOMPOSITION ANALYSIS VAR
%%------------------------------------------------------------------

close all;clc;clear;

load VDU1
load VDU4
load VDISV
load VDE
load VDW

%take vatiables for the variance decomposition analysis
VDU1ip=squeeze(VDU1(:,:,1));
VDU1emp=squeeze(VDU1(:,:,2));
VDU1unemp=squeeze(VDU1(:,:,3));
VDU1cpi=squeeze(VDU1(:,:,4));
VDU1tretailt=squeeze(VDU1(:,:,5));
VDU1wage=squeeze(VDU1(:,:,6));
VDU1intrate=squeeze(VDU1(:,:,7));
VDU1stock=squeeze(VDU1(:,:,8));

VDU4ip=squeeze(VDU4(:,:,1));
VDU4emp=squeeze(VDU4(:,:,2));
VDU4unemp=squeeze(VDU4(:,:,3));
VDU4cpi=squeeze(VDU4(:,:,4));
VDU4tretailt=squeeze(VDU4(:,:,5));
VDU4wage=squeeze(VDU4(:,:,6));
VDU4intrate=squeeze(VDU4(:,:,7));
VDU4stock=squeeze(VDU4(:,:,8));

VDISVip=squeeze(VDISV(:,:,1));
VDISVemp=squeeze(VDISV(:,:,2));
VDISVunemp=squeeze(VDISV(:,:,3));
VDISVcpi=squeeze(VDISV(:,:,4));
VDISVtretailt=squeeze(VDISV(:,:,5));
VDISVwage=squeeze(VDISV(:,:,6));
VDISVintrate=squeeze(VDISV(:,:,7));
VDISVstock=squeeze(VDISV(:,:,8));

VDEip=squeeze(VDE(:,:,1));
VDEemp=squeeze(VDE(:,:,2));
VDEunemp=squeeze(VDE(:,:,3));
VDEcpi=squeeze(VDE(:,:,4));
VDEtretailt=squeeze(VDE(:,:,5));
VDEwage=squeeze(VDE(:,:,6));
VDEintrate=squeeze(VDE(:,:,7));
VDEstock=squeeze(VDE(:,:,8));

VDWip=squeeze(VDW(:,:,1));
VDWemp=squeeze(VDW(:,:,2));
```

```matlab
VDWunemp=squeeze(VDW(:,:,3));
VDWcpi=squeeze(VDW(:,:,4));
VDWtretailt=squeeze(VDW(:,:,5));
VDWwage=squeeze(VDW(:,:,6));
VDWintrate=squeeze(VDW(:,:,7));
VDWstock=squeeze(VDW(:,:,8));




horizon=[0:19]';
T=length(horizon);

%%-------------------------------------------------------------------
%Plot the variance decomposition CPI
%%-------------------------------------------------------------------
fig8 = figure(8);
cpiVDU1=VDU1cpi(:,9);
cpiVDU4=VDU4cpi(:,9);
cpiVDISV=VDISVcpi(:,9);
cpiVDE=VDEcpi(:,9);
cpiVDW=VDWcpi(:,9);
plot(horizon,cpiVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,cpiVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,cpiVDISV,'color','r','linewidth',0.5);
plot(horizon,cpiVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,cpiVDW,'color','#a366ff','linewidth',0.5);
title('FE variance of Consumer Price Index explained by...');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig8,'-dpdf','FE variance of CPI');




%%-------------------------------------------------------------------
%Plot the variance decomposition WAGE
%%-------------------------------------------------------------------
fig4 = figure(4);
wageVDU1=VDU1wage(:,9);
wageVDU4=VDU4wage(:,9);
```

```matlab
wageVDISV=VDISVwage(:,9);
wageVDE=VDEwage(:,9);
wageVDW=VDWwage(:,9);
plot(horizon,wageVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,wageVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,wageVDISV,'color','r','linewidth',0.5);
plot(horizon,wageVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,wageVDW,'color','#a366ff','linewidth',0.5);
title('FE variance of Wage explained by...');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,25]);


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig4,'-dpdf','FE variance of WAGE');

%%%-----------------------------------------------------------------------
%Plot the variance decomposition TRETAILT
%%%-----------------------------------------------------------------------
fig5 = figure(5);
tretailtVDU1=VDU1tretailt(:,9);
tretailtVDU4=VDU4tretailt(:,9);
tretailtVDISV=VDISVtretailt(:,9);
tretailtVDE=VDEtretailt(:,9);
tretailtVDW=VDWtretailt(:,9);
plot(horizon,tretailtVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,tretailtVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,tretailtVDISV,'color','r','linewidth',0.5);
plot(horizon,tretailtVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,tretailtVDW,'color','#a366ff','linewidth',0.5);
title('FE variance of Total Retail Trade explained by...');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,30]);
```

```matlab
% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig5,'-dpdf','FE variance of TRETAILT');

%%------------------------------------------------------------------------
%Plot the variance decomposition INTRATE
%%------------------------------------------------------------------------
fig6 = figure(6);
intrateVDU1=VDU1intrate(:,9);
intrateVDU4=VDU4intrate(:,9);
intrateVDISV=VDISVintrate(:,9);
intrateVDE=VDEintrate(:,9);
intrateVDW=VDWintrate(:,9);
plot(horizon,intrateVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,intrateVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,intrateVDISV,'color','r','linewidth',0.5);
plot(horizon,intrateVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,intrateVDW,'color','#a366ff','linewidth',0.5);
title('FE variance of Long Term Interest Rate explained by...');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig6,'-dpdf','FE variance of INTRATE');

%%------------------------------------------------------------------------
%Plot the variance decomposition STOCK
%%------------------------------------------------------------------------
fig7 = figure(7);
stockVDU1=VDU1stock(:,9);
stockVDU4=VDU4stock(:,9);
stockVDISV=VDISVstock(:,9);
stockVDE=VDEstock(:,9);
stockVDW=VDWstock(:,9);
plot(horizon,stockVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,stockVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,stockVDISV,'color','r','linewidth',0.5);
plot(horizon,stockVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,stockVDW,'color','#a366ff','linewidth',0.5);
title('FE variance of Stock Price explained by...');
```

```matlab
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig7,'-dpdf','FE variance of STOCK');

fig10 = figure(10);
subplot(2,3,1);
cpiVDU1=VDU1cpi(:,9);
cpiVDU4=VDU4cpi(:,9);
cpiVDISV=VDISVcpi(:,9);
cpiVDE=VDEcpi(:,9);
cpiVDW=VDWcpi(:,9);
plot(horizon,cpiVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,cpiVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,cpiVDISV,'color','r','linewidth',0.5);
plot(horizon,cpiVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,cpiVDW,'color','#a366ff','linewidth',0.5);
title('FEVD CPI');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);

subplot(2,3,2);
tretailtVDU1=VDU1tretailt(:,9);
tretailtVDU4=VDU4tretailt(:,9);
tretailtVDISV=VDISVtretailt(:,9);
tretailtVDE=VDEtretailt(:,9);
tretailtVDW=VDWtretailt(:,9);
plot(horizon,tretailtVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,tretailtVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,tretailtVDISV,'color','r','linewidth',0.5);
plot(horizon,tretailtVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,tretailtVDW,'color','#a366ff','linewidth',0.5);
title('FEVD Retail trade');
```

```matlab
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,30]);

subplot(2,3,3);
wageVDU1=VDU1wage(:,9);
wageVDU4=VDU4wage(:,9);
wageVDISV=VDISVwage(:,9);
wageVDE=VDEwage(:,9);
wageVDW=VDWwage(:,9);
plot(horizon,wageVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,wageVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,wageVDISV,'color','r','linewidth',0.5);
plot(horizon,wageVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,wageVDW,'color','#a366ff','linewidth',0.5);
title('FEVD Wage');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,25]);

subplot(2,3,4);
intrateVDU1=VDU1intrate(:,9);
intrateVDU4=VDU4intrate(:,9);
intrateVDISV=VDISVintrate(:,9);
intrateVDE=VDEintrate(:,9);
intrateVDW=VDWintrate(:,9);
plot(horizon,intrateVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,intrateVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,intrateVDISV,'color','r','linewidth',0.5);
plot(horizon,intrateVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,intrateVDW,'color','#a366ff','linewidth',0.5);
title('FEVD Long term int rate');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
```

```matlab
ylim([0,20]);


subplot(2,3,5);
stockVDU1=VDU1stock(:,9);
stockVDU4=VDU4stock(:,9);
stockVDISV=VDISVstock(:,9);
stockVDE=VDEstock(:,9);
stockVDW=VDWstock(:,9);
plot(horizon,stockVDU1,'color','#0dade3','linewidth',2); hold on;
plot(horizon,stockVDU4,'color','#086f91','linewidth',0.5);
plot(horizon,stockVDISV,'color','r','linewidth',0.5);
plot(horizon,stockVDE,'color','#ffcc00','linewidth',0.5);
plot(horizon,stockVDW,'color','#a366ff','linewidth',0.5);
title('FEVD Stock price');
lab1 = sprintf('U(1)');
lab2 = sprintf('U(4)');
lab3 = sprintf('ISV');
lab4 = sprintf('EPUI');
lab5 = sprintf('WUI');
leg = legend(lab1, lab2, lab3, lab4, lab5);
set(leg,'location','northwest','box','off');
xlim([horizon(1),horizon(end)]);
ylim([0,20]);

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig10,'-dpdf','FE variance of remaining variables');

close all;
```

Figure 28 Combined Uncertainty Measure and Recession Dates

```matlab
% ------------------------------------------------------------------
% Plot combined uncertainty estimates
% ------------------------------------------------------------------

% Load estimates
clear; clc; close all;
load aggu;
T = length(dates);

%shades options
SwatheOpt = PlotSwatheOption;
SwatheOpt.trans = 1;

%load recession dates
[rdata,rtxt] = xlsread('rdatesitaly.xlsx',1);




[utcsa1]=xlsread('UTCSA1.xlsx',2);

[data]=xlsread("combined uncertainty measure.xlsx",1);
data=data(:,[1 4]);



%dates
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (13:end,:);



%create the combined uncertainty measure
CU=max(data,[],2);
%meanCU=mean(data,2);
%w=[6/10;1/10;1/10;2/10]';
%CU=sum(data.*w,2)/sum(w);



% Plot csa estimates
fig1 = figure(1);
CU = CU(:,1);
plot(dates,CU,'color','#0dade3','linewidth',1.5); hold on;

for i=1:88
    if rdata(i)==1
      xline(dates(i),':r');
    end
end

txt1  = '$C\overline{\mathcal{U}}^y_t(1)$';
text(1999,-1,txt1,'interpreter','latex','color','#0dade3');
```

```matlab
xlim([dates(1),dates(end)]);
ylim([-2,5]);


title('Combined Uncertainty Measure(1)');


% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','combined_commented');
```

Figure 29 Combined Uncertainty Measure and Real Activity

```matlab
% ---------------------------------------------------------------------
% Create combined measure of uncertainty for Italy
% ---------------------------------------------------------------------

[utcsa1]=xlsread('UTCSA1.xlsx',2);

[data]=xlsread("combined uncertainty measure.xlsx",1);
data=data(:,[1 4]);

% Load Industrial production growth
[ipgrowth]=xlsread('ProductionIndexGrowth',2);

%Load Employment rate growth
[empgrowth]=xlsread('EmploymentRateGrowth',2);

%Load Unemployment rate growth
[unempgrowth]=xlsread('UnemploymentRateGrowth',2);

%dates
dates   = 1900+(95:1/4:120-1/4)';
dates = dates (13:end,:);


%create the combined uncertainty measure
CU=max(data,[],2);
%meanCU=mean(data,2);
%w=[6/10;1/10;1/10;2/10]';
%CU=sum(data.*w,2)/sum(w);

%IP
%plot the max combined uncertainty measure
fig1= figure(1);
subplot(3,1,1);
CU = CU(:,1);
cucorrip=corr(CU,ipgrowth);
plot(dates,CU,'color','#00cc99','linewidth',2); hold on
plot(dates,ipgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(cucorrip)];
text (1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('IP CU(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

%plot the mean combined uncertainty measure
%subplot(2,1,2);
%meanCU = meanCU(:,1);
%meancucorrip=corr(meanCU,ipgrowth);
%plot(dates,meanCU,'color','#00cc99','linewidth',2); hold on
%plot(dates,ipgrowth,'k','linewidth',1);
%txt1  = ['?= ', num2str(meancucorrip)];
%text (1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
```

```matlab
%title('mean CU(1)');
%xlim([dates(1),dates(end)]);
%ylim([-5,6]);

%EMP
%plot the max combined uncertainty measure
dates=dates(5:end,:);
subplot(3,1,2);
CU = CU(5:end,1);
cucorremp=corr(CU,empgrowth);
plot(dates,CU,'color','#00cc99','linewidth',2); hold on
plot(dates,empgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(cucorremp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('EMP CU(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

%UNEMP
%plot the max combined uncertainty measure
subplot(3,1,3);
cucorrunemp=corr(CU,unempgrowth);
plot(dates,CU,'color','#00cc99','linewidth',2); hold on
plot(dates,unempgrowth,'k','linewidth',1);
txt1  = ['?= ', num2str(cucorrunemp)];
text(1999,5,txt1,'interpreter','latex','color','k','FontSize', 8);
title('UNEMP CU(1)');
xlim([dates(1),dates(end)]);
ylim([-5,6]);

% Print figure
dim = [6,5];
set(gcf,'paperpositionmode','manual','paperunits','inches');
set(gcf,'papersize',dim,'paperposition',[0,0,dim]);
print(fig1,'-dpdf','combined uncertainty measure and IP, EMP, UNEMP');
```

Bibliographical References

Uncertainty measure construction data and indicators

Quarterly Consumer Price Index- all items: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 01-12 - All items" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 10:55 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- food and non- alcoholic beverages: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 01 - Food and non-Alcoholic beverages" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 10:58 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- alcoholic beverages, tobacco, narcotics: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 02 - Alcoholic beverages, tobacco and narcotics" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:00 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- clothing and footwear: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 03 - Clothing and footwear" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:02 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- housing, water, electricity, gas and other fuels: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 04 - Housing, water, electricity, gas and other fuels" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:04 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- furnishing, household equipment, routine household manteinance: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 05 - Furnishings, household equipment and routine household maintenance" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:15 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- health: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 06 - Health" [online]. Available at:

< *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:18 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- transportation: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 07 - Transport" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:19 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- communication: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 08 - Communication" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:20 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- recreation and culture: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 09 - Recreation and culture" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:21 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- restaurants and hotels: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 11 - Restaurants and hotels" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:25 UTC (GMT) from OECD.Stat].

Quarterly Consumer Price Index- miscellaneus goods and services: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy CPI: 12 - Miscellaneous goods and services" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 11:31 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- manufacturing: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Economic activities - Domestic producer prices - Manufacturing" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 17:36 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- industrial activities: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Economic activities - Domestic producer prices - Industrial Activities" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 17:37 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- mining and quarrying activities: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Economic activities -

Domestic Producer prices - Mining and quarrying activities" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 17:38 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- manufacture of food products: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Economic activities - Domestic Producer prices - Manufacture of food products" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 17:39 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- energy: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Economic activities - Domestic Producer prices - Energy" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 17:40 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- investment goods: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Type of goods - Domestic Producer prices - Investment goods" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 20:44 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- intermediate goods: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Type of goods - Domestic Producer prices - Intermediate goods" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 20:46 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- consumer goods: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Type of goods - Domestic Producer prices - Consumer goods" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 20:48 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- durable consumer goods: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Type of goods - Domestic Producer prices - Durable consumer goods" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 20:49 UTC (GMT) from OECD.Stat].

Quarterly Producer Price Index- non- durable consumer goods: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Type of goods - Domestic Producer prices – Non- durable consumer goods" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 20:50 UTC (GMT) from OECD.Stat].

Quarterly Production Index- Total industry: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy PRINTO01: Production of total industry

sa, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:49 UTC (GMT) from OECD.Stat].

Quarterly Production Index- Manufacturing: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy PRMNTO01: Production in total manufacturing sa, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:52 UTC (GMT) from OECD.Stat].

Quarterly Production Index- Electricity gas steam air conditioning: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy PREND401: Production of electricity, gas, steam and air conditioning supply sa, index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:55 UTC (GMT) from OECD.Stat].

Quarterly Production Index- Construction: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy PRCNTO01: Production of total construction sa, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:58 UTC (GMT) from OECD.Stat].

Quarterly Manufacturing total orders value: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Total Orders- Value" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 21 Sep 2021 09:56 UTC (GMT) from OECD.Stat].

Quarterly Total retail trade: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy SLRTTO01: Total retail trade (Volume) sa, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 23:00 UTC (GMT) from OECD.Stat].

Quarterly GDP: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Gross domestic product - expenditure approach" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 22 Sep 2021 11:29 UTC (GMT) from OECD.Stat].

Quarterly GDP private final consumption: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy GDP Private final consumption expenditure; constant prices, s.a." [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:42 UTC (GMT) from OECD.Stat].

Quarterly GDP government final consumption: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy GDP Government consumption expenditure; constant prices, s.a." [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:43 UTC (GMT) from OECD.Stat].

Quarterly GDP government final consumption: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy GDP Government consumption expenditure; constant prices, s.a." [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:43 UTC (GMT) from OECD.Stat].

Quarterly Spot exchange rate to $: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Currency Conversions > US$ exchange rate > Spot, end of period > USD:national currency" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 21 Sep 2021 14:09 UTC (GMT) from OECD.Stat].

Quarterly Long- term interest rate: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Long-term interest rate" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:31 UTC (GMT) from OECD.Stat].

Quarterly Short- term interest rate: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Short-term interest rates, Per cent per annum" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:38 UTC (GMT) from OECD.Stat].

Quarterly Stock prices: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Share Prices, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:40 UTC (GMT) from OECD.Stat].

Quarterly Compensation of employees by industry: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Compensation of employees by industry> D11: Wages and salaries, total" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 23:22 UTC (GMT) from OECD.Stat].

Quarterly Hourly earnings: manufacturing, s.a.: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Hourly earnings: manufacturing, s.a." [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:49 UTC (GMT) from OECD.Stat].

Quarterly Labour compensation per employed person: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Labour Compensation per employed

person" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 21 Sep 2021 17:55 UTC (GMT) from OECD.Stat].

Quarterly Unit labor cost: total economy: ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2021. "Italy Unit labour cost: Total Economy, s.a." [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 21:51 UTC (GMT) from OECD.Stat].

Quarterly Housing prices: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "ITA > HOUSECOST > NOMINAL" [online]. Available at: < *https://data.oecd.org/price/housing-prices.htm#indicator-chart* > [Data extracted in Sep 2021 from OECD.org].

Quarterly Rent prices: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "ITA > HOUSECOST > RENT" [online]. Available at: < *https://data.oecd.org/price/housing-prices.htm#indicator-chart* > [Data extracted in Sep 2021 from OECD.org].

Quarterly GDP Index: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "ITA > QGDP > VOLIDX" [online]. Available at: < *https://data.oecd.org/gdp/quarterly-gdp.htm* > [Data extracted in Sep 2021 from OECD.org].

Quarterly Unemployment rate: ISTITUTO NAZIONALE DI STATISTICA, 2021. "tasso di disoccupazione" [online]. Available at: < *https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati/statbase* > [Dati estratti il 19 Sep 2021 14:36 UTC (GMT) da I.Stat].

Quarterly Employment rate: ISTITUTO NAZIONALE DI STATISTICA, 2021. "tasso di occupazione" [online]. Available at: < *https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati/statbase* > [Dati estratti il 19 Sep 2021 14:26 UTC (GMT) da I.Stat].

Quarterly Activity rate: ISTITUTO NAZIONALE DI STATISTICA, 2021. "tasso di attività" [online]. Available at: < *https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati/statbase* > [Dati estratti il 19 Sep 2021 14:29 UTC (GMT) da I.Stat].

Quarterly Hours worked in the economy: ISTITUTO NAZIONALE DI STATISTICA, 2021. "ore lavorate (migliaia)" [online]. Available at: < *https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati/statbase* > [Dati estratti il 18 set 2021 11:00 UTC (GMT) da I.Stat].

Quarterly Working positions in the economy: ISTITUTO NAZIONALE DI STATISTICA, 2021. "posizioni lavorative (migliaia)" [online]. Available at: < *https://www.istat.it/it/dati-*

analisi-e-prodotti/banche-dati/statbase > [Dati estratti il 18 set 2021 11:04 UTC (GMT) da I.Stat].

Quarterly Gross investment different sectors: ISTITUTO NAZIONALE DI STATISTICA, 2021. "investimenti fissi lordi" [online]. Available at: < *https://www.istat.it/it/dati-analisi-e-prodotti/banche-dati/statbase* > [Dati estratti il 17 set 2021 15:15 UTC (GMT) da I.Stat].

Quarterly Exports: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Exports of Goods and Services in Italy, Index Q1 2015=100, Quarterly, Seasonally Adjusted" [online]. Available at: < *https://fred.stlouisfed.org/series/ITAEXPORTQDSMEI* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Imports: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Imports of Goods and Services in Italy, Index Q1 2015=100, Quarterly, Seasonally Adjusted" [online]. Available at: < *https://fred.stlouisfed.org/series/ITAIMPORTQDSMEI* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Common uncertainty proxies and recession dates

Recession dates for Italy: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "OECD based Recession Indicators for Italy from the Period following the Peak through the Trough" [online]. Available at: < *https://fred.stlouisfed.org/series/ITARECD* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Monthly Italian Stock Market Volatility: CAGGIANO, G. and CASTELNUOVO, E., 2021. "Global Uncertainty", CAMA Working Paper No. 21/2021, Available at SSRN: *https://ssrn.com/abstract=3785777* or *http://dx.doi.org/10.2139/ssrn.3785777*. Data are available at the following address: *https://docs.google.com/spreadsheets/d/10DGnp-Rryf7-HInGyiOgjc4GPSk7YFx9/edit#gid=1155950240*. [Data extracted in Sep 2021].

World Uncertainty Index for Italy: AHIR, H., BLOOM, N. and FURCERI, D., World Uncertainty Index for Italy [WUIITA], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/WUIITA*. [Data extracted in Sep 2021].

Economic Policy Uncertainty Index for Italy: BAKER, S. R., BLOOM, N., and DAVIS, S. J., Economic Policy Uncertainty Index for Italy [ITEPUINDXM], retrieved from FRED, Federal Reserve Bank of St. Louis; *https://fred.stlouisfed.org/series/ITEPUINDXM*. [Data extracted in Sep 2021].

Macroeconomic Uncertainty Measure for the U.S.: JURADO, K., LUDVIGSON, S. and NG, S., 2015. "Measuring Uncertainty", The American Economic Review, 2015, 105(3): 1177-1215. Data are available at the following address: *https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes*. [Data extracted in Sep 2021].

Var Analysis

Quarterly Production Index: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Production of Total Industry in Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/ITAPROINDMISMEI#0* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Employment: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Employment Rate: Aged 15-64: All Persons for Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/LREM64TTITQ156S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Unemployment: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Unemployment Rate: Aged 15-64: All Persons for Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/LRUN64TTITQ156S#0* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Consumer Price Index: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Consumer Price Index of All Items in Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/ITACPIALLMINMEI#0* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Total Retail Trade: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Value of Total Retail Trade sales for Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/SLRTTO02ITQ661S#0* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Hourly Wage Rate: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Hourly Wage Rate: Industry for Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/LCWRIN01ITM661S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Long- Term Interest Rate: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Interest Rates, Government Securities, Government Bonds for Italy" [online]. Available at: <

https://fred.stlouisfed.org/series/INTGSBITM193N#0 > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Hourly Wage Rate: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Hourly Wage Rate: Industry for Italy" [online]. Available at: < *https://fred.stlouisfed.org/series/LCWRIN01ITM661S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Stock prices: ORGANISATION FOR ECONOMIC CO- OPERATION AND DEVELOPMENT, 2021. "Italy Share Prices, Index" [online]. Available at: < *https://stats.oecd.org/#* > [Data extracted on 20 Sep 2021 22:40 UTC (GMT) from OECD.Stat].

Quarterly Production Index Euro Area: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Total Industry Production Excluding Construction for the Euro Area" [online]. Available at: < *https://fred.stlouisfed.org/series/PRINTO01EZQ661S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Consumer Price Index Euro Area: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Harmonized Index of Consumer Prices: All Items for Euro area (19 countries)" [online]. Available at: < *https://fred.stlouisfed.org/series/CP0000EZ19M086NEST* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly ECB Deposit Facility Rate: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "ECB Deposit Facility Rate for Euro Area" [online]. Available at: < *https://fred.stlouisfed.org/series/ECBDFR* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Employment Euro Area: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Employment Rate: Aged 15-64: All Persons for the Euro Area" [online]. Available at: < *https://fred.stlouisfed.org/series/LREM64TTEZQ156S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Quarterly Unemployment Euro Area: FEDERAL RESERVE BANK OF ST. LOUIS, 2021. "Unemployment Rate: Aged 15-64: All Persons for the Euro Area" [online]. Available at: < *https://fred.stlouisfed.org/series/LRUN64TTEZQ156S* > [Data extracted in Sep 2021 from fred.stlouisfed.org].

Bibliography

AHIR, H., BLOOM, N. and FURCERI, D., 2018. "The World Uncertainty Index", available at SSRN: *https://ssrn.com/abstract=3275033* or *http://dx.doi.org/10.2139/ssrn.3275033*.

ARIAS, J. E., RUBIO-RAMIREZ, J. F. and WAGGONER, D., 2018. "Inference Based on Structural Vector Autoregressions Identified with Sign and Zero Restrictions: Theory and Applications", Econometrica, 86(2), pp. 685-720.

ARORA, V. AND VAMVAKIDIS, A., 2006. "The Impact of U.S. Economic Growth on the Rest of the World: How Much Does It Matter?", Journal of Economic Integration, 21(1), 21–39. http://www.jstor.org/stable/23000816.

BACHMANN, R., ELSTNER, S. and SIMS, E. R., 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data." American Economic Journal: Macroeconomics, 5 (2): 217-49.

BAI, J. and NG, S., 2004. "A PANIC Attack on Unit Roots and Cointegration", Econometrica, 72: 1127-1177. Available at: *https://doi.org/10.1111/j.1468-0262.2004.00528.x*.

BAI, J. and NG, S., 2006. "Confidence Intervals for Diffusion Index Forecasts and Inference for Factor-Augmented Regressions", Econometrica, 74: 1133-1150. Available at: *https://doi.org/10.1111/j.1468-0262.2006.00696.x*.

BAI, J. and NG, S., 2008. "Forecasting economic time series using targeted predictors", Journal of Econometrics, Volume 146, Issue 2, 2008, Pages 304-317, ISSN 0304-4076. Available at: *https://doi.org/10.1016/j.jeconom.2008.08.010*.

BAI, Y., KEHOE, P. AND ARELLANO, C., 2011. "Financial Markets and Fluctuations in Uncertainty", Meeting Papers 896, Society for Economic Dynamics.

BAKER, S. R., BLOOM, N. and DAVIS, S. J., 2012. "Has Economic Policy Uncertainty Hampered the Recovery?", Becker Friedman Institute for Research in Economics Working Paper No. 2012-003, Available at SSRN: https://ssrn.com/abstract=2009451 or *http://dx.doi.org/10.2139/ssrn.2009451*.

BAKER, S. R., BLOOM, N. and DAVIS, S. J., 2012. "Policy uncertainty: a new indicator", CentrePiece - The Magazine for Economic Performance 362, Centre for Economic Performance, LSE.

BAKER, S. R., BLOOM, N. and DAVIS, S. J., 2016. "Measuring Economic Policy Uncertainty", The Quarterly Journal of Economics, Volume 131, Issue 4, November 2016, Pages 1593–1636. Available at: *https://doi.org/10.1093/qje/qjw024*.

BASU, S. and BUNDICK, B, 2017. "Uncertainty Shocks in a Model of Effective Demand", Econometrica, 85: 937-958. Available at: *https://doi.org/10.3982/ECTA13960*.

BASU, S. AND BUNDICK, B., 2012. "Uncertainty Shocks in a Model of Effective Demand", No 18420, NBER Working Papers, National Bureau of Economic Research, Inc. https://EconPapers.repec.org/RePEc:nbr:nberwo:18420.

BAUM, C. F., CAGLAYAN, M. AND TALAVERA, O., 2008. "Uncertainty determinants of firm investment", Economics Letters, Volume 98, Issue 3, Pages 282-287, ISSN 0165-1765. https://doi.org/10.1016/j.econlet.2007.05.004.

BAYOUMI, T. AND BUI, T. T., 2010. "Deconstructing the International Business Cycle: Why Does a U.S. Sneeze Give the Rest of the World a Cold?", IMF Working Paper No. 10/239, Available at SSRN: https://ssrn.com/abstract=1750728 or http://dx.doi.org/10.2139/ssrn.1750728.

BEKAERT, G., HOEROVA, M. and LO DUCA, M., 2013. "Risk, uncertainty and monetary policy", Journal of Monetary Economics, Volume 60, Issue 7, 2013, Pages 771-788, ISSN 0304-3932. Available at: *https://doi.org/10.1016/j.jmoneco.2013.06.003*.

BENIGNO, P. and WOODFORD, M., 2012. "Linear-quadratic approximation of optimal policy problems", Journal of Economic Theory, Volume 147, Issue 1, 2012, Pages 1-42, ISSN 0022-0531. Available at: *https://doi.org/10.1016/j.jet.2011.10.012*.

BERNANKE, B. S., BOIVIN, J. and ELIASZ, P., 2005. "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach", The Quarterly Journal of Economics, Volume 120, Issue 1, February 2005, Pages 387–422. Available at: *https://doi.org/10.1162/0033553053327452*.

BERNSTEIN, J., PLANTE, M. D., RICHTER, A. W. AND THROCKMORTON, N. A., 2021a. "Countercyclical Fluctuations in Uncertainty are Endogenous", FRB of Dallas Working Paper No. 2109, Available at SSRN: https://ssrn.com/abstract=3888550 or http://dx.doi.org/10.24149/wp2109. Paper renamed "A Simple Explanation of Countercyclical Uncertainty".

BLOOM, N., 2009. "The Impact of Uncertainty Shocks", Econometrica, 77: 623-685. Available at: *https://doi.org/10.3982/ECTA6248*.

BLOOM, N., BOND, S. AND VAN REENEN, J., 2007. "Uncertainty and Investment Dynamics", The Review of Economic Studies, Volume 74, Issue 2, Pages 391–415. https://doi.org/10.1111/j.1467-937X.2007.00426.x.

CAGGIANO, G. and CASTELNUOVO, E., 2021. "Global Uncertainty", CAMA Working Paper No. 21/2021, Available at SSRN: *https://ssrn.com/abstract=3785777* or *http://dx.doi.org/10.2139/ssrn.3785777*.

CALDARA, D., FUENTES-ALBERO, C., GILCHRIST, S. and ZAKRAJŠEK, E., 2016. "The macroeconomic impact of financial and uncertainty shocks", European Economic Review, Volume 88, 2016, Pages 185-207, ISSN 0014-2921. Available at: *https://doi.org/10.1016/j.euroecorev.2016.02.020*.

CARRIERO, A., CLARK, T. E. and MARCELLINO, M., 2012. "Common Drifting Volatility in Large Bayesian VARs", London, Centre for Economic Policy Research. Available at: *https://cepr.org/active/publications/discussion_papers/dp.php?dpno=8894*.

CARRIERO, A., CLARK, T. E. and MARCELLINO, M., 2016. "Common Drifting Volatility in Large Bayesian VARs", Journal of Business & Economic Statistics, 34:3, 375-390.

CHRISTIANO, L. J., EICHENBAUM, M. and EVANS, C. L., 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy", Journal of Political Economy 2005 113:1, 1-45.

CHUDIK, A. and FRATZSCHER, M., 2011. "Identifying the global transmission of the 2007–2009 financial crisis in a GVAR model", European Economic Review, Volume 55, Issue 3, Pages 325-339, ISSN 0014-2921. https://doi.org/10.1016/j.euroecorev.2010.12.003.

CLEARLY CULTURAL. Online article available at: *https://clearlycultural.com/geert-hofstede-cultural-dimensions/uncertainty-avoidance-index/*.

COLOMBO, V., 2013. "Economic policy uncertainty in the US: Does it matter for the Euro area?", Economics Letters, Volume 121, Issue 1, 2013, Pages 39-42, ISSN 0165-1765. Available at: *https://doi.org/10.1016/j.econlet.2013.06.024*.

DEES, S. and SAINT-GUILHEM, A., 2011. "The role of the United States in the global economy and its evolution over time", Empir Econ 41, 573–591. https://doi.org/10.1007/s00181-010-0407-2.

DEES, S. AND VANSTEENKISTE, I., 2007. "The Transmission of US Cyclical Developments to the Rest of the World", ECB Working Paper No. 798, Available at SSRN: https://ssrn.com/abstract=1005117 or http://dx.doi.org/10.2139/ssrn.1005117.

DIETHER, K.B., MALLOY, C.J. AND SCHERBINA, A., 2002. "Differences of Opinion and the Cross Section of Stock Returns", The Journal of Finance, 57: 2113-2141. Available at: https://doi.org/10.1111/0022-1082.00490.

DONADELLI, M., GUFLER, I. and PELLIZZARI, P., 2020. "The macro and asset pricing implications of rising Italian uncertainty: Evidence from a novel news-based macroeconomic policy uncertainty index", Economics Letters, Volume 197, 2020, 109606, ISSN 0165-1765. Available at: https://doi.org/10.1016/j.econlet.2020.109606.

FANG, T., SU, Z. and YIN, L., 2019. "The North American Journal of Economics and Finance", Volume 48, Pages 582-590, ISSN 1062-9408. https://doi.org/10.1016/j.najef.2018.07.014.

FERNÁNDEZ-VILLAVERDE, J., GUERRÓN-QUINTANA, P., RUBIO-RAMÍREZ, J. F. and URIBE, M., 2011. "Risk Matters: The Real Effects of Volatility Shocks." American Economic Review, 101 (6): 2530-61.

FORONI, C., 2015. "A Primer on Structural VARs", lecture notes [online]. Available at: https://www.uio.no/studier/emner/sv/oekonomi/ECON4160/h15/teaching-material/svar_lecturenotes.pdf

FRY, R. and PAGAN, A., 2011. "Sign Restrictions in Structural Vector Autoregressions: A Critical Review", Journal of Economic Literature, 49(4), pp. 938-960.

GAYER, C., REUTER, A. and MORICE, F., 2021. "A new survey-based measure of economic uncertainty", European Commission. Available at: https://voxeu.org/article/new-survey-based-measure-economic-uncertainty.

GREASLEY, D. and MADSEN, J.B., 2006. "Investment and Uncertainty: Precipitating the Great Depression in the United States", Economica, 73: 393-412. https://doi.org/10.1111/j.1468-0335.2006.00505.x.

GRIER, K.B., HENRY, Ó.T., OLEKALNS, N. AND SHIELDS, K., 2004. "The asymmetric effects of uncertainty on inflation and output growth", Journal of Applied Econometrics, 19: 551-565. Available at: https://doi.org/10.1002/jae.763.

HAMILTON, J. D., 1994. "Time series analysis", Princeton, New Jersey, Princeton University Press, 1994.

HASSLER, J., 2001. "Uncertainty and the Timing of Automobile Purchases", Scandinavian Journal of Economics, 103: 351-366. https://doi.org/10.1111/1467-9442.00249.

IMF, 2021. "Understanding the Rise in Long-Term Rates". Available at: https://blogs.imf.org/2021/04/22/understanding-the-rise-in-us-long-term-rates/.

JURADO, K., LUDVIGSON, S. C. and NG, S., 2015. "Measuring Uncertainty." American Economic Review, 105 (3): 1177-1216. Additional information and data available at: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

KILIAN, L. and MURPHY, D. P., 2012. "Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market Var Models", Journal of the European Economic Association, Volume 10, Issue 5, 1 October 2012, Pages 1166–1188. Available at: https://doi.org/10.1111/j.1542-4774.2012.01080.x.

KIRCHGÄSSNER, G. and WOLTERS, J., 2007. "Introduction to Modern Time Series Analysis", Berlin, Springer, 2007.

LAFREE, G., MORRIS, N. A. and DUGAN, L., 2010. "Cross-National Patterns of Terrorism: Comparing Trajectories for Total, Attributed and Fatal Attacks, 1970–2006", The British Journal of Criminology, Volume 50, Issue 4, July 2010, Pages 622–649. Available at: https://doi.org/10.1093/bjc/azp066.

LAHIRI, K. and SHENG, X., 2010. "Measuring forecast uncertainty by disagreement: The missing link", Journal of Applied Econometrics, 25: 514-538. Available at: https://doi.org/10.1002/jae.1167.

LEDUC, S. and LIU, Z., 2016. "Uncertainty shocks are aggregate demand shocks", Journal of Monetary Economics, Volume 82, Pages 20-35, ISSN 0304-3932. https://doi.org/10.1016/j.jmoneco.2016.07.002.

LIU, L. and ZHANG, Z., 2015. "Economic policy uncertainty and stock market volatility", Finance Research Letters, Volume 15, Pages 99-105, ISSN 1544-6123. https://doi.org/10.1016/j.frl.2015.08.009.

LUDVIGSON, S. C. and NG, S., 2007. "The empirical risk–return relation: A factor analysis approach", Journal of Financial Economics, Volume 83, Issue 1, 2007, Pages 171-222, ISSN 0304-405X. Available at: https://doi.org/10.1016/j.jfineco.2005.12.002.

LUDVIGSON, S. C. and NG, S., 2009. "Macro Factors in Bond Risk Premia", The Review of Financial Studies, Volume 22, Issue 12, December 2009, Pages 5027–5067. Available at: https://doi.org/10.1093/rfs/hhp081.

MANKIW, N. G., REIS, R. AND WOLFERS, J., 2004. "Disagreement About Inflation Expectations.", NBER Macroeconomics Annual 2003, edited by Mark Gertler and Kenneth Rogoff, 209–48. Cambridge, MA: MIT Press.

MEGARITIS, A., VLASTAKIS, N. and TRIANTAFYLLOU, A., 2021. "Stock market volatility and jumps in times of uncertainty", Journal of International Money and Finance, Volume 113, 2021, 102355, ISSN 0261-5606. Available at: https://doi.org/10.1016/j.jimonfin.2021.102355.

MUMTAZ, H. and THEODORIDIS, K., 2016. "Volatility co-movement and the great moderation: An empirical analysis", Working Paper, 2016.

PELLEGRINO, G., 2021. "Uncertainty and monetary policy in the US: A journey into nonlinear territory", Economic Inquiry, 59: 1106– 1128. Available at: https://doi.org/10.1111/ecin.12986.

ROMER, P. M., 1990. "Capital, Labor, and Productivity", Brookings Papers on Economic Activity. Microeconomics, 1990, 337–367. https://doi.org/10.2307/2534785.

SHIN, M., ZHANG, B., ZHONG, M. and JIN LEE, D., 2018. "Measuring international uncertainty: The case of Korea", Economics Letters, Volume 162, 2018, Pages 22-26, ISSN 0165-1765. Available at: https://doi.org/10.1016/j.econlet.2017.10.014.

SIM, J., ZAKRAJSEK, E. AND GILCHRIST, S., 2010. "Uncertainty, Financial Frictions, and Investment Dynamics", 2010 Meeting Papers 1285, Society for Economic Dynamics.

SIMS, C. A., 1980. "Macroeconomics and Reality", Econometrica, 48(1), 1–48. Available at: https://doi.org/10.2307/1912017.

SO, E. C., 2013. "A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?", Journal of Financial Economics, Volume 108, Issue 3, 2013, Pages 615-640, ISSN 0304-405X. Available at: https://doi.org/10.1016/j.jfineco.2013.02.002.

STOCK, J. H. and WATSON, M. W., 2001. "Vector Autoregressions", Journal of Economic Perspectives, 15, pp. 101-115.

STOCK, J. H. and WATSON, M. W., 2002. "Forecasting Using Principal Components from a Large Number of Predictors", Journal of the American Statistical Association 97 (460): 1167–79.

STOCK, J. H. and WATSON, M. W., 2002. "Macroeconomic Forecasting Using Diffusion Indexes", Journal of Business and Economic Statistics 20 (2): 147–62.

WILMS, R., MÄTHNER, E., WINNEN, L. and LANWEHR, R., 2021. "Omitted variable bias: A threat to estimating causal relationships", Methods in Psychology, Volume 5, 2021, 100075, ISSN 2590-2601. Available at: *https://doi.org/10.1016/j.metip.2021.100075*.