Uncertainty and the Macroeconomy: Evidence from an uncertainty composite indicator *

Amélie Charles, Olivier Darné, Fabien Tripier

Uncertainty and the Macroeconomy: Evidence from an uncertainty composite indicator*

Amélie CHARLES†

Audencia Business School

Olivier DARNÉ‡

LEMNA, University of Nantes

Fabien TRIPIER§

EPEE, University of Evry & CEPII

*Amélie Charles and Olivier Darné gratefully acknowledge financial support from the Région des Pays de la Loire (France) through the grant PANORisk.

†Audencia Business School, 8 route de la Jonelière, 44312 Nantes Cedex 3. Email: acharles@audencia.com.

‡Corresponding author. LEMNA, University of Nantes, Chemin de la Censive du Tertre, BP 52231, 44322 Nantes, France. Email: olivier.darne@univ-nantes.fr.

§EPEE, University of Evry, University Paris-Saclay, 4, Boulevard Franois Mitterrand, 91025 Evry, France. CEPII, 113 Rue de Grenelle, 75007 Paris, France. Email: fabien.tripier@univ-evry.fr.

Abstract

This paper proposes a uncertainty composite indicator (UCI) based on three distinct sources of uncertainty (namely financial, political, and macroeconomic) for the US economy on the period 1985-2015. For that, we use the dynamic factor model proposed by Doz et al. (2012), summarizing efficiently six individual uncertainty proxies, namely two macroeconomic and financial uncertainty factors based on the unpredictability, a measure of (micro)economic uncertainty, the implied volatility index, the corporate bond spreads, and an index of economic policy uncertainty. We then compare the effects of uncertainty on economic activity when the UCI is used instead of individual uncertainty proxies in structural VAR models. The interest of our UCI is to synthesize theses effects within one measure of uncertainty. Overall, the UCI was able to account for the most important dynamics of uncertainty which play an important role in business cycles.

Keywords: Uncertainty; dynamic factor model; economic activity.

JEL Classification: C38, C32, E32.

1 Introduction

It is well-known that uncertainty about the future has real implications on economic agents' behavior (Dixit, 1989), and also on the economic activity (Bloom et al., 2007; Bloom, 2009; Bachmann et al., 2013; Jurado et al., 2015).[1] Uncertainty as a driver of business cycle fluctuations have been first proposed by Bloom (2009) and Bloom et al. (2012), who argue that on average uncertainty goes up by almost 50% in an US recession and that uncertainty shocks lead to a significant, albeit temporary fall in output and productivity.

Uncertainty is difficult to quantify since it is intrinsically unobservable concept, and there are different sources of uncertainty, such as, for example, macroeconomics, financial markets or economic policy. However, it is possible to observe uncertainty indirectly using a number of proxy indicators. A number of alternative measures of uncertainty have been proposed, such as variations in the cross-sectional dispersion of firms' or industry's earnings or productivity (Bloom, 2009; Bloom et al., 2012), the VIX implied volatility index (Bloom, 2009), the economic policy uncertainty index (Baker et al., 2016; Brogaard and Detzel, 2015), the conditional variance of the unforecastable component in statistical models (Scotti, 2012; Jurado et al., 2015; Rossi and Sekhposyan, 2015; Ludvigson et al., 2015), forecast disagreement and disconformity (Bachmann et al., 2013), the variance risk premium (Zhou, 2009; Bali and Zhou, 2015), the perceived uncertainty by consumers from survey data (Leduc and Liu, 2016) or the volatility of fiscal instruments estimated under time-varying volatility (Fernandez-Villaverde et al., 2015), among others.[2] Most of these uncertainty measures take into account one of the sources of uncertainty, namely macroeconomics, financial markets or economic policy. The few studies that compare

[1]See Bloom (2014) and Bloom et al. (2014) for a comprehensive survey of the literature on uncertainty shocks.

[2]Most of studies analyzing the impact of uncertainty shocks have employed VAR models, whereas some studies have used Dynamic Stochastic General Equilibrium models, such as Bloom et al. (2012), Christiano et al. (2014), and Leduc and Liu (2016).

the effect of different uncertainty measures on the economic activity find substantial differences in their effect on economic activity. For example, Jurado et al. (2015) and Rossi and Sekhposyan (2015) find that an uncertainty innovation in the macroeconomic uncertainty has a larger and prolonged negative effect on manufacturing production and (un)employment than others uncertainty measures, such as economic policy uncertainty and/or implied volatility.[3]

To the best of our knowledge, only one study proposes an aggregate measure of the economic uncertainty based on a number of proxy indicators. Haddow et al. (2013) use principal component analysis (PCA) to construct an uncertainty index based on four indicators (financial and survey data) for the UK on the 1985-2013 period. However, their uncertainty index does not take into account economic policy uncertainty in their uncertainty proxy. In this paper, we construct a uncertainty composite indicator (UCI) for the US economy, by using three different sources of uncertainty, namely macroeconomics, financial markets or economic policy, based on six uncertainty proxies which are usually used in the literature, namely two macroeconomic and financial uncertainty factors based on the unpredictability (MACRO-JLN and FIN-LMN) proposed by Jurado et al. (2015) and Ludvigson et al. (2015), respectively, a measure of (micro)economic uncertainty (FDISP) with the forecast disagreement index proposed by Bachmann et al. (2013), the implied volatility index (VXO), the corporate bond spreads (BSREAD), and an index of economic policy uncertainty (EPU) proposed by Baker et al. (2016).[4] For that, we use the dynamic factor model (DFM) proposed

[3]Bachmann et al. (2013) compare the effects of four measures of uncertainty related to forecast disagreement, economic policy uncertainty, stock market volatility, and interest rate spreads in Germany and in the US. Born et al. (2014) quantify the contribution of various uncertainty shocks to the Great Recession and the slow recovery in the US.

[4]Knight (1921) established a distinction between risk and true uncertainty. Risk refers to the possibility of a future outcome for which the probabilities of the different possible states of the world are known. Uncertainty refers to a future outcome that has unknown probabilities associated with the different possible states of the world. Note that some of what we call uncertainty may indeed be risk as defined by Knight (1921). Thus, we use different proxies for economic uncertainty, which can differ

by Doz et al. (2012) based on the quasi maximum likelihood method that allows summarizing efficiently the six uncertainty proxies in an indicator. For our purpose, this approach has two advantages. First, the dynamic factor approach has the advantage of capturing both the significance and the variability of the components, unlike the weighting schemes in the traditional and principal component approaches (Lim and Nguyen, 2015). Second, this maximum likelihood approach is more efficient for small samples (Doz et al., 2012).[5] The interest of our UCI is to synthesize the effects of different uncertainty measures within one aggregate measure of uncertainty. By doing so, we attempt to capture the core effects of uncertainty to economic activity, which are not specific to particular measure of this phenomenon (removing the idiosyncratic component that any individual uncertainty measure may have), and therefore to better identify its contribution to economic activity.

Then, we investigate the interest of our UCI when compared with six individual measures of uncertainty by analyzing the consequences of uncertainty on US economic activity. For that, we use the empirical strategy proposed by Jurado et al. (2015) by estimating a eight-variable VAR model. We compare the dynamic responses of economic activity variables to innovations in uncertainty for our UCI and six individual measures of uncertainty principally used in the literature on the economic activity.

Our results are in line with the previous studies on US economic activity, namely an increase in uncertainty leads first to a drop of all series, which are significantly different from zero, and then a positive rebound in real series (manufacturing production, employment, hours) which are however not significantly different from zero. Nevertheless, the novelty of our approach is to synthesize theses effects within one measure of

from Knightian uncertainty.

[5]Other studies also use the DFM to construct uncertainty proxies but not a composite indicator based on uncertainty proxies as we do here. Jurado et al. (2015), Ludvigson et al. (2016) and Henzel and Rangel (2017) construct uncertainty measures based on common forecast errors (that they associate to uncertainty) on a large number of macroeconomic variables with a DFM. Chauvet et al. (2015) also construct a common factor on different measures of (realized and implied) volatility from a DFM.

uncertainty (namely, the UCI). Overall, the UCI is able to account for the most important dynamics of uncertainty which play an important role in business cycles. We find that the individual uncertainty proxies MACRO-JLN and BSPREAD are also important source in explaining the volatility of the macroeconomic variables. However, these two individual proxies are not the dominant source of fluctuations (compared to the other uncertainty variables) in some cases. Therefore, these findings show the interest to use this uncertainty composite index in macroeconomic modelling.

The rest of the paper is organized as follows. Section 2 presents the dynamic factor model. Section 3 briefly describes the various proxies of uncertainty, and the uncertainty composite index is defined in Section 4. Section 5 displays the results regarding the impact of uncertainty on economic activity from a VAR model. Section 6 concludes the paper.

2 Factor models

In the factor model framework, the N variables (x_{it}), for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, are represented as the sum of two mutually orthogonal unobservable components: the common component χ_t and the idiosyncratic component ξ_t. For a given t, $t = 1, \ldots, T$, the static factor model is defined by

$$X_t = \Lambda F_t + \xi_{t,} \tag{1}$$

where $X_t = [x_{1t}, ..., x_{Nt}]^{'}$ is a vector of N stationary time series and it is assumed that the series have zero mean and covariance matrix $\Gamma(0)$, Λ is the loading matrix such that $\Lambda = [\lambda_1, ..., \lambda_N]'$, the common components $\chi_t = \Lambda F_t$ are driven by a small number r of factors F_t common to all the variables in the model such that $F_t = [F_{1t}, ...F_{rt}]^{'}$, and $\xi_t = [\xi_{1t}, ..., \xi_{Nt}]^{'}$ is a vector of N idiosyncratic mutually uncorrelated components, driven by variable-specific shocks. In our study, X_t is the a vector of N individual uncertainty proxies and the first component of the factors F_t is interpreted hereafter as the CUI.

To take dynamics into account in modelling, it is possible to model explicitly the dynamics of the factors F_t from dynamic factor models (DFM).[6] Thus, in the DFM, the common component can be seen as a sum of common shocks, whether contemporaneous or lagged. More precisely, we assume that the DFM representation is given by the following equation:

$$X_t = A(L)F_t + \xi_t, \tag{2}$$

where the common components $\chi_t = A(L)F_t$ integrate a linear dynamics where $A(L)$ is a $(n \times r)$ matrix describing the autoregressive form of the r factors. If we assume that there exists a $(n \times q)$ matrix $B(L)$ such that $B(L) = A(L)N(L)$ with $N(L)$ of dimension $(r \times q)$, then the dynamic factor is such that $F_t = N(L)U_t$ where U_t is a $(q \times 1)$ independent vector containing the dynamic shocks. It follows that the factor dynamics are described by

$$A(L)F_t = B(L)U_t \tag{3}$$

Equation (3) specifies a VAR(p) model for the factor F_t with lag polynomial $A(L) = \sum_{i=1}^{p} A_i L^i$. F_t is thus the $(r \times 1)$ vector of the stacked factors with $r = q(p+1)$.

Doz, Giannone and Reichlin (DGR) (2012) propose a dynamic factor model that can be represented in a space-state form. Specifically, DGR (2012) estimate their dynamic factor model using the quasi maximum likelihood method.[7] The main aim of this approach is to consider the strict factor model as a misspecification of the approximate factor model and to analyze the properties of the maximum likelihood indicator of the factors under this misspecification. This estimator is called the quasi maximum likelihood (QML) in the sense of White (1982).[8] The model defined by means of equations (2) and

[6] See Barhoumi et al. (2013) for a survey on DFMs.

[7] Doz et al. (2011) also propose an alternative approach, the so-called two-step approach.

[8] By analyzing the properties of the maximum likelihood estimator under several sources of misspecifications, such as an omitted serial correlation of the observations or a cross-sectional correlation of the idiosyncratic components, DGR (2012) show that these misspecifications do not affect the robustness of the common factors, particularly for fairly large N and T. More specifically, this estimator is a valid parametric alternative for the estimator resulting from a principal component analysis (PCA).

(3) can be put in a space-state form, with a number of states equal to the number of common factors r. It is noteworthy that the estimation of the parameters of the model, particularly the common factors, by the QML can be approximated by their anticipated values, using the Kalman filter. The likelihood can be maximized by means of the Expectation Maximization (EM) algorithm of Dempster et al. (1977), which requires the use of the Kalman filter for each iteration.

3 Data

While uncertainty is not directly observable it is possible to observe uncertainty indirectly using a number of proxy indicators. The alternative measures of uncertainty differ substantially, especially in terms of the data inputs of the uncertainty proxies and methodologies used for constructing the indicators.
In this study, we use three types of US uncertainty measure, namely macroeconomics, financial markets or economic policy. We focus on uncertainty measures which are usually used in the literature and available at a monthly frequency, on the period from January 1985:1 to December 2015, and from author's websites.[9] Table 1 summarizes the information on the various uncertainty measures with their source, sample and type of uncertainty (see Figure 1).

The macroeconomic uncertainty variable is the macro uncertainty factor (MACRO-JLC) developed by Jurado et al. (2015), based on a common factor extracted from a panel containing the unforecastable component of a large number of monthly economic and financial indicators (132 macro and 147 financial series). The authors compute macroeconomic uncertainty by aggregating the conditional volatility of the purely unpredictable component of the realization of each underlying macroeconomic time series. We also use a measure of (micro)economic uncertainty with the forecast disagreement

[9]We would like to thank the authors to share their data. Others uncertainty measures have been proposed but on a shorter period or a quarterly frequency.

index (FDISP) based on the forecast dispersion in the general business situation question from the Business Outlook Survey proposed by Bachmann et al. (2013). FDISP can be interpreted as a measure of (idiosyncratic) microeconomic uncertainty as opposed to uncertainty about the macroeconomic environment (Bloom, 2014).

For the uncertainty measures in financial markets we employ (i) the implied volatility of the stock market returns as measured by the VXO index and constructed by CBOE, also known as the "fear index" or the "fear gauge", based on trading of S&P 100 (OEX) options;[10] (ii) the corporate bond spreads (BSPREAD), defined as the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield; and (iii) the financial uncertainty index (FIN-LMN) developed by Ludvigson et al. (2015) based on the methodology of Jurado et al. (2015) and a large number of financial indicators (147 financial series including bond market, stock market portfolio returns and commodity markets).

Finally, we use the index of economic policy uncertainty (EPU) proposed by Baker et al. (2016), built on three components: (i) the frequency of newspaper references to economic policy uncertainty (containing the words uncertainty or uncertain, economic or economy, and one or more policy-related terms), (ii) the number of federal tax code provisions set to expire, and (iii) the extent of forecaster disagreement over future inflation and government purchases.

[10] As an alternative to the VXO index, we could have used the newer VIX index, which was introduced by the CBOE on September 22, 2003. The VIX is obtained from the European style S&P500 index option prices and incorporates information from the volatility skew by using a broader range of strike prices than just at-the-money strike series as in the VXO. However, the daily data on VIX starts from January 2, 1990, which does not cover our full sample period, beginning in January 1986. The pre-1986 VXO data are calculated by Bloom (2009). See Whaley (2009) for a history of the VIX and a summary on its calculation.

4 The Uncertainty Composite Index

Most of the uncertainty proxies exhibit significant high positive first-order autocorrelation, indicating that uncertainty is persistent, and are highly positively correlated with each other (see Table 2). This result is consistent with the findings of Orlik and Veldkamp (2014) and Caldara et al. (2016). They tend to move together, suggesting there is a common uncertainty component to all the measures.

We thus propose to identify this common uncertainty component with the uncertainty composite indicator (UCI) constructed from 1985:01 to 2015:12 by using the dynamic factor model proposed by Doz et al. (2012). The DFM allows to extract the common component of the six uncertainty proxies that capture different dimensions of the economic uncertainty: economic policy, finance and macroeconomics. The DFM has the advantage of capturing both the significance and the variability of the components, unlike the weighting schemes in the traditional and principal component approaches (Lim and Nguyen, 2015).[11] The first common factor is highly correlated with all the uncertainty proxies, except for FDISP (Table 3), thus sufficiently captures the common variation among the uncertainty measures, and defines an aggregate uncertainty measure. The UCI also displays significant high positive first-order autocorrelation ($\rho(1) = 0.97$, Table 3).

Figure 2 presents the UCI, together with the NBER recession dates in the US. Picks of the UCI coincide with well-documented uncertainty episodes, such as economic recessions, especially during the 2008 global financial crisis, and also around the October 1987 financial crisis, the LTCM and Russian Debt crisis of 1998, and the terrorist attacks

[11]We have also applied the principal component analysis (PCA) as in Haddow et al. (2013) who construct an uncertainty index based on four indicators for the UK on the 1985-2013 period. This alternative common factor closely resembles that from the DFM, with a coefficient of correlation close to 0.99. We have also replicated the impact of uncertainty on economic activity under this alternative factor and the results are qualitatively similar. Nevertheless, we obtain slightly different results on the forecast error variance (FEV) decomposition as the UCI obtained from the DFM explains a higher fraction of the FEV than that from obtained from the PCA for most economic variables (see Online Appendix).

of 09/11. This result is consistent with Bloom (1999) who finds that recessions appear in periods of significantly higher economic uncertainty. Nevertheless, when comparing the levels of the UCI with some uncertainty measures, such as EPU, MACRO-JLC and VXO, we find some differences (see Figure 1), such as during the first and second Golf War in December 1990 and February 2003, respectively, and the US midterm election in September 2010 for the EPU, or the Asian crisis of 1997 for the VXO. These differences can be explained by the fact that these uncertainty events are very specific to one source of uncertainty (economic policy, financial or macroeconomic) and are not common to the three sources of uncertainty. Therefore, the UCI is particularly appealing because it has the advantage of being based on an underlying uncertainty indicator which is related to three sources of uncertainty.

5 Structural VAR models

We now turn our attention to the issues of the consequences of uncertainty on economic activity raised by Bloom (1999). We instigate the interest of our synthetic measure of uncertainty when compared with the six individual measures of uncertainty as usually done in the literature. To meet this concern we use the empirical strategy proposed by Jurado et al. (2015). They estimate a eight-variable VAR model ordered as follows: log level of S&P 500 stock index (STOCK), log manufacturing production (MP), log manufacturing employment (EMP), log average hours worked in manufacturing (HRS), the log wage in manufacturing (WAGE), the log aggregate CPI (CPI), the Federal Funds rate (FFR), and uncertainty. The measure of uncertainty is ordered at the end. This choice of ordering represents a more conservative setup which precludes a contemporaneous response of the remaining variables to an uncertainty shock. The VAR-8 is estimated with 12 lags which is sufficient to control for the dynamic history of the variables (Bachmann et al., 2013; Jurado et al., 2015). The sample period is January 1985 to December 2015.

We compare the dynamic responses of economic activity variables to innovations in uncertainty for our uncertainty composite indicator (UCI) and six individual measures of uncertainty available on the same sample, namely VXO, EPU, MACRO-JLC, SPREAD, FDISP and FIN-LMN.[12]

5.1 Impulse Response Functions

Figure 3 presents the impulse responses in the VAR-8 model of economic activity to various uncertainty measures by one standard deviation. The shaded gray region is the +/- one standard error confidence band obtained from the system using UCI as the uncertainty measure computed using the bootstrap method developed by Kilian (1998). An increase in the index of uncertainty leads first to a drop of all series, which are significantly different from zero, and then a positive rebound in real series (manufacturing production, employment, hours) which is significantly different from zero. These effects of uncertainty on real, nominal, and financial series are in line with the recent, but already large, literature on this topic (e.g., Bloom, 2009; Colombo, 2013; Caggiano et al., 2014; Nodari, 2014; Jurado et al., 2015).

The reaction to UCI shocks is in few cases similar to that of some individual uncertainty measures. For example, the reaction of production and employment to UCI shocks is closed to that of MACRO-JLC and SPREAD shocks, since production and employment decrease following a positive uncertainty shock (in smaller magnitude for employment) and the impact persists beyond the two-year horizon (more in employment than in production). The pattern of the stock price reaction after an increment in uncertainty is similar between UCI, FIN-LMN and VXO shocks, namely a very short-term negative impact and then a positive rebound. However, the novelty of our approach is to synthesize these effects with one measure of uncertainty while some individual series of uncertainty

[12] As in Bachmann et al. (2013) and Jurado et al. (2015), we do not detrend any variables using the Hodrick-Prescott filter, while Bloom (2009) did so for every series except the VXO index. Because the HP filter uses information over the entire sample, it is difficult to interpret the timing of an observation.

may miss some of these effects. For example, the FDISP series does not account for the negative impact of uncertainty on inflation, wage, and federal fund rates. Similarly, the size of the effects of uncertainty are notably lower with EPU uncertainty measure on real series (production, employment and hours) and with MACRO-JLC and EPU on stock prices than with our UCI.

5.2 Forecast Error Variance Decomposition

Figure 4 shows the associated forecast error variance decomposition (FEVD) that is the share of the variance explained by the uncertainty measure at various forecast horizons. This figure reinforces the interest of the UCI: it is the measure of uncertainty that gives to this phenomena the most important role in business cycles, with more than 20% of the forecast errors for the most of variables. For example, the UCI shock explain 43% of the forecast errors for the sixth month after the innovation for stock series and 37% for the eighteenth month for employment. There are some exceptions to this conclusion: the FDISP variable explains a higher share of the variance of wages series in the short-run, the EPU variable for federal fund rate, the MACRO-JLC variable for production, and SPREAD variable for the CPI series. Nevertheless, even the UCI does not explain the highest share of the variance in these cases, it explains a higher share than the others individual uncertainty measures. Overall, by synthesizing the common dynamics of each measure of uncertainty, the UCI is able to account for the most important dynamics of uncertainty which play an important role in business cycles. This is particularly true when the UCI is compared with the VXO, which is the most popular measure of uncertainty in the literature. When the VXO is used, the share of variance explained by uncertainty shocks do not go beyond 12% for manufacturing production, employment, or hours, while it reaches respectively 24%, 35%, and 20% when the UCI is used. Then, the UCI leads to a substantial upward revision of the role of uncertainty in business cycle.

Table 5 documents the FEVD attributable to each uncertainty proxy at various forecast horizons ($h = 1, 12, 24, 36$). The results show that the UCI and the individual uncertainty proxies explain a very large fraction of the forecast error variance over the different forecast horizons, except for the FDISP series. The UCI turns out to be the dominant source of employment and hours fluctuations (27% and 16%, respectively, for a 24-month horizon), and also plays an important role in explaining the volatility of the others economic variables by giving the second (stock, CPI and federal fund rates) or third (manufacturing production and wage) highest fraction of the FEV (more than 15%).

For the individual uncertainty proxies we find that MACRO-JLN and BSPREAD are important source in business cycle fluctuations. For example, MACRO-JLN and BSPREAD shocks explain up to 15% of the FEV in manufacturing production for a 12-month horizon. This result confirms that of Jurado et al. (2015) and Rossi and Sekhposyan (2015) who find that an uncertainty innovation in the macroeconomic uncertainty has a larger and prolonged negative effect on manufacturing production than others (individual) uncertainty measures, such as economic policy uncertainty and/or implied volatility. However, these two individual proxies are not the dominant source of fluctuations (compared to the other uncertainty variables) in stock, hours, wages and federal fund rate for MACRO-JLN, and stock, employment and hours for BSPREAD.

5.3 Robustness Checks

Inspecting the second and third factors. To confirm that the first common factor (UCI) well captures all the interesting information among the uncertainty measures when analyzing its consequences on economic activity we estimate the VAR-8 with the second and third common factors of DFM. Figure 5 shows that the reaction to shocks from factors 2 and 3 are not significant, whatever the economic variable. This result is confirmed by the associated FEVD (Figure 6) where the UCI gives to this phenomena the most important role in business cycles, with more than 20% of the forecast errors for the most of variables whereas the two others factors represent less than 2%, except for wages and federal fund rate.

Alternative specification for the VAR. As a robustness check to model specification we also estimate impulse responses from a VAR-8 model with the measure of uncertainty ordered second after the stock market level as in Bachmann et al. (2013). This choice of ordering implies that the uncertainty shock is identified as a shock that moves instantaneously all series. Figure 6 displays the IRFs and shows that the impulse responses of macroeconomic variables to the uncertainty shocks are quite similar to those obtained from the previous VAR-8 with the uncertainty ordered in last but they are less significant. Figure 7 displays the FEVD and Table 6 summarizes the FEVD at various forecast horizons. Overall, the FEVD are also quite similar to those under the previous VAR-8. We only find slight differences in the contribution in some cases which change the dominant source of fluctuation for some macroeconomic variables. For example, the UCI becomes the second source of employment fluctuations whereas it was the dominant source in the previous VAR-8. Nevertheless, we find that the UCI, MACRO-JLN and BSPREAD still play an important source in business cycle fluctuations.

Subsample analysis. To examine whether the effect of uncertainty on economic activity is different over the time we analyze the dynamic responses of economic activity variables to innovations in uncertainty on two subsamples, namely 1985-2000 and 2000-2015. The VAR-8 is estimated with 6 lags and the measure of uncertainty is ordered at the end. Figures 8 and 9 present the IRFs for the two subsamples and show that the impulse responses of macroeconomic variables to the uncertainty shocks are stronger in the second subsample than in the first subsample, except for wages and federal fund rates. This result is confirmed by Tables 6 and 7 displaying the associated FEVD. For example, the UCI shocks explain around 15% of the FEV in stock, manufacturing production and employment for a 12-month horizon in the first subsample whereas they explain more than 30% in the second subsample. Finally, from the individual uncertainty proxies, EPU is the dominant source of fluctuations in most economic variables during the period 1985-2000 whereas the financial and macroeconomic uncertainties become the main source of fluctuations during the period 2000-2015.

6 Conclusion

This paper proposed an uncertainty composite indicator (UCI) based on three distinct sources of uncertainty (namely financial, political, and macroeconomic) for the US economy on the period 1985-2015. For that, we used the dynamic factor model proposed by Doz et al. (2012) based on the quasi maximum likelihood method, summarizing efficiently six uncertainty proxies, namely two macroeconomic and financial uncertainty factors based on the unpredictability, a measure of (micro)economic uncertainty, the implied volatility index, the corporate bond spreads, and an index of economic policy uncertainty. We then compared the sensitivity of macroeconomic variables to the UCI and six individual standard proxies of uncertainty from VAR models as in Bachmann et al. (2013) and Jurado et al. (2015).

We showed that an increase in uncertainty leads first to a drop of all macroeconomic series, which are significantly different from zero, and then a positive rebound in real series (manufacturing production, employment, hours) which are however not significantly different from zero. The interest of our UCI is to synthesize these effects within one measure of uncertainty. Overall, the UCI was able to account for the most important dynamics of uncertainty which play an important role in business cycles. We found that the individual uncertainty proxies based macro unpredictability and corporate bond spread are also important source in explaining the volatility of the macroeconomic variables. However, these two individual proxies are not the dominant source of fluctuations (compared to the other uncertainty variables) in some cases. Therefore, these findings show the interest to use this uncertainty composite index in macroeconomic modelling.

Table 1: Some proxies of uncertainty.

Studies or Sources	Name	Sample	Type of uncertainty
CBOE	VXO	1985.01 - 2015.12	Finance
Baker et al. (2016)	EPU	1985.01 - 2015.12	Economic Policy
Jurado et al. (2015)	MACRO-JLC	1985.01 - 2015.12	Macroeconomic
Fed. Reserve Eco. Data	SPREAD	1985.01 - 2015.12	Finance
Bachmann et al. (2013)	FDISP	1985.01 - 2015.12	Microeconomic
Ludvigson et al. (2015)	FIN-LMN	1985.01 - 2015.12	Finance

Table 2: Correlation matrix between uncertainty variables.

	VXO	EPU	MACRO-JLC	BSPREAD	FDISP	FIN-LMN
VXO	1.00	0.50	0.59	0.61	0.21	0.84
EPU		1.00	0.33	0.60	0.01	0.41
MACRO-JLC			1.00	0.68	0.17	0.68
BSPREAD				1.00	-0.02	0.63
FDISP					1.00	0.17
FIN-LMN						1.00
$\rho(1)$	0.89	0.70	0.99	0.97	0.68	0.98

Table 3: Statistic descriptives for the uncertainty composite indicator.

	Mean (%)	Std	Min	Max	Skew	Kur	$\rho(1)$
UCI	0.001	1.87	-2.52	8.75	1.52	6.69	0.97
Correlation	VXO	EPU	MACRO-JLC	BSPREAD	FDISP	FIN-LMN	
UCI	0.83	0.66	0.80	0.85	0.18	0.91	

Notes: For the uncertainty composite indicator (UCI) we display the time-series average (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kur), and first-order autocorrelation ($\rho(1)$).

Table 4: Correlations between uncertainty variables and macroeconomic variables.

	MP	EMP	HRS	CPI	WAGE	STOCK	FFR
VXO	0.043	0.048	-0.356	-0.025	-0.006	-0.070	-0.013
EPU	0.086	-0.308	-0.168	0.230	0.239	0.065	-0.358
MACRO-JLC	0.252	-0.301	-0.562	0.247	0.273	0.120	-0.168
BSPREAD	0.319	-0.540	-0.316	0.455	0.483	0.289	-0.579
FDISP	-0.184	0.258	-0.067	-0.241	-0.250	-0.227	0.401
FIN-LMN	0.103	-0.039	-0.365	0.056	0.079	0.058	-0.085
UCI	0.191	-0.268	-0.420	0.230	-0.030	0.127	-0.279

	HORIZON	STOCK	MP	EMP	HRS	CPI	WAGE	FFR
UCI	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.21	0.12	0.22	0.15	0.10	0.01	0.13
	24	0.19	0.13	0.27	0.16	0.14	0.02	0.15
	36	0.18	0.11	0.25	0.15	0.13	0.05	0.14
FDISP	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.04	0.00	0.02	0.01	0.00	0.02	0.00
	24	0.04	0.00	0.02	0.01	0.00	0.02	0.05
	36	0.03	0.01	0.01	0.02	0.00	0.02	0.08
VX0	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.10	0.02	0.07	0.03	0.07	0.01	0.03
	24	0.06	0.01	0.04	0.03	0.06	0.01	0.02
	36	0.04	0.01	0.03	0.03	0.05	0.01	0.02
EPU	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.02	0.01	0.02	0.02	0.03	0.02	0.10
	24	0.02	0.01	0.01	0.02	0.03	0.05	0.15
	36	0.02	0.01	0.01	0.02	0.03	0.08	0.14
MACRO-JLC	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.11	0.16	0.18	0.11	0.22	0.01	0.02
	24	0.08	0.13	0.21	0.12	0.25	0.02	0.02
	36	0.08	0.11	0.20	0.11	0.22	0.04	0.01
BSPREAD	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.03	0.15	0.12	0.10	0.05	0.02	0.16
	24	0.06	0.19	0.18	0.10	0.09	0.03	0.22
	36	0.06	0.16	0.15	0.12	0.12	0.07	0.20
FIN-LMN	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12	0.24	0.06	0.15	0.11	0.07	0.00	0.07
	24	0.19	0.08	0.21	0.14	0.10	0.00	0.08
	36	0.17	0.07	0.20	0.13	0.09	0.02	0.07

Table 5: Forecast Error Variance Decomposition: UCI vs univariate measures with uncertainty series in last position in the VAR-8 model. This table presents the contribution of the respective uncertainty shocks (UCI, FDISP, EPU, VXO, BSPREAD, MACRO-JLN, FIN-LMN) to the forecast error variance of variables at different forecast horizons. For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

	HORIZON	STOCK	MP	EMP	HRS	CPI	WAGE	ffr
UCI	1	0.00	0.01	0.00	0.00	0.00	0.00	0.00
	12	0.23	0.17	0.26	0.18	0.09	0.01	0.15
	24	0.22	0.19	0.33	0.19	0.13	0.02	0.18
	36	0.21	0.17	0.31	0.18	0.12	0.06	0.17
FDISP	1	0.00	0.00	0.00	0.00	0.00	0.02	0.00
	12	0.05	0.01	0.02	0.02	0.01	0.07	0.00
	24	0.05	0.01	0.03	0.02	0.00	0.07	0.03
	36	0.04	0.02	0.02	0.03	0.00	0.06	0.05
VX0	1	0.00	0.01	0.00	0.00	0.00	0.00	0.02
	12	0.08	0.01	0.05	0.02	0.09	0.01	0.05
	24	0.05	0.01	0.03	0.02	0.09	0.01	0.04
	36	0.04	0.02	0.02	0.02	0.08	0.01	0.04
EPU	1	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	12	0.02	0.01	0.02	0.02	0.02	0.03	0.15
	24	0.02	0.01	0.01	0.02	0.02	0.06	0.20
	36	0.02	0.01	0.01	0.02	0.02	0.09	0.17
MACRO-JLC	1	0.00	0.05	0.03	0.01	0.02	0.02	0.00
	12	0.13	0.31	0.32	0.18	0.20	0.03	0.08
	24	0.13	0.28	0.35	0.17	0.23	0.04	0.08
	36	0.14	0.24	0.33	0.16	0.21	0.08	0.07
BSPREAD	1	0.00	0.00	0.00	0.00	0.04	0.00	0.03
	12	0.02	0.16	0.16	0.11	0.16	0.01	0.25
	24	0.04	0.15	0.17	0.10	0.22	0.04	0.29
	36	0.04	0.13	0.14	0.11	0.25	0.10	0.26
FIN-LMN	1	0.00	0.01	0.01	0.00	0.01	0.01	0.02
	12	0.26	0.08	0.20	0.13	0.05	0.01	0.04
	24	0.21	0.10	0.25	0.14	0.06	0.01	0.05
	36	0.21	0.09	0.25	0.13	0.05	0.02	0.05

Table 6: Forecast Error Variance Decomposition: UCI vs univariate measures with uncertainty series in second position in the VAR-8 model. This table presents the contribution of the respective uncertainty shocks (UCI, FDISP, EPU, VXO, BSPREAD, MACRO-JLN, FIN-LMN) to the forecast error variance of variables at different forecast horizons. For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

	HORIZON	STOCK	MP	EMP	HRS	CPI	WAGE	FFR
UCI	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.16	0.12	0.17	0.05	0.12	0.11	0.20
	24.00	0.12	0.12	0.17	0.06	0.15	0.17	0.15
	36.00	0.09	0.08	0.14	0.09	0.18	0.24	0.15
FDISP	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.02	0.01	0.01	0.02	0.05	0.06	0.01
	24.00	0.04	0.01	0.03	0.04	0.03	0.08	0.02
	36.00	0.04	0.00	0.04	0.04	0.02	0.05	0.05
VX0	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.25	0.01	0.01	0.02	0.11	0.04	0.06
	24.00	0.18	0.01	0.01	0.03	0.13	0.10	0.03
	36.00	0.13	0.01	0.02	0.03	0.12	0.13	0.02
EPU	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.05	0.17	0.23	0.08	0.12	0.21	0.33
	24.00	0.06	0.16	0.24	0.08	0.11	0.24	0.28
	36.00	0.06	0.10	0.20	0.12	0.11	0.27	0.25
MACRO-JLC	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.03	0.07	0.12	0.05	0.02	0.03	0.04
	24.00	0.03	0.06	0.15	0.05	0.02	0.03	0.12
	36.00	0.02	0.04	0.13	0.07	0.03	0.04	0.13
BSPREAD	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.05	0.11	0.24	0.08	0.05	0.02	0.28
	24.00	0.04	0.06	0.19	0.09	0.04	0.02	0.23
	36.00	0.03	0.06	0.16	0.13	0.05	0.04	0.21
FIN-LMN	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.22	0.03	0.04	0.02	0.11	0.06	0.06
	24.00	0.17	0.04	0.04	0.02	0.13	0.11	0.04
	36.00	0.12	0.03	0.04	0.03	0.16	0.16	0.04

Table 7: Forecast Error Variance Decomposition: Subsample 1985-2000 with uncertainty series in last position in the VAR-8 model. This table presents the contribution of the respective uncertainty shocks (UCI, FDISP, EPU, VXO, BSPREAD, MACRO-JLN, FIN-LMN) to the forecast error variance of variables at different forecast horizons. For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

	HORIZON	STOCK	MP	EMP	HRS	CPI	WAGE	FFR
UCI	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.44	0.36	0.33	0.36	0.10	0.02	0.12
	24.00	0.45	0.41	0.47	0.39	0.14	0.01	0.13
	36.00	0.42	0.37	0.46	0.37	0.13	0.02	0.13
FDISP	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00
	24.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01
	36.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01
VX0	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.19	0.16	0.14	0.13	0.07	0.01	0.06
	24.00	0.18	0.18	0.18	0.13	0.07	0.00	0.09
	36.00	0.16	0.16	0.18	0.13	0.07	0.01	0.09
EPU	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.02	0.01	0.01	0.04	0.03	0.01	0.02
	24.00	0.02	0.01	0.02	0.04	0.02	0.01	0.01
	36.00	0.02	0.01	0.02	0.04	0.01	0.01	0.01
MACRO-JLC	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.17	0.17	0.18	0.31	0.24	0.01	0.02
	24.00	0.16	0.11	0.19	0.27	0.20	0.01	0.01
	36.00	0.15	0.10	0.19	0.23	0.14	0.01	0.01
BSPREAD	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.10	0.22	0.06	0.07	0.04	0.00	0.03
	24.00	0.13	0.37	0.20	0.10	0.07	0.01	0.09
	36.00	0.11	0.32	0.20	0.10	0.10	0.02	0.12
FIN-LMN	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	12.00	0.46	0.20	0.32	0.31	0.09	0.01	0.05
	24.00	0.45	0.22	0.43	0.30	0.12	0.01	0.06
	36.00	0.43	0.20	0.40	0.26	0.11	0.01	0.06

Table 8: Forecast Error Variance Decomposition: Subsample 2000-2015 with uncertainty series in last position in the VAR-8 model. This table presents the contribution of the respective uncertainty shocks (UCI, FDISP, EPU, VXO, BSPREAD, MACRO-JLN, FIN-LMN) to the forecast error variance of variables at different forecast horizons. For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

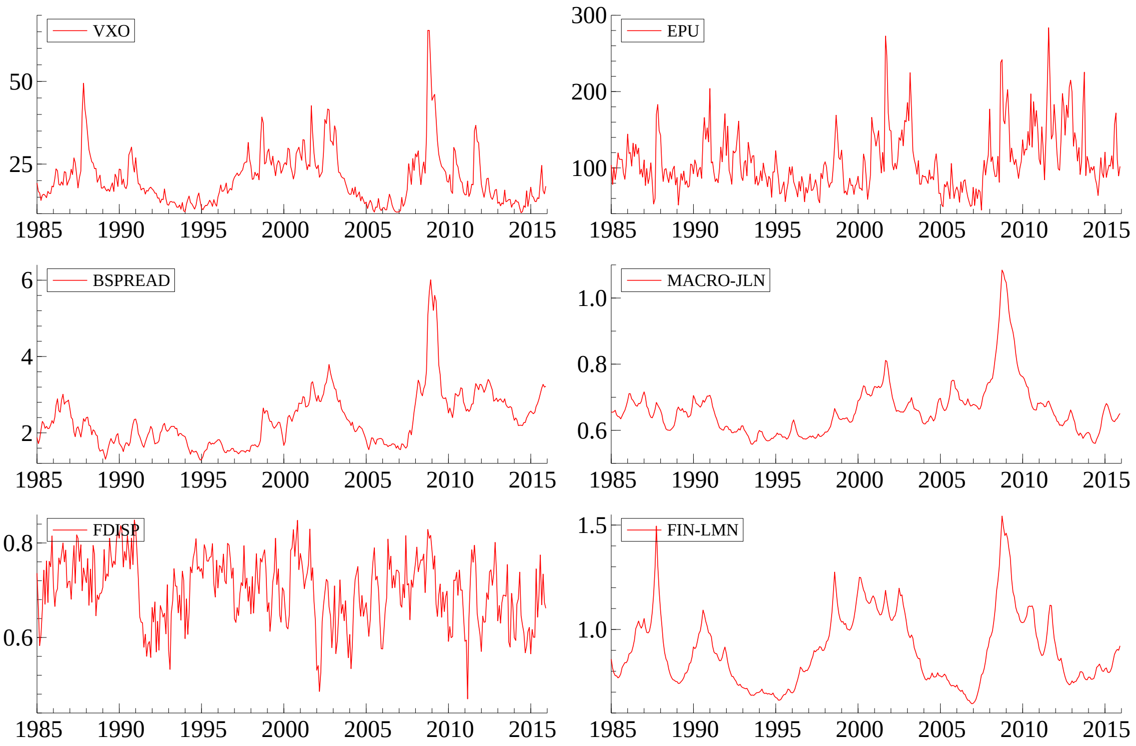

Figure 1: Various proxies of uncertainty.

Notes: MACRO-JLC denotes the macro uncertainty factor developed by Jurado et al. (2015); VXO the CBOE volatility index; BSPREAD the corporate bond spreads; EPU the index of economic policy uncertainty proposed by Baker et al. (2016); FDISP the forecast disagreement index proposed by Bachmann et al. (2013); and FIN-LMN the financial uncertainty measure proposed by Ludvigson et al. (2015). The data are monthly and span the period 1985:01-2015:12.

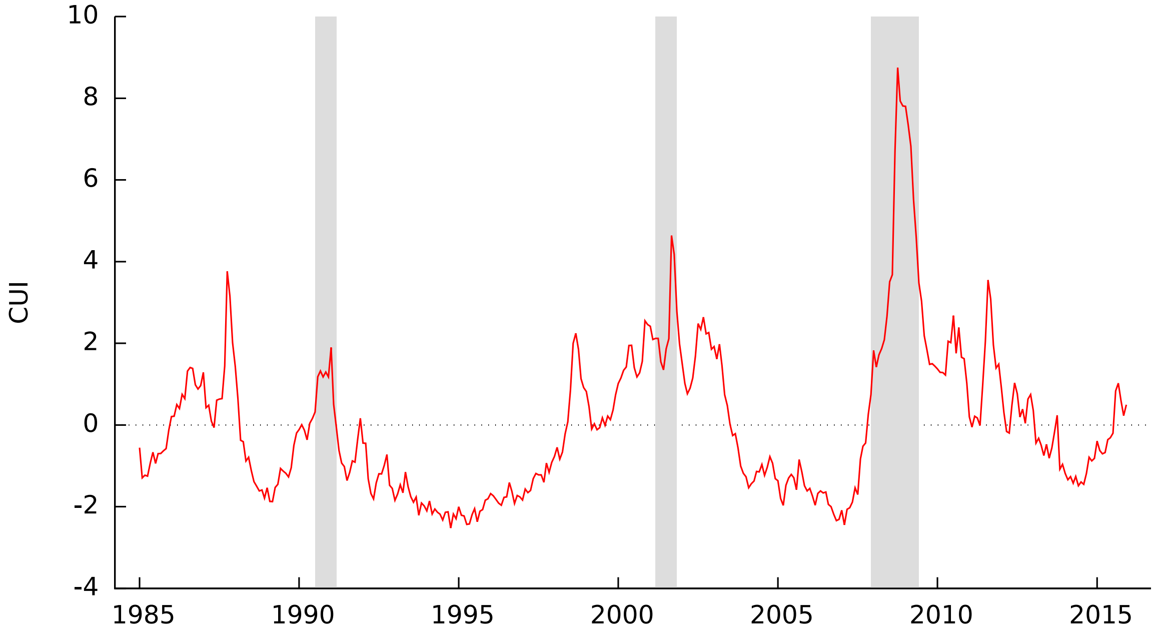

Figure 2: Composite Uncertainty Indicator.

Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2015:12.

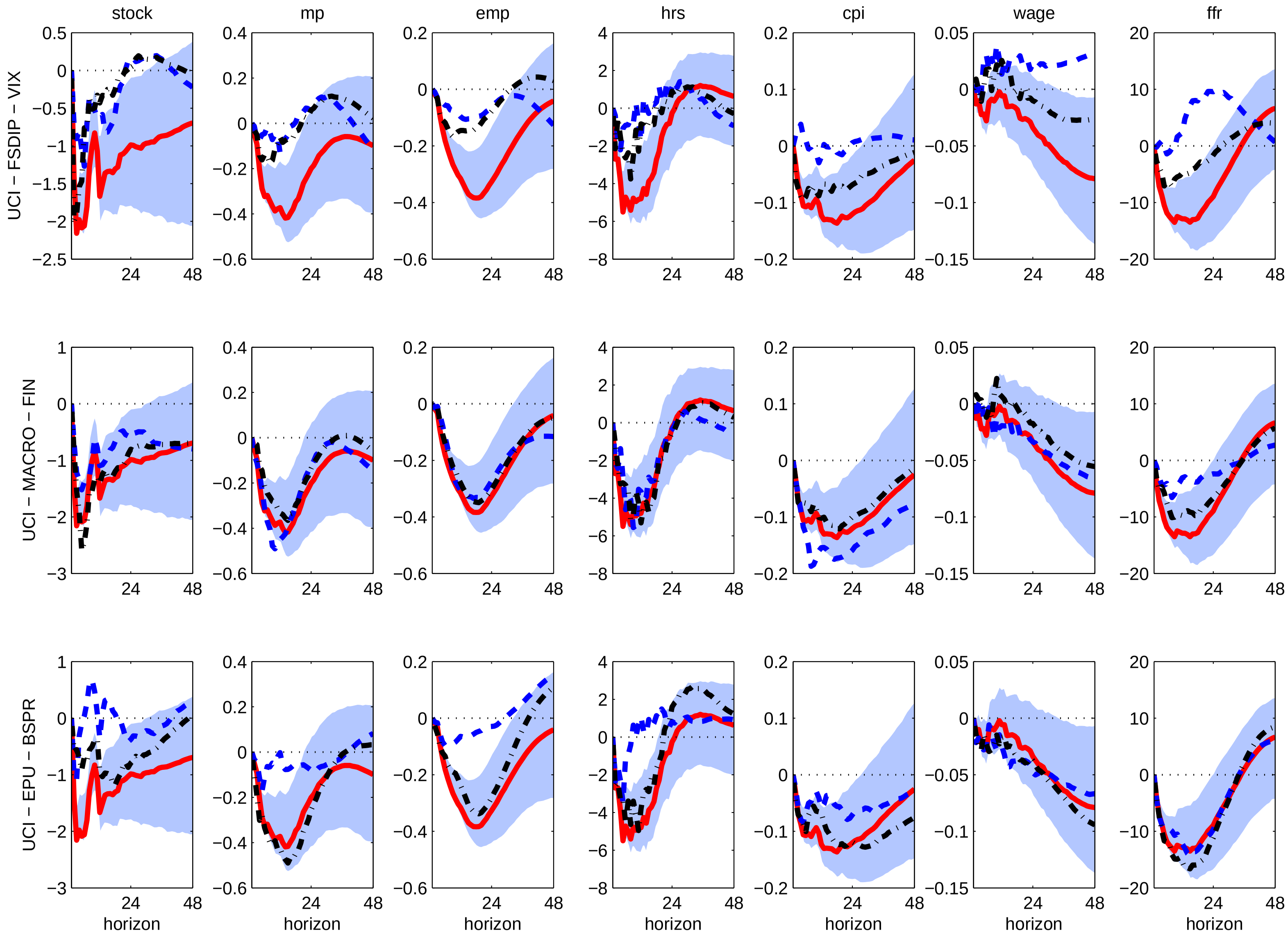

Figure 3: IRFs to uncertainty: UCI vs univariate measures with uncertainty series in last position in the VAR-8 model.

For all panels, the solid red lines show the IRF to a shock to the uncertainty composite indicator with its 95% confidence interval represented by the grey area. The dashed blue lines are for a shock to FDISP (for the panels of the first row), to MACRO-JLC (for those of the second row), and to EPU (for those of the third row). The dashed-dotted black lines are for a shock to VXO (for the panels of the first row), to FIN-LMN (for those of the second row), and to BSPREAD (for those of the third row). For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate. See Bachmann (2013) for a full description of the source of series and Table 6 for the definition of uncertainty variables.

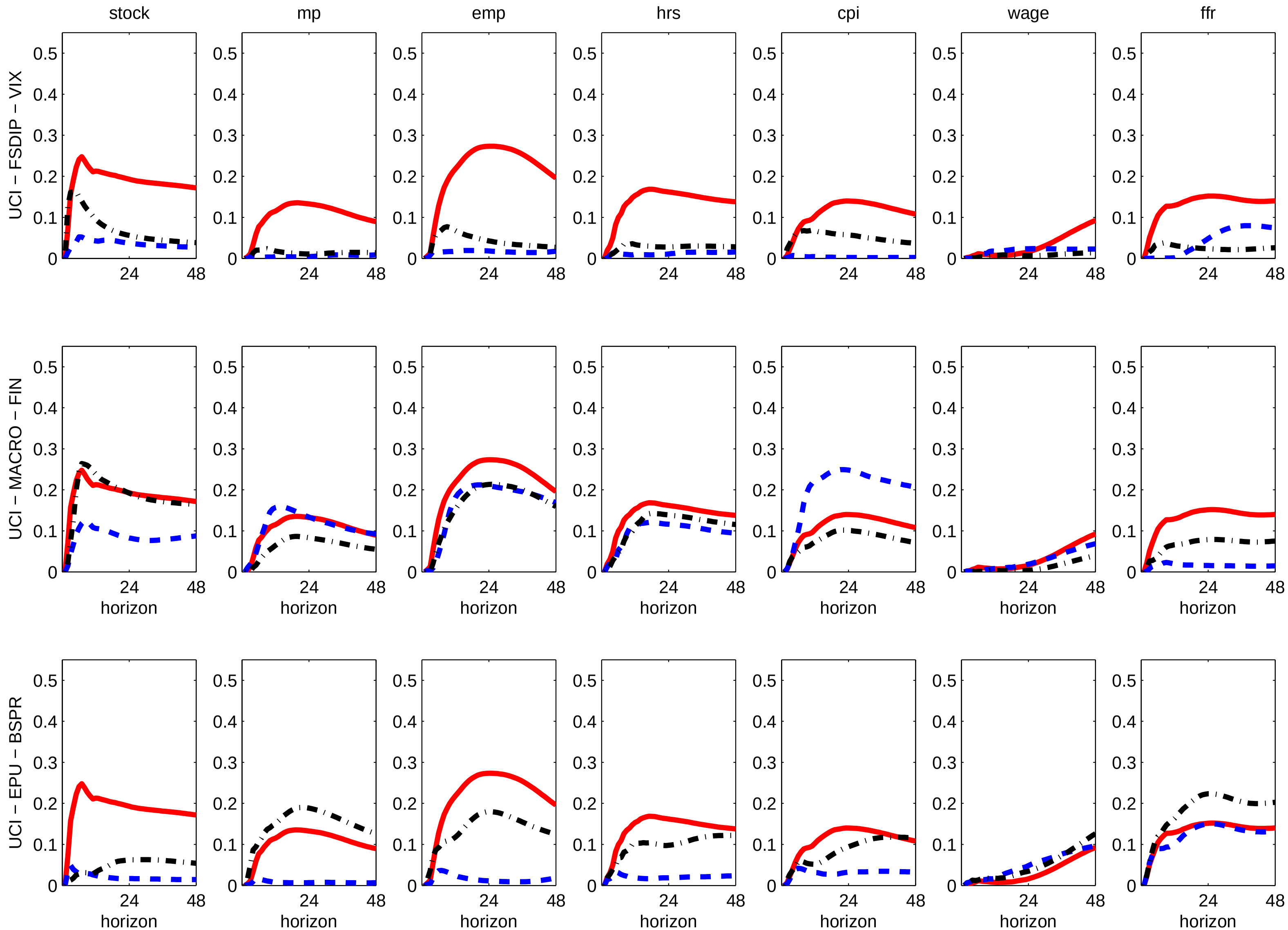

Figure 4: Forecast Error Variance decomposition: UCI vs univariate measures with uncertainty series in last position in the VAR-8 model.

For all panels, the solid red lines show the IRF to a shock to the uncertainty composite indicator with its 95% confidence interval represented by the grey area. The dashed blue lines are for a shock to FDISP (for the panels of the first row), to MACRO-JLC (for those of the second row), and to EPU (for those of the third row). The dashed-dotted black lines are for a shock to VXO (for the panels of the first row), to FIN-LMN (for those of the second row), and to BSPREAD (for those of the third row). For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate. See Bachmann (2013) for a full description of the source of series and Table 6 for the definition of uncertainty variables.

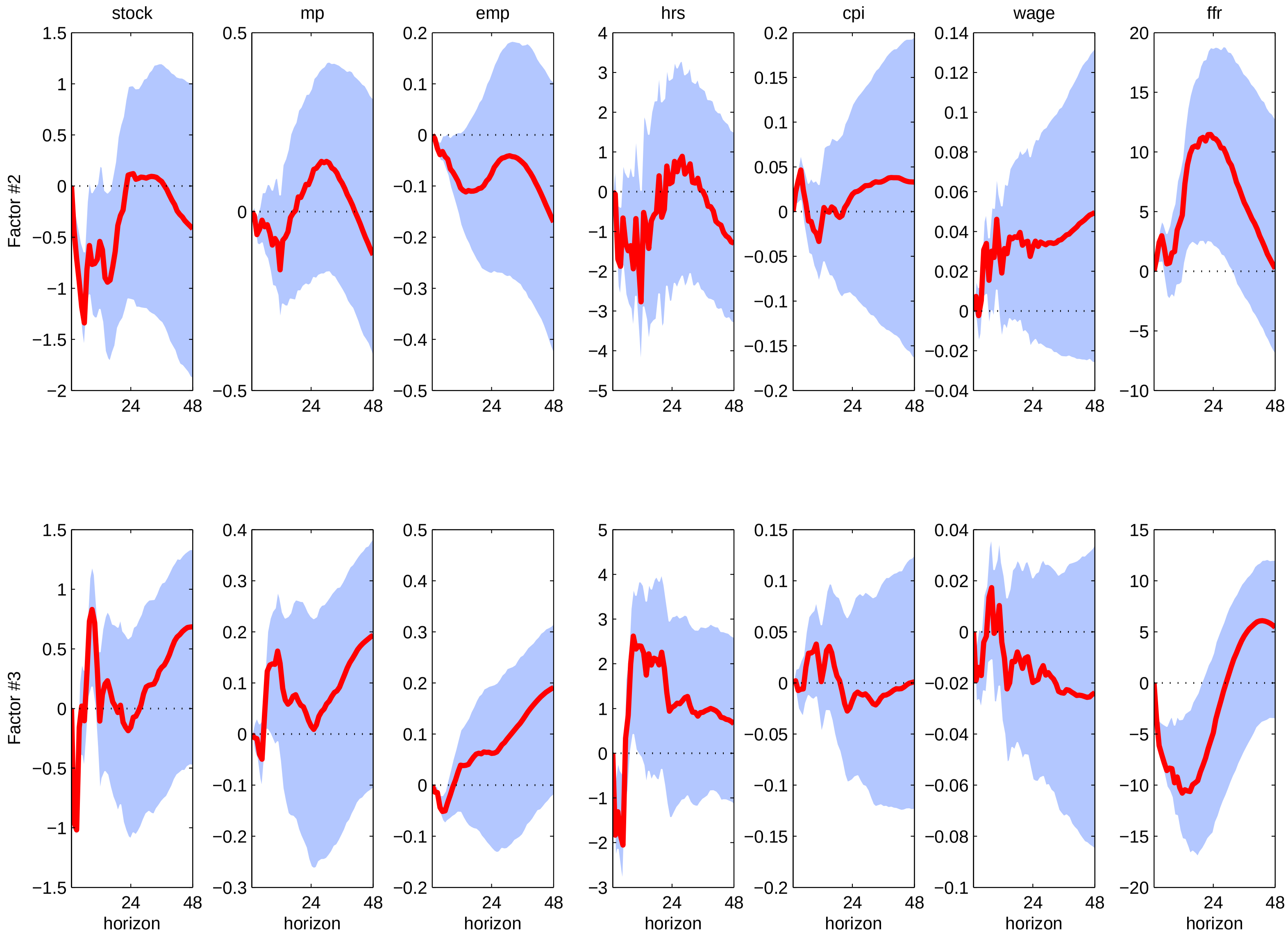

Figure 5: IRFs to uncertainty: Factors 2 and 3 of DFM as uncertainty series ordered in last position in the VAR-8 model.

For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

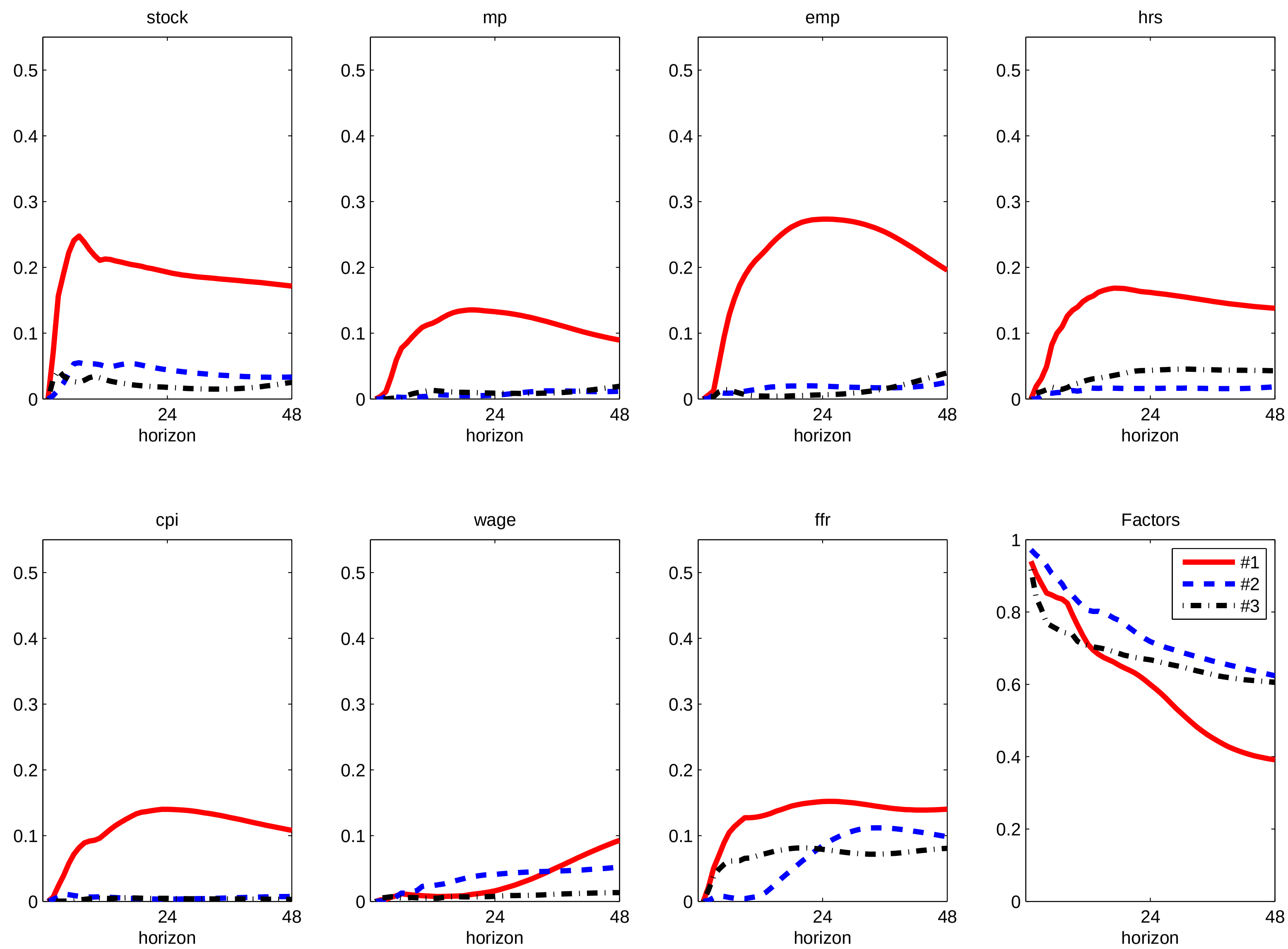

Figure 6: Forecast Error Variance decomposition: Factors 2 and 3 of DFM as uncertainty series ordered in last position in the VAR-8 model.

For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

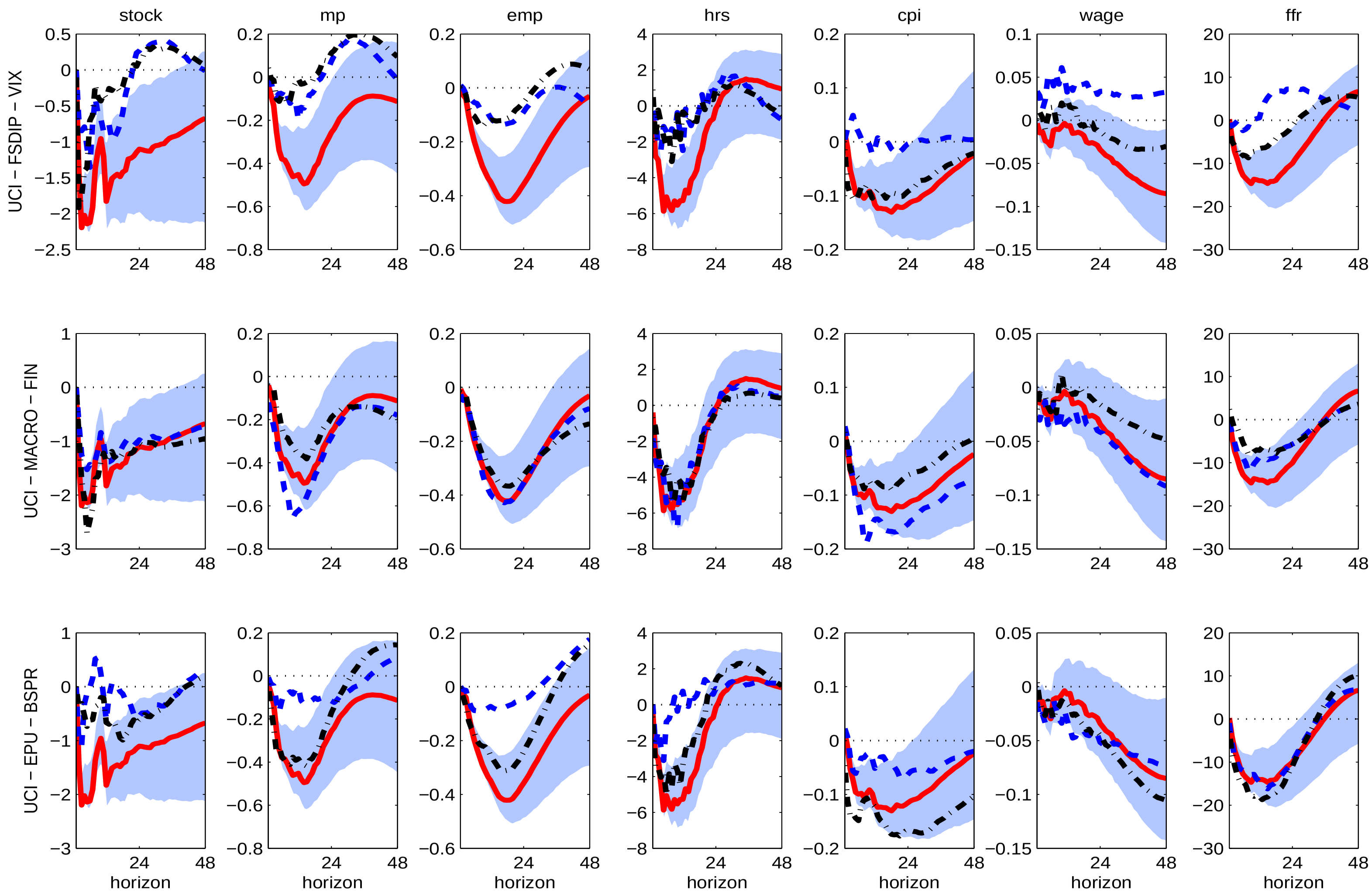

Figure 7: IRFs to uncertainty: UCI vs univariate measures with uncertainty series in second position in the VAR-8 model.

For all panels, the solid red lines show the IRF to a shock to the uncertainty composite indicator with its 95% confidence interval represented by the grey area. The dashed blue lines are for a shock to FDISP (for the panels of the first row), to MACRO-JLC (for those of the second row), and to EPU (for those of the third row). The dashed-dotted black lines are for a shock to VXO (for the panels of the first row), to FIN-LMN (for those of the second row), and to BSPREAD (for those of the third row). For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

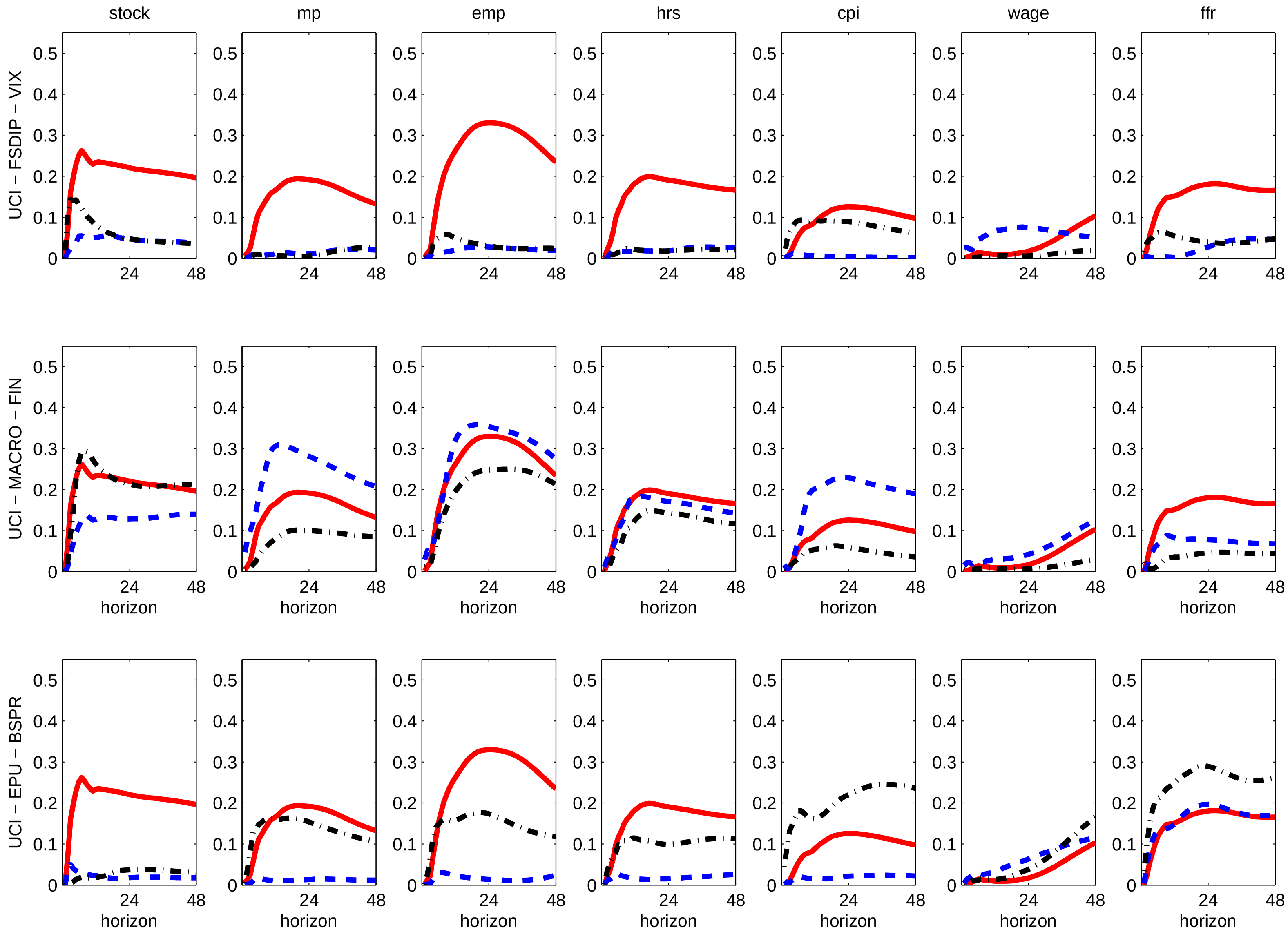

Figure 8: Forecast Error Variance Variance decomposition: UCI vs univariate measures with uncertainty series in second position in the VAR-8 model.

For all panels, the solid red lines show the IRF to a shock to the uncertainty composite indicator with its 95% confidence interval represented by the grey area. The dashed blue lines are for a shock to FDISP (for the panels of the first row), to MACRO-JLC (for those of the second row), and to EPU (for those of the third row). The dashed-dotted black lines are for a shock to VXO (for the panels of the first row), to FIN-LMN (for those of the second row), and to BSPREAD (for those of the third row). For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

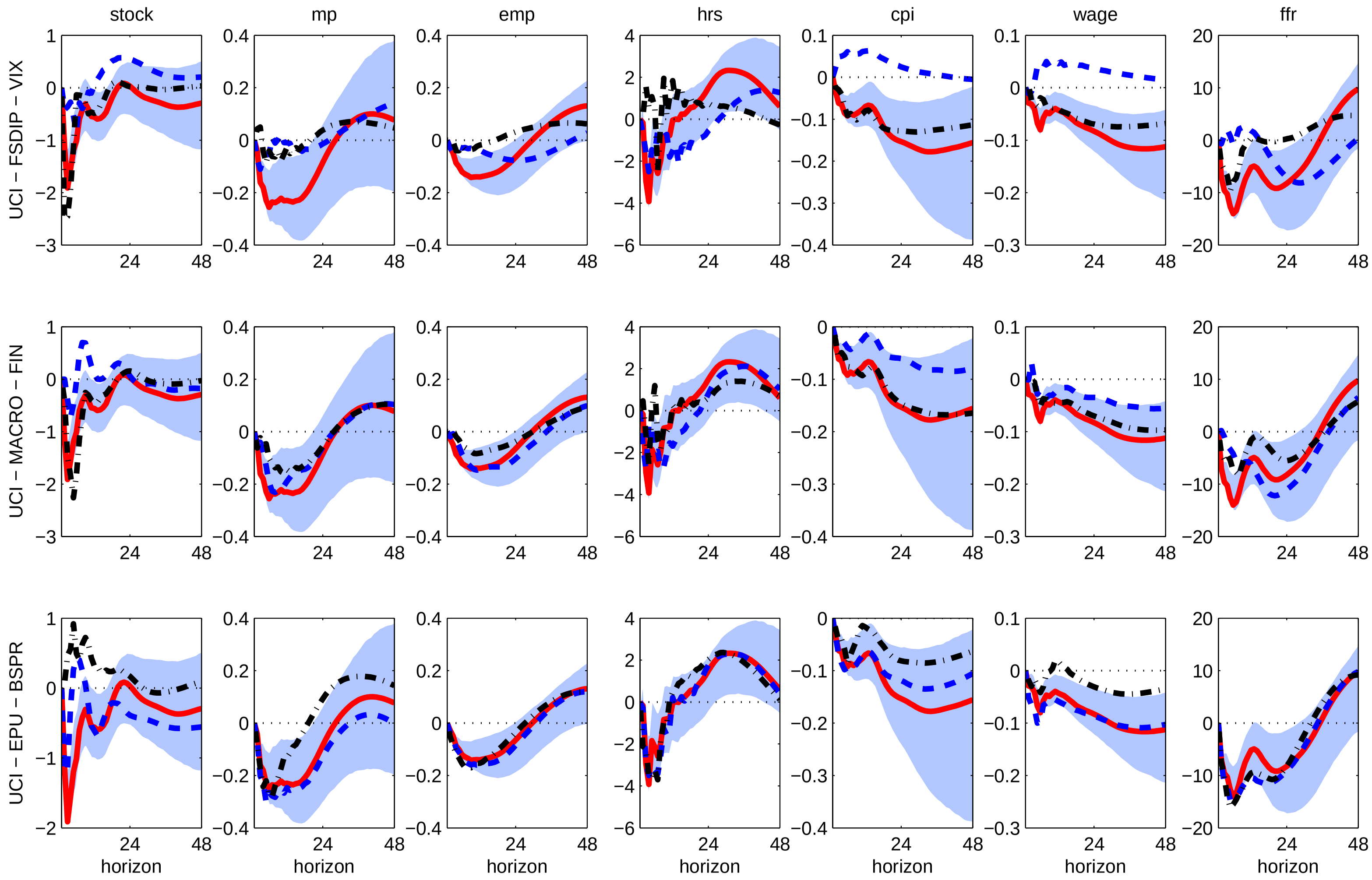

Figure 9: IRFs to uncertainty: Subsample 1985-2000 with uncertainty in last position in the VAR-8 model.

For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

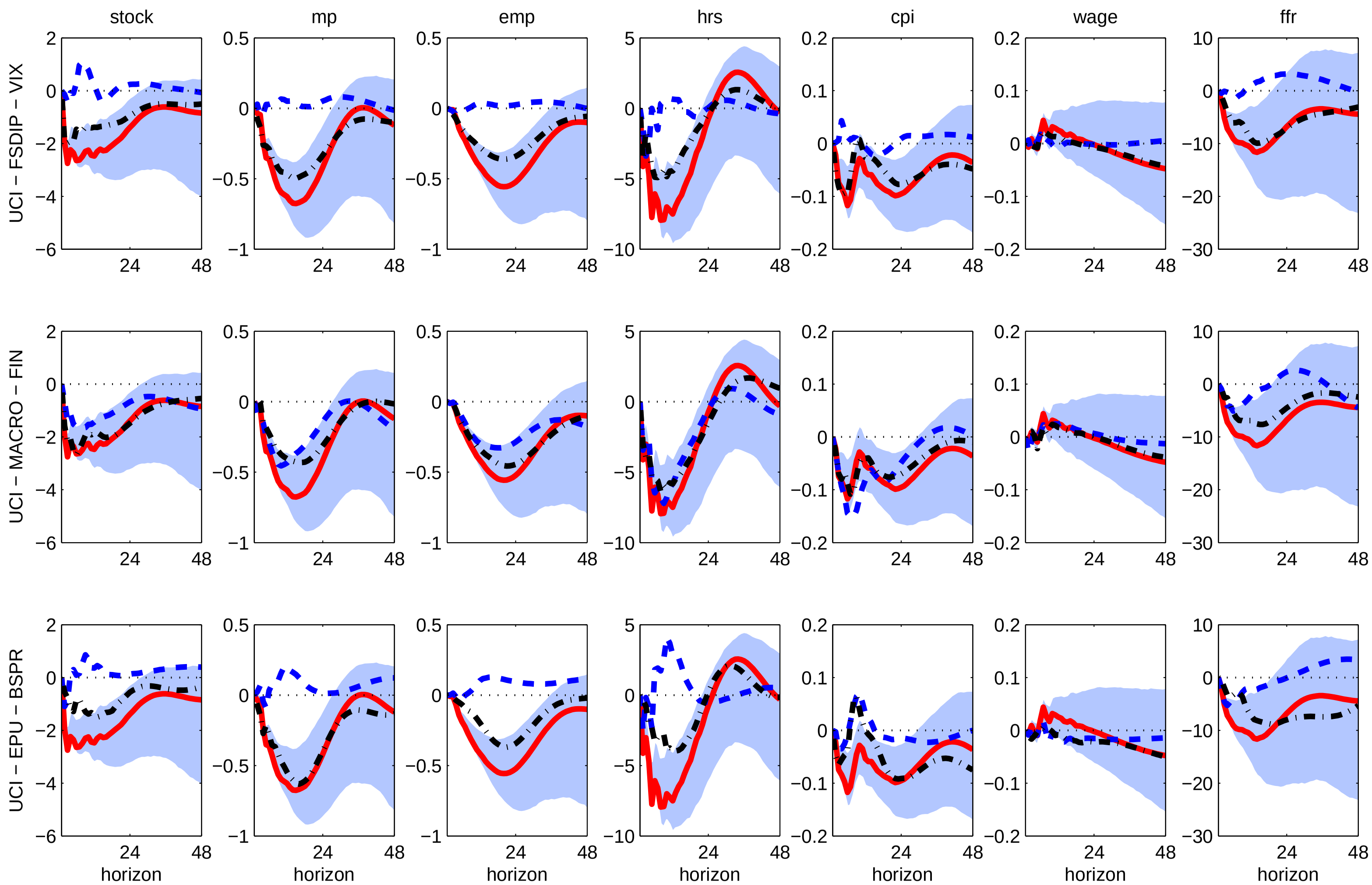

Figure 10: IRFs to uncertainty: Subsample 2000-2015 with uncertainty in last position in the VAR-8 model.

For the series, "stock" refers to the S&P500, "mp" to the manufacturing production, "emp" to employment, "hrs" to hours worked, "cpi" to the consumers price index, "wage" to the nominal wage, and "ffr" to the federal funds rate.

References

[1] Bachmann, R., Elstner, S., Sims, E. (2013). Uncertainty and economic activity: Evidence from business survey data. American Economic Journal: Macroeconomics, 5, 217-249.

[2] Baker, S.R., Bloom, N., Davis, S.J. (2016). Measuring Economic Policy Uncertainty. The Quarterly Journal of Economic, 131, 1593-1636.

[3] Bali, T.G., Zhou, H. (2016). Risk, uncertainty, and expected returns. Journal of Financial and Quantitative Analysis, 51, 707-735.

[4] Barhoumi, K., Darn, O., Ferrara, L. (2013). Dynamic factor models: A review of the literature. Journal of Business Cycle Measurement and Analysis, 8, 73-107.

[5] Bloom, N. (2009). The impact of uncertainty shocks. Econometrica, 77, 623-685.

[6] Bloom, N. (2014). Fluctuations in uncertainty. Journal of Economic Perspectives, 28, 153-76.

[7] Bloom, N., Bond, S., Van Reenen, J. (2007). Uncertainty and investment dynamics. Review of Economic Studies, 74, 391-415.

[8] Bloom, N., Fernandez-Villaverde, J., Schneider, M. (2014). The macroeconomics of uncertainty and volatility. Journal of Economic Literature, forthcoming.

[9] Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S.J. (2012). Really uncertain business cycles. Working Paper No 18245, NBER.

[10] Born, B., Breuer, S., Elstner, S. (2014). Uncertainty and the Great Recession, Working Paper No. 04/2014, German Council of Economic Experts.

[11] Brogaard, J., Detzel, A. (2015). The asset pricing implications of government economic policy uncertainty. Management Science, 61, 3-18.

[12] Caggiano, G., Castelnuovo, E., Groshenny, N. (2013). Uncertainty shocks and unemployment dynamics in US recessions. Journal of Monetary Economics, 67, 78-92.

[13] Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajsek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. European Economic Review, 88, 185-207.

[14] Chauvet, M., Senyuz, Z., Yoldas, E. (2015). What does financial volatility tell us about macroeconomic fluctuations?. Journal of Economic Dynamics and Control, 52, 340-360.

[15] Christiano, L. J, Motto, R., Massimo Rostagno, M. (2014). Risk Shocks. American Economic Review, 104(1), 27-65.

[16] Colombo, V. (2013). Economic policy uncertainty in the US: Does it matter for the Euro area? Economics Letters, 121, 39-42.

[17] Denis, S., Kannan, P. (2013). The impact of uncertainty shocks on the UK economy. Working Paper No. 13/66, IMF.

[18] Dixit, A. (1989). Entry and exit decisions under uncertainty. Journal of Political Economy, 97, 620-638.

[19] Doz, C., Giannone, D., Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. Journal of Econometrics, 164, 188-205.

[20] Doz, C., Giannone, D., Reichlin, L. (2012). A quasi maximum likelihood approach for large approximate dynamic factor models. The Review of Economics and Statistics, 94, 1014-1024.

[21] Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K., Rubio-Ramirez, J. (2015). Fiscal volatility shocks and economic activity. American Economic Review, 105, 3352-3384.

[22] Giannone, D., Reichlin, L., Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics, 55, 665-676.

[23] Haddow, A., Hare, C., Hooley, J., and Shakir, T. (2013). Macroeconomic uncertainty: What is it, how can we measure it and why does it matter? Bank of England Quarterly Bulletin, 53, 100-109.

[24] Henzel, S.R., Rengel, M. (2017). Dimensions of macroeconomic uncertainty: A common factor analysis. Economic Inquiry, forthcoming.

[25] Jurado, K., Ludvingson, S.C., Ng, S. (2015). Measuring uncertainty. American Economic Review, 105, 1177-1216.

[26] Knight, F. (1921). Risk, Uncertainty, and Profit. Boston: Houghton Mifflin.

[27] Leduc, S., Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. Journal of Monetary Economics, 82, 20-35.

[28] Lim, G.C., Nguyen, V.H. (2015). Alternative weighting approaches to computing indexes of economic activity. Journal of Economic Surveys, 29, 287-300.

[29] Ludvingson, S.C., Ma, S., Ng, S. (2015). Uncertainty and business cycles: Exogenous impulse or endogenous response? Working paper No 21803, NBER.

[30] Nodari, G. (2014). Financial regulation policy uncertainty and credit spreads in the US. Journal of Macroeconomics, 41, 122-132.

[31] Orlik, A., Veldkamp, L. (2014). Understanding uncertainty shocks and the role of black swans. Discussion Paper Series No 10147, CEPR.

[32] Rossi, B., Sekhposyan, T. (2015). Macroeconomic uncertainty indices based on nowcast and forecast error distributions. American Economic Review: Papers & Proceedings, 105, 650-655.

[33] Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. Journal of Monetary Economics, 82, 1-19.

[34] Stock, J.H., Watson, M.W. (2002). Macroeconomic forecasting using diffusion indexes. Journal of Business and Economic Statistics, 20, 147-162.

[35] Whaley, R.E. (2009). Understanding the VIX. Journal of Portfolio Management, 35, 98-105.

[36] Zhou, H. (2009). Variance risk premia, asset predictability puzzles, and macroeconomic uncertainty. Working Paper, Federal Reserve Board.