

Henzel, Steffen; Rengel, Malte

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Dimensions of macroeconomic uncertainty: A common factor analysis

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Dimensions of macroeconomic uncertainty: A common factor analysis

Steffen R. Henzel
Malte Rengel

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Dimensions of macroeconomic uncertainty: A common factor analysis*

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Abstract

In the current literature uncertainty about the future course of the economy is identified as a possible driver of business cycle fluctuations. In fact, uncertainty surrounds the movements of all economic variables which gives rise to a monitoring problem. We identify the different dimensions of uncertainty in the macroeconomy. To this end, we construct a large dataset covering all forms of economic uncertainty and unravel the fundamental factors that account for the common dynamics therein. These common factors are interpreted as macroeconomic uncertainty. Our results show that the first factor captures business cycle uncertainty while the second factor is identified as oil and commodity price uncertainty. Finally, we demonstrate that a distinction between both types of macroeconomic uncertainty is essential since they have rather different implications for economic activity.

JEL Code: C32, C38, E32.

Keywords: Macroeconomic uncertainty, factor model, factor-augmented VAR, aggregate fluctuation.

Steffen R. Henzel
Ifo Institute – Leibniz Institute for
Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1652
henzel@ifo.de

Malte Rengel
Department of Economics
University of Göttingen
Platz der Göttinger Sieben 5
37073 Göttingen, Germany
Phone: +49(0)551/39-7175
mregel@uni-goettingen.de

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1 Introduction

Uncertainty about the future course of the economy is identified as a possible driving force behind business cycle fluctuations in recent research (see, for instance, Bloom, 2009; Alexopoulos and Cohen, 2009; Knotek II and Khan, 2011; Bachmann, Elstner, and Sims, 2013). However, many different dimensions of uncertainty are considered in the economic literature.¹ In fact, time varying uncertainty surrounds the movements of almost all macroeconomic variables (Gonçalves and Kilian, 2004). Policy makers and researchers thus face a monitoring and decision problem pertaining to the different types of uncertainty prevailing in the macroeconomy.

In this paper, we consider the (fundamental) types of macroeconomic uncertainty which affect all firms and households in the economy.² In this context, a number of questions arise which we address in this paper: How many fundamental types of macroeconomic uncertainty do exist? What are these different types of uncertainty? How does macroeconomic uncertainty compare to familiar uncertainty measures such as financial market risk? What is the impact of macroeconomic uncertainty on economic activity?

A large body of literature on factor models documents that there are only a handful of fundamental first moment shocks which are relevant for explaining the business cycle (see, among others, Sargent and Sims, 1977; Forni and Reichlin, 1998; Stock and Watson, 2002; Giannone, Reichlin, and Sala, 2004; Stock and Watson, 2005). Since the number of fundamental shocks contained in a factor model is typically much smaller than the number of variables in the dataset, factor models provide a justification for the modeling strategy underlying modern business cycle models. Recent studies enhance business cycle models with shocks to second moments and analyze their role for business cycle fluctuations, for instance, during the recent global financial crisis (see, for instance, Gilchrist, Sim, and Zakrajšek, 2010; Born and Pfeifer, 2011; Arellano, Bai, and Kehoe, 2012; Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe, 2011; Basu and Bundick, 2012; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012; Schaal, 2012; Bachmann and Bayer, 2013). In this paper, we provide an empir-

¹Among many others, Friedman (1977), Ball (1992), and Bernanke and Mishkin (1997) examine the effects of inflation uncertainty. Furthermore, Ramey and Ramey (1995), Grier and Perry (2000), Grier, Henry, Olekalns, and Shields (2004) are concerned with the effects of production uncertainty. Born and Pfeifer (2011), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2012), and Baker, Bloom, and Davis (2013) model policy uncertainty. Oil price uncertainty is analyzed by Elder and Serletis (2010) and Jo (2011).

²Note that macroeconomic uncertainty relates to aggregate shocks, as opposed to idiosyncratic (e.g. firm-specific) uncertainty which results from the dispersion of idiosyncratic shocks which themselves average out over many units (e.g. firms).

ical justification for the number of fundamental second moment shocks. We analyze a large dataset in the spirit of Giannone et al. (2004) which allows us to consider all types of uncertainty. Using a factor model, we condense the information contained in 164 individual uncertainty measures and unravel the fundamental shocks that have an impact on the bulk of these uncertainty measures. To account for the dynamic patterns of macroeconomic uncertainty we estimate a dynamic factor model (Doz, Giannone, and Reichlin, 2011, 2012). Finally, we apply matrix rotation to identify the fundamental shocks which govern macroeconomic uncertainty empirically.

The factor approach enables us to summarize the information contained in a large dataset in only a handful of common factors. We can thus use these common factors as measures of time-varying macroeconomic uncertainty. Moreover, using a large cross-section helps us to eliminate possible measurement error from the data such that the signal in the time series is revealed with greater precision. In order to identify the common factors separately we again employ a rotation procedure. The different factors are then used to assess the properties of the different dimensions of macroeconomic uncertainty. For instance, we study the relation of our uncertainty measures to other measures such as financial market risk which is used in Bloom (2009) or Basu and Bundick (2012), among others, as a proxy for overall economic uncertainty. We also consider bond spreads as in Gilchrist et al. (2010), idiosyncratic (firm-specific) uncertainty proposed by Bachmann et al. (2013), and uncertainty about economic policy put forward by Baker et al. (2013). Note that, all of the aforementioned studies concentrate on a particular aspect of macroeconomic uncertainty while we adopt a comprehensive perspective.³

Our results provide evidence that macroeconomic uncertainty in the US economy is governed by two fundamental shocks governing the same number of common factors. We document that the first fundamental shock triggers uncertainty associated with demand related variables such as aggregate production and capacity utilization. We thus identify the corresponding factor as ‘business cycle uncertainty’. The second fundamental shock mainly affects uncertainty associated with supply related variables such as oil and commodity prices. We thus interpret the related factor as ‘oil and commodity price uncertainty’. Using the common factors to measure macroeconomic uncertainty, we demonstrate that business cycle uncertainty and oil and commodity price uncertainty peak at business cycle and oil-market related events, respectively. Moreover, both types

³We have recently become aware of independently conducted work by Jurado, Ludvigson, and Ng (2013). In their paper, the authors adopt a view on macroeconomic uncertainty which is similar to ours. However, we distinguish between different fundamental types of macroeconomic uncertainty while Jurado et al. (2013) concentrate on one measure and document that there is a noticeable difference between macroeconomic uncertainty and financial market uncertainty.

of macroeconomic uncertainty are countercyclical.

Given these distinct types of macroeconomic uncertainty we investigate their role in explaining economic activity. In related work it is documented that uncertainty shocks decrease production and employment (Bloom, 2009; Bachmann et al., 2013; Baker et al., 2013; Jurado et al., 2013). In a related VAR experiment we document the dynamic correlations of both types of macroeconomic uncertainty, and impulse response analysis reveals that both types of macroeconomic uncertainty depress real activity. The impact of a surprise increase in business cycle uncertainty is, however, limited. Notably, the dynamic correlation with nominal variables differs between the two types of macroeconomic uncertainty. While a sudden increase in business cycle uncertainty is accompanied by a marked decrease in prices, an unexpected increase in oil and commodity price uncertainty tends to foreshadow price increases. Not many studies consider the relation of uncertainty to variables other than aggregate production. Notably, Leduc and Liu (2012) construct a measure of uncertainty from household and firm surveys and argue that an uncertainty shock is similar to a (negative) aggregate demand shock. Likewise, a surprise innovation in business cycle uncertainty leads to reactions that are comparable to those from a negative aggregate demand shock. In contrast, an unforeseen increase in oil and commodity price uncertainty induces similar responses as a contractionary aggregate supply shock. Particularly, we demonstrate that a distinction between business cycle uncertainty and oil and commodity price uncertainty is essential for policy analysis and theoretical research since both types uncertainty have rather different implications for business cycle dynamics.

The remainder of the paper is structured as follows. In section 2, we explain how we measure economic uncertainty. The common factor model is introduced in section 3. The number of fundamental factors of macroeconomic uncertainty is analyzed in section 4. There, we also give an interpretation of the factors and compare these to related proxy variables of uncertainty applied in the literature. In the last part of section 4 we analyze how macroeconomic uncertainty contributes to economic activity. The paper concludes in section 5.

2 Measuring overall economic uncertainty

2.1 The dataset

To obtain a comprehensive view on economic uncertainty, our analysis relies on a large-scale dataset which has been studied in Giannone et al. (2004). This kind of dataset is commonly applied to describe the development of the US economy over the business cycle (see also Stock and Watson, 2002). It is collected on a monthly frequency which is advantageous since uncertainty may materialize quickly. The data can be split up into 14 categories: industrial production, capacity utilization, employment, sales and consumption, housing and construction, inventories, new and unfilled orders, financial variables, interest rates, monetary variables, prices, wages, merchandise ex- and imports, business outlook. The variables are transformed to obtain stationary series.⁴ They cover the time span from 1970M1 to 2011M4 ($T = 496$) and, thus, extend to the global financial crisis. During this period, the Federal Reserve has undertaken a number of unconventional policy measures ('quantitative easing') leading to a structural break and severe outliers in monetary aggregates. Hence, we exclude the monetary base (series 117 in table A.1), the depository institutions reserves (series 118-119) and the loans and securities at all commercial banks (series 125). Further, consistent data for the commercial paper outstanding (series 104), the delinquency rate on bank-held consumer installment loans (series 126), and the index of sensitivity materials prices (series 132) are not available. This leaves us with $n = 164$ variables.

2.2 A simple measure of economic uncertainty

Before turning to the main analysis we require a measure of unobserved uncertainty. In this study we rely on the time-series dimension to measure uncertainty for each of the variables in our dataset.⁵

One approach is to estimate a GARCH model and use the conditional (in-sample) forecast error variance as a time-varying measure of uncertainty (see Baillie, Chung, and Tieslau, 1996; Grier and Perry, 1998; Karanasos, Kranassou, and Fountas, 2004,

⁴A detailed list and description of the transformation of each single series is provided in table A.1 in the appendix.

⁵A number of studies measure uncertainty by the average standard deviation of the subjective probability distributions polled in the Survey of Professional Forecasters (see Zarnowitz and Lambros, 1987; Lahiri, Teigland, and Zaporowski, 1988; Giordani and Söderlind, 2003; D'Amico and Orphanides, 2008; Rich and Tracy, 2010, among others). However, the survey is limited to the variables GDP, GDP deflator, and CPI inflation.

among others). As an alternative, we may introduce stochastic volatility (SV) into a time series model. Compared to the GARCH approach the SV model brings about the advantage that it involves an independent shock impinging on the second moments of a process which lends itself to an economic interpretation (see Fernández-Villaverde and Rubio-Ramírez, 2010, for a discussion). It is thus extensively applied in the recent empirical macroeconomic literature studying time varying second moments (Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez, 2010; Born and Pfeifer, 2011; Fernández-Villaverde et al., 2012). Finally, measures of conditional volatility have the advantage that they are not affected by time-varying risk aversion as opposed to observable indicators of financial market risk such as the option-based CBOE implied volatility index (VXO) used in Bloom (2009), and interest rate spreads (see Bekaert, Hoerova, and Lo Duca, 2012, for a discussion).

However, the calculation of GARCH and SV measures necessitates an explicit formulation of the data generating process. The estimation of the model calls for a well-specified time series process of the variable under concern, and each model has to pass a battery of specification tests (Lundbergh and Teräsvirta, 2002). To avoid misspecification, innumerable extensions of the basic GARCH and SV model have been proposed to meet the specific requirements of a certain variable (see Bollerslev, 2009, for an overview). Finally, convergence of the estimation has to be ensured. Since we consider a multitude of time series there is a significant drawback associated with GARCH and SV models.

This drawback can, however, be overcome by using a basic data driven filter which enables us to measure the uncertainty surrounding an individual variable in a transparent and robust manner. A straightforward proxy for uncertainty may be obtained when we estimate the variance of a variable within a rolling window (Andersen, Bollerslev, Christoffersen, and Diebold, 2006). However, such an estimator suffers from the so-called variance-bias trade-off.⁶ This trade-off can be resolved if more recent observations receive a larger weight. This can be achieved by calculating an exponentially weighted moving average which is known as the 'RiskMetrics' procedure (Morgan,

⁶The variance of the estimated volatility decreases with an increasing window size while the bias of the estimator increases.

1996). We calculate the time varying variance σ_t^2 for each individual series as⁷

$$\sigma_t^2 = \gamma \sigma_{t-1}^2 + (1 - \gamma) e_{t-1}^2 \quad (1)$$

$$= (1 - \gamma) \sum_{i=1}^{\infty} \gamma^{i-1} e_{t-i}^2. \quad (2)$$

Here, e_t denotes the residual of the regression relating the respective variable y_t to its P own lagged values

$$y_t = \beta_0 + \sum_{p=1}^P \beta_p y_{t-p} + e_t. \quad (3)$$

The lag-length P is determined by means of BIC. We apply the autoregressive model in (3) to account for the serial correlation of macroeconomic variables such as, for instance, industrial production growth and inflation. Moreover, the AR-model is a straightforward forecast device and a common benchmark model in forecast competitions since it is hard to beat. It should thus deliver an appropriate approximation of how private agents form expectations. As e_t can be interpreted as (in-sample) forecast error the approach enforces a forecaster's perspective which bears a close similarity to a GARCH model. The decay factor that controls the smoothness of the variance process in (2) is denoted by γ .⁸ Note that the infinite sum on the right hand side of (2) is truncated at $t - 1$ due to the sample range. Andersen et al. (2006) stress that this leads to distortions of the uncertainty measure at the beginning of the sample; i.e. when t is small. To attenuate this drawback, we apply the multiplicative adjustment factor $1/(1 - \gamma^t)$ and measure uncertainty associated with each of the 164 variables in our dataset by means of the RiskMetrics approach.

2.3 The RiskMetrics approach and SV measures of uncertainty

Since the uncertainty measure specified in (2) is rather simple, it may be questioned whether it is able to retrace alternative measures of economic uncertainty that have been used in the literature. To meet this concern, we turn our attention to two important monthly business cycle variables: industrial production and consumer prices. For each variable we compare indices of uncertainty measured by means of the RiskMetrics

⁷To simplify notation we suppress the index for an individual variable.

⁸We set $\gamma = 0.7$ which implies a half-life period of the innovation e_t of approximately two months. After one year 98.62% of the innovation has disappeared. As proposed by Morgan (1996) we use the same value for γ for all series in the considered dataset.

approach and the SV model used by, for instance, Fernández-Villaverde et al. (2012):

$$y_t = \beta_0 + \sum_{p=1}^P \beta_p y_{t-p} + \exp(\log(\sigma_{t,SV}^2)/2)\zeta_t, \quad (4)$$

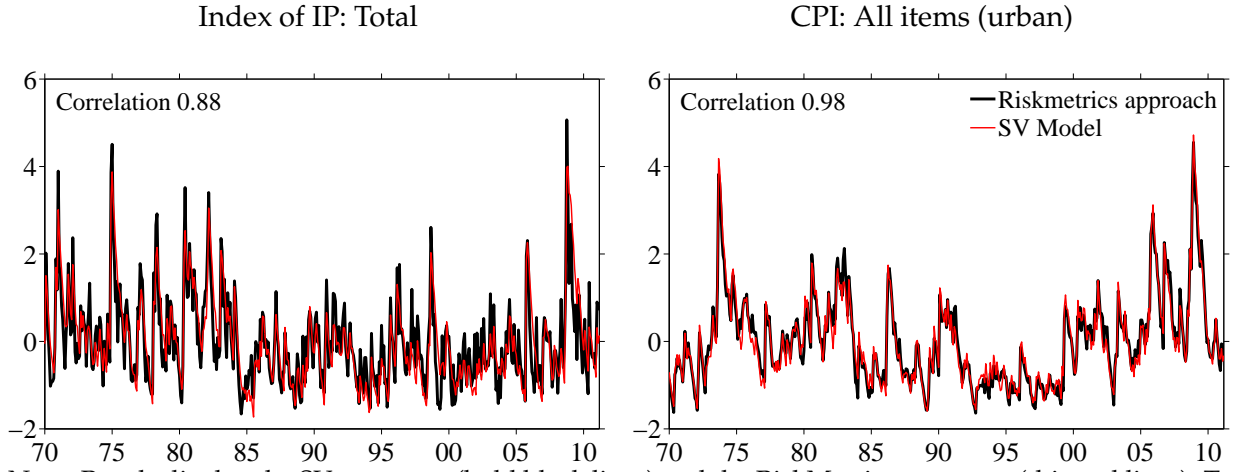
$$\log(\sigma_{t,SV}^2) = \gamma_0 + \gamma_1 \log(\sigma_{t-1,SV}^2) + \omega v_t. \quad (5)$$

For each individual variable, the lag-length P is, again, chosen by means of BIC. The logarithmic conditional variance in (5) is modeled as a stationary AR(1) process. The innovations ζ_t and v_t are both $N(0, 1)$ distributed and mutually independent.

We estimate the model using a Maximum Likelihood approach. Due to the non-linearity of the model we simulate the likelihood function by means of the Efficient Importance Sampler (EIS) (Richard and Zhang, 2007; DeJong, Liesenfeld, Moura, Richard, and Dharmarajan, 2013).⁹ Given the parameter estimates, we also use efficient importance sampling to filter the variance process.

In figure 1 we compare the RiskMetrics measure of uncertainty associated with industrial production growth (IP) and consumer price inflation (CPI) to the respective SV measure. For each respective variable both uncertainty series co-move closely, and their correlation amounts to 0.88 (IP), and 0.98 (CPI), respectively. The uncertainty measures derived from the RiskMetrics procedure peak whenever the corresponding SV measures reach a local maximum. We conclude that the RiskMetrics measure is a simple, transparent, and robust but nevertheless admissible method to measure uncertainty related to individual variables.

⁹Since the Likelihood function approximated by means of the EIS is continuous in the parameters the application of numerical optimization techniques and classical inference is straightforward (see Liesenfeld and Richard, 2003, for a description). Many studies rely on the particle filter to approximate the likelihood function of a non-linear state space model. However, the resulting likelihood function is not continuous in the parameters and, thus, exacerbates numerical optimization. The particle filter is often used in combination with Bayesian simulation techniques.



Note: Panels display the SV measures (bold black lines) and the RiskMetrics measures (thin red lines). To facilitate comparability all measures are demeaned and have a standard deviation of one.

Figure 1: Comparison of SV and RiskMetrics measures

3 The common factor approach

Having derived 164 individual measures of economic uncertainty by means of the RiskMetrics approach we now identify their common driving forces which we interpret as macroeconomic uncertainty. To this end, we apply the factor model

$$X_t = \lambda f_t + \xi_t, \quad (6)$$

$$f_t = \Psi(L)f_{t-1} + \epsilon_t, \quad (7)$$

which assumes that the dynamics of the data are described by means of a common component ($X_t = \lambda f_t$) and idiosyncratic component (ξ_t). The data vector $X_t = (\log(\sigma_{1,t}), \dots, \log(\sigma_{n,t}))'$ of dimension $n \times 1$ contains the standardized individual uncertainty measures. In the factor model we use the logarithmic square roots of the variances to allow factors to adopt negative values. To explore macroeconomic uncertainty we are, in particular, interested in the vector of fundamental factors f_t which is of dimension $r \times 1$ and responsible for the common dynamics of individual uncertainty measures. We allow f_t in (7) to follow a vector autoregressive process. The lag polynomial $\Psi(L) = \Psi_1 + \dots + \Psi_h L^{h-1}$ is of dimension $r \times r$. The corresponding innovations are denoted by the $r \times 1$ dimensional vector ϵ_t , and can be decomposed into $\epsilon_t = R u_t$. The r -dimensional vector u_t contains orthogonal white noise shocks and R is a $r \times r$ conformable matrix. Further, factor innovations and idiosyncratic components are assumed to be independent at all leads and lags. However, the idiosyncratic components

themselves are allowed to be weakly correlated which constitutes an ‘approximate factor model’ (see, for instance, Stock and Watson, 2002). We assume that the number of fundamental shocks u_t is identical to the number common factors r . This entails that f_t follows a simple vector autoregression. The number of fundamental shocks r defines the reduced dimension of the dataset ($r \ll n$).

We estimate the model in (6) and (7) by means of the Quasi Maximum Likelihood procedure proposed by Doz et al. (2012). Technically, we apply an EM algorithm combined with Kalman smoothing. Doz et al. (2012) show that the unobserved factors f_t of an approximate factor model are estimated consistently if n and T go to infinity even if cross-sectional and serial correlation of idiosyncratic processes is not modeled explicitly.¹⁰

4 Estimation results

4.1 How many fundamental types of macroeconomic uncertainty do exist?

To determine the number of fundamental types of macroeconomic uncertainty we make use of the factor representation of macroeconomic uncertainty. That is, we unravel the number of factors (r) which have an impact on a broad range of the individual uncertainty measures in our dataset. To obtain a first impression we estimate the model in (6) and (7) for different numbers of fundamental factors and report the average R^2 over individual uncertainty series in the upper panel of table 1. The first factor explains 20% of the variation of uncertainty measures. The gain in explained variance by adding a second factor is 9% while the third and the fourth factor add about 6% and 4%, respectively. The gain of an additional factor thus decreases relatively fast which points towards a rather low number of common factors. Further note that our dataset consists of monthly data, which usually carries more noise than data collected at a lower frequency. In fact, the noise component, on average, accounts for roughly one third of the total variance of

¹⁰A detailed description of the estimation procedure is provided in appendix B. To ensure the robustness of results we also compare the estimates from this baseline model with those from an extended specification where the idiosyncratic processes each follow a stationary first order autoregressive process. The estimation procedure relies on the generalization of the EM algorithm proposed by Bańbura and Modugno (2012). The pairwise correlations of the factors from both models are all greater than 0.98. The economic interpretation of the fundamental shocks and factors stays qualitatively unchanged.

the set of individual uncertainty series.¹¹

For the purpose of model validation, different test criteria have been proposed in the literature. Table 1 collects also the number of factors implied by these test procedures.

| | $r = 1$ | $r = 2$ | $r = 3$ | $r = 4$ |
|----------|-------------|-----------|-----------|-------------|
| R^2 | 0.20 | 0.29 | 0.35 | 0.39 |
| | IC_{p1} | IC_{p2} | IC_{p3} | IC_{BN08} |
| Bai / Ng | 20 | 15 | 20 | 3 |
| | IC_{ON10} | ER | GR | |
| Other | 1 | 1 | 1 | |

Note: The upper panel reports models' average R^2 for different numbers of fundamental factors (r). The middle panel displays the number of fundamental factors determined by means of the $IC_{p\bullet}$ of Bai and Ng (2002) and IC_{BN08} of Bai and Ng (2008). Calculations are based on a maximum number of factors $r_{max} = 20$. The lower panel reports the number of factors indicated by estimators IC_{ON10} proposed by Onatski (2010) and ER and GR proposed by Ahn and Horenstein (2013).

Table 1: Tests to determine the number of fundamental factors

Results differ quite a bit depending on the test procedure implemented. The information criteria proposed in Bai and Ng (2002) are given in the middle panel of table 1. They suggest a rather large number of fundamental factors and seem to tend towards $r = 20$ which is the maximum number of factors we allow for in these tests. Most likely these criteria overestimate the number of factors when the idiosyncratic components are correlated which is probably the case in our dataset since it contains subcategories of a number of variables (see Onatski, 2010, for a discussion). Bai and Ng (2008) suggest the criterion IC_{BN08} which works well particularly when idiosyncratic components are cross correlated. According to IC_{BN08} there are three fundamental factors. The results of the more recently introduced estimators of Onatski (2010) (IC_{ON10}) and Ahn and Horenstein (2013) (ER, GR) are reported in the lower part of table 1. These estimators uniformly indicate one common factor. Although information criteria do not provide a unique indication of the precise number of fundamental factors they support the notion that r is less than or equal to three.

To dig a little deeper we display the variance proportion explained by the common component for each individual uncertainty measure in figure 2.¹² In the upper panel the grey bars indicate the R^2 when $r = 1$. In this specification the common components are

¹¹To arrive at this number we estimate the spectral density of each series and calculate the average contribution to the total variance of the frequencies smaller than 18 months. These frequencies are usually attributed to the noise component of a time series in the business cycle literature (see, for instance, the seminal work of Burns and Mitchell, 1946).

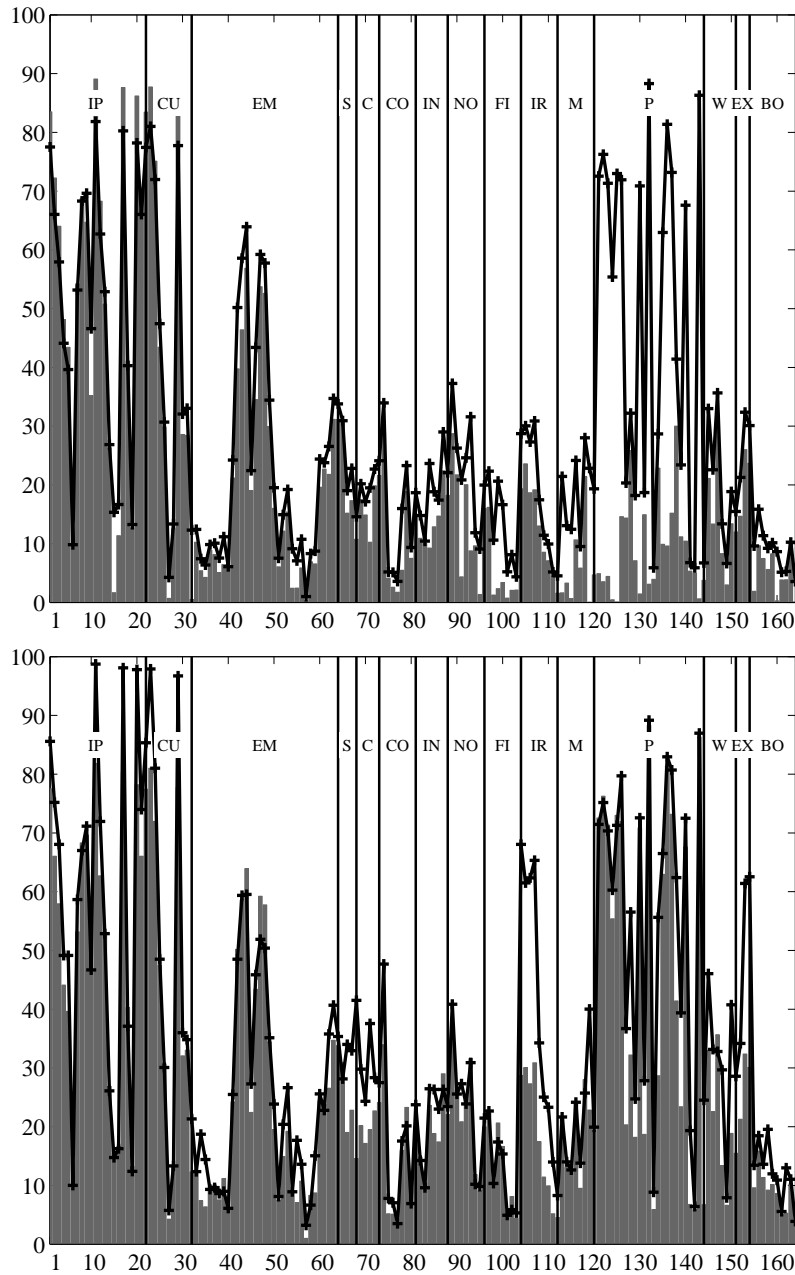
¹²Consider also table A.1 for the precise proportions obtained for the individual uncertainty measures.

able to explain the variation of uncertainty associated with most production variables, capacity utilization and some employment variables rather well. However, the explanatory power for other uncertainty measures, especially those of most price variables, is relatively low. One factor thus appears to be insufficient to capture the common dynamics of macroeconomic uncertainty. Consequently, we introduce a second fundamental factor and calculate the individual R^2 for this model specification which is represented by means of the crossed line in the upper panel of figure 2. As a result, the variance proportion which is explained by the common component improves for a broad range of uncertainty variables. Particularly, most price related uncertainty measures experience an increase in R^2 . In the lower panel of figure 2 we display the effect of adding a third factor to the model. The grey bars now document the variance proportion explained by the common component of the two-factor model while the crossed line represents the results in case of three factors. An improvement appears only for a rather narrow group of variables which are related to the uncertainty surrounding short-term interest rates (variables 105 to 108). Individual measures where the model fit improves only marginally are related to CPI inflation and some subgroups of CPI such as housing or services. The third factor does thus not add much explanatory power for the dataset as a whole.¹³

Two common factors thus provide a good description of the dynamics common to the individual uncertainty measures since further factors capture variable-specific rather than macroeconomic uncertainty.¹⁴ In particular, these two factors explain a large fraction of the common variation in uncertainty associated with the most important business cycle variables such as industrial production ($R^2 = 0.78$), industrial production in manufacturing ($R^2 = 0.82$), capacity utilization ($R^2 = 0.77$), employment ($R^2 = 0.59$), and consumer prices ($R^2 = 0.72$). Since there are two fundamental shocks, in the following, we discriminate between two distinct types of macroeconomic uncertainty.

¹³We provide a comparison of the variance proportions explained by the common component of the three-factor and four-factor model in figure D.1 in the appendix. The additional information from adding a fourth factor is only marginal for most uncertainty series.

¹⁴Notably, such a small number has also been obtained in studies analyzing the common movements of economic variables in first moments (see, for instance, Giannone et al., 2004).



Note: The upper panel displays on the y-axis the respective proportion of the explained variance for $r = 1$ (grey bars) and $r = 2$ (crossed line). The lower panel documents the explained variance shares for $r = 2$ (grey bars) and $r = 3$ (crossed line). On the x-axis it depicts the individual uncertainty measures in the same order as in table A.1. They are grouped into the following categories: IP (1-21, industrial production), CU (22-31, capacity utilization), EM (32-63, employment), S (64-67, sales), C (68-72, consumption), CO (73-80, housing and construction), IN (81-87, inventories), NO (88-95, new and unfilled orders), FI (96-104, financial variables), IR (105-113, interest rates), M (114-126, monetary variables), P (127-151, prices), W (152-158, wages), EX (159-161, merchandize ex- and imports), BO (162-167, business outlook).

Figure 2: Explained variance proportions for different numbers of factors

4.2 What are the different types of macroeconomic uncertainty?

To interpret the two shocks that govern macroeconomic uncertainty we calculate the response of each individual uncertainty measure to a surprise increase in the common factors. To this end, we require to identify the fundamental shocks u_t separately. The factors have the moving average representation

$$f_t = [I_r - \Psi(L)L]^{-1} R u_t. \quad (8)$$

It follows that the impulse response function of the common component $\mathcal{X}_t = \lambda f_t$ is

$$\mathcal{X}_t = \lambda [I_r - \Psi(L)L]^{-1} R u_t, \quad (9)$$

$$= B(L) u_t. \quad (10)$$

Given a rotation matrix H with $HH' = I_r$ the common component can be rewritten as $\mathcal{X}_t = C(L)v_t$, where $C(L) = B(L)H$ and $v_t = H'u_t$. However, there is an infinite number of rotation matrices H and impulse response functions (see, for instance, Forni, Giannone, Lippi, and Reichlin, 2009; Forni and Gambetti, 2010).

As proposed by Giannone et al. (2004) we solve the identification problem by selecting the rotation matrix H such that the target function

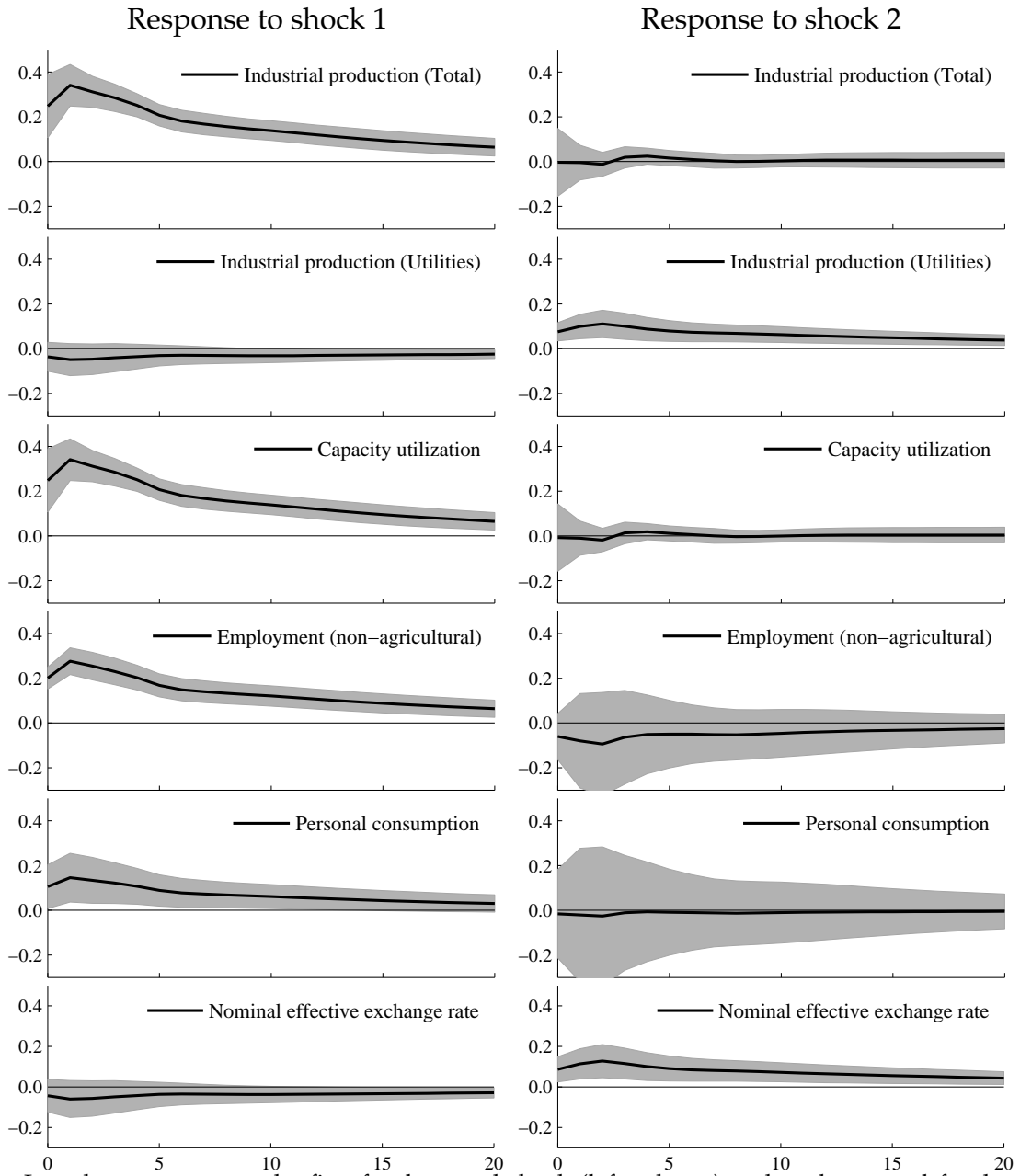
$$g(H) = \frac{\sum_{i \in D} \sum_{l=0}^{\infty} (c_{i1}^l)^2}{\sum_{i \in D} \sum_{l=0}^{\infty} (c_{i1}^l)^2 + \sum_{i \in D} \sum_{l=0}^{\infty} (c_{i2}^l)^2} \quad (11)$$

is maximized. The item c_{ij}^l denotes the response of individual uncertainty measure i to innovation j (for $j = 1, 2$) after l periods. The target function is thus based on the forecast error variance decomposition. The selection vector D identifies a subset of uncertainty measures which enters the target function. In the baseline specification, D identifies all types of uncertainty related to output (series 1 to 31). The denominator is the forecast error variance of the selected uncertainty measures which is explained by the two shocks jointly. We thus identify the first shock such that its explanatory power for uncertainty surrounding all of the production variables is maximized. The second shock is left unrestricted.

The responses of a selection of individual uncertainty measures to a one standard deviation surprise increase in the first fundamental factor are displayed in the left column of figures 3 and 4, respectively. The responses to a similarly designed increase of the second fundamental factor are depicted in the corresponding right column. In figure 3,

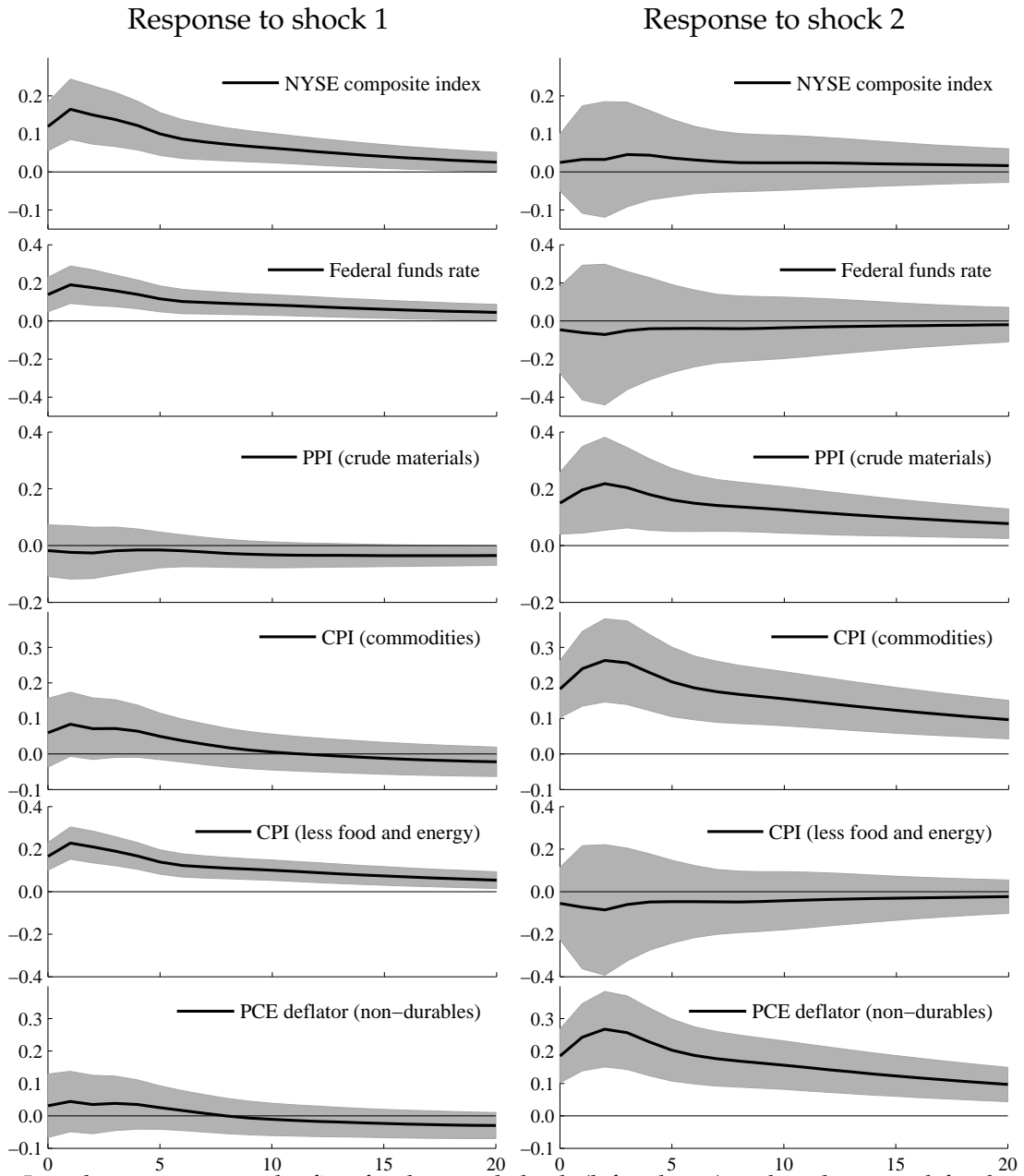
an increase in the first shock is followed by higher uncertainty related to total industrial production. Similarly, it precedes a significant rise in uncertainty surrounding capacity utilization. Moreover, other uncertainty variables linked to aggregate demand such as employment uncertainty and personal consumption uncertainty increase in response to shock 1. However, the first fundamental shock does not lead to an increase in uncertainty related to utility production and the nominal effective exchange rate. Turning to the second fundamental shock, we observe that it foreshadows an increase in uncertainty associated with the production of utilities, and it precedes a rise in uncertainty surrounding the nominal effective exchange rate. In fact, shock 2 is not followed by a significant rise in uncertainty associated with most demand side variables. Figure 4 provides the responses of uncertainty related to important nominal variables. As before, the response to shock 1 is given in the left column. A surprise increase in the first fundamental factor governs financial market uncertainty surrounding the NYSE composite index. Likewise, the uncertainty attached to the federal funds rate is affected positively. Moreover, shock 1 precedes a rise in uncertainty related to core inflation (CPI less food and energy) while there is no significant reaction of the inflation uncertainty measures for non-processed goods. These comprise uncertainty associated with PPI for crude materials, the CPI for commodities, and the deflator of non-durable consumption goods, which comprises mainly gasoline. The right column of figure 4 reveals that shock 2 increases uncertainty surrounding the prices of non-processed goods.

Overall, impulse response analysis suggests that shock 1 governs uncertainty surrounding variables which are for the most part linked to aggregate demand while shock 2 impacts uncertainty about prices of goods such as oil which typically determine the supply conditions in an economy. As a robustness check we perform an alternative rotation of the fundamental shocks. In contrast to the baseline rotation, we now maximize the variance share explained by shock 2 for variables representing oil and commodity price uncertainty while shock 1 is left unrestricted. To be specific, D in the target function (11) now selects the following individual uncertainty measures: total energy production (series 16), PPI of crude materials (series 130), CPI of commodities (series 139) and CPI of durable commodities (series 140). A comparison of the impulse response functions obtained from this alternative rotation with those from the baseline rotation is provided in figures E.1 and E.2 in appendix E. It turns out that the interpretation of the two fundamental shocks is robust to a change in the identification strategy since the impulse responses are almost identical.



Note: Impulse responses to the first fundamental shock (left column) and to the second fundamental shock (right column) are indicated by the bold lines. Shaded areas display bootstrapped 90% confidence intervals.

Figure 3: Impulse responses of individual uncertainty measures (1)



Note: Impulse responses to the first fundamental shock (left column) and to the second fundamental shock (right column) are indicated by the bold lines. Shaded areas display bootstrapped 90% confidence intervals.

Figure 4: Impulse responses of individual uncertainty measures (2)

To assess the quantitative importance of the two fundamental shocks we also conduct a forecast error variance decomposition. Moreover, we evaluate the relative importance of each shock for each of the 164 individual uncertainty measures. Results for the 12-month horizon for all individual uncertainty measures are reported in the columns labeled shock 1 and 2 in table A.1. Not surprisingly, the first fundamental shock is important for fluctuations of uncertainty associated with almost all measures of total production and capacity utilization. Moreover, uncertainty related to employment, sales, consumption, inventories, and new orders as well exports and imports is captured in most cases by shock 1. Also uncertainty surrounding housing starts is in large parts governed by the first fundamental shock. The same shock explains a major fraction of stock market uncertainty which we calculate for the NYSE and the S&P composite index. Moreover, shock 1 is an important driver of uncertainty related to the federal funds rate as well as for uncertainty surrounding assets which usually carry little risk such as the different treasuries. A mixed picture is obtained for the different inflation uncertainty measures. While shock 1 seems to be unimportant for producer price uncertainty, in general, it is important for uncertainty about core inflation. It operates on CPI less food and energy as well as the PCE deflator excluding food and energy. Moreover, there is a noticeable contribution for many consumer price measures, particularly those which do not directly reflect energy price movements. These comprise, among others, the CPI for food and beverages, housing, medical care, or services. Similarly, shock 1 governs uncertainty about hourly earnings.

Turning to the second fundamental shock we observe that it is an important driver of fluctuations of uncertainty surrounding the production of utilities. Moreover, it explains a major fraction of the fluctuations of exchange rate uncertainty as well as uncertainty related to the money stock. Finally, shock 2 is quantitatively important for the uncertainty of all producer prices. Other price variables which are driven by this shock are those consumer prices which reflect energy price movements such as the CPI for transportation, for commodities, or the PCE deflator for non-durables.

There are also a number of individual uncertainty measures for which both types of macroeconomic uncertainty play a role. Notably, 69% (76%) of the common variation in uncertainty surrounding CPI (PCE deflator) headline inflation is attributable to the second shock, and 31% (24%) are explained by shock 1. Furthermore, uncertainty related to total loans and securities is governed by both shocks. However, shock 2 is relatively more important for the uncertainty surrounding loans (real estate and commercial) whereas the uncertainty associated with securities is governed for the most part by shock 1.

Overall, our results support the notion that the first fundamental shock governs uncertainty surrounding variables which are closely linked to aggregate demand such as production and capacity utilization. Since these variable bear a close relation to the business cycle we identify the first fundamental shock as a driver of ‘business cycle uncertainty’. By contrast, the second fundamental shock mainly affects uncertainty associated with supply related variables such as oil and commodity prices. We thus interpret this shock as ‘oil and commodity price uncertainty’.

Note that Kilian (2009) introduces a precautionary oil-market specific demand shock which is induced by uncertainty about an expected oil production surplus or deficit caused by, for instance, political events. The interpretation of this oil-market specific demand shock thus bears some resemblance with our oil and commodity price uncertainty shock. In appendix F we compare the historical movements of these two shocks and find that their peaks are highly synchronized. However, both shocks do not operate in the same direction throughout. The conclusions we draw from this observation are twofold. First, we are able to verify that both shocks are closely related to the same oil-market specific events. Second, the economic interpretation of the oil-market specific demand shock and a shock to oil and commodity price uncertainty is rather different.

4.3 Indicators of macroeconomic uncertainty

The common factors collected in f_t summarize the common movements of individual uncertainty measures and, thus, may be used to obtain two indicators of macroeconomic uncertainty. Such a measure has the additional advantage that possible measurement error which may be hidden in the idiosyncratic component of the individual uncertainty measures is eliminated. However, since the factors are latent, we encounter an identification problem. In the following, we present the rotation strategy that we use to separately identify the factors f_t . The rotation matrix G may be used to rewrite the factor model in (6) such that

$$X_t = \lambda GG'f_t + \xi_{t,} \quad (12)$$

with $GG' = I$. To derive the covariance matrix of the factors we rewrite their process in (7) as a first order VAR

$$F_t = \mathcal{A}F_{t-1} + \mathcal{R}U_t, \quad (13)$$

where $F_t = (f'_t, f'_{t-1}, \dots, f'_{t-h+1})'$ denotes a vector containing the stacked factors. It follows that the residual vector $U_t = (u'_t, 0 \dots, 0)'$, $\mathcal{R} = (R', 0, \dots, 0)'$, and \mathcal{A} have the usual companion form. The vectorized covariance matrix \mathcal{S}_F of the stacked factors F_t can be expressed as

$$\text{vec}(\mathcal{S}_F) = (\mathbf{I}_{(rh)^2} - [\mathcal{A} \otimes \mathcal{A}])^{-1} \text{vec}(\mathcal{R}\mathcal{R}'), \quad (14)$$

where the covariance matrix \mathcal{S}_f of the factors f_t corresponds to the upper left $r \times r$ sub matrix of \mathcal{S}_F . We define the corresponding covariance matrix of the rotated factors $G'f_t$ as

$$\mathcal{S}_f^* = G' \mathcal{S}_f G. \quad (15)$$

Further, we introduce the matrix $\mathcal{S}_{f_1}^*$ ($\mathcal{S}_{f_2}^*$) which is a zero matrix except for the upper left (lower right) hand side element which equals the corresponding element of \mathcal{S}_f^* . The i -th diagonal element of the covariance matrix of the idiosyncratic processes \mathcal{S}_ξ is denoted as $\mathcal{S}_{\xi,i}$ and the i -th row of loadings matrix λ as λ_i . To determine the rotation matrix G we maximize the target function

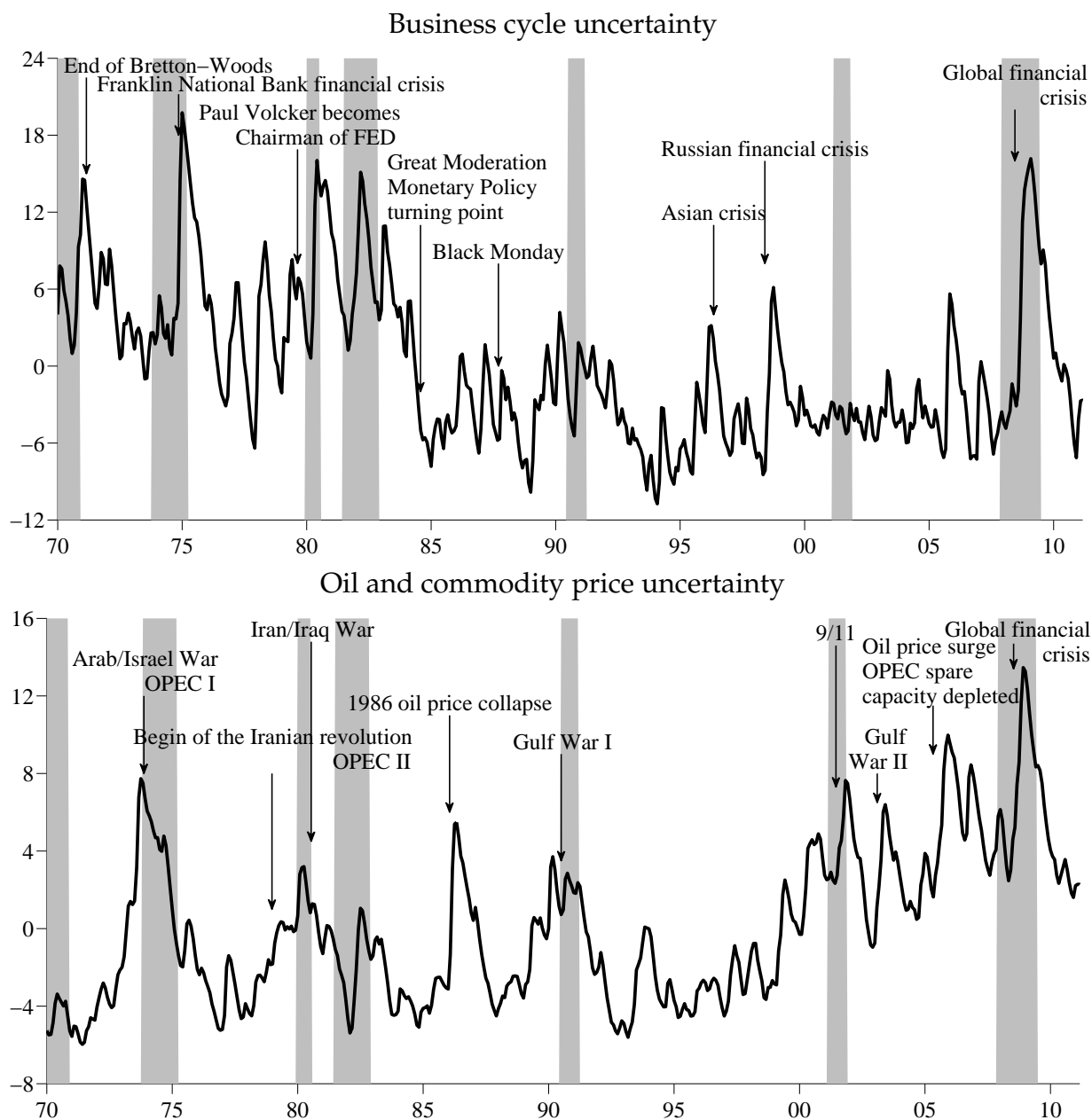
$$k(G) = \frac{\sum_{i \in D} \lambda_i G \mathcal{S}_{f_1}^* G' \lambda_i'}{\sum_{i \in D} (\lambda_i G \mathcal{S}_{f_1}^* G' \lambda_i' + \lambda_i G \mathcal{S}_{f_2}^* G' \lambda_i' + \mathcal{S}_{\xi,i})}. \quad (16)$$

This function summarizes the variance proportions explained by the first factor for a selection of individual uncertainty measures defined in D . We define this selection matrix again such that it selects the uncertainty measures associated with output (series 1 to 31). This rotation procedure thus maximizes the variance proportions of selected individual uncertainty measures which are explained by a particular factor's variance.¹⁵

Note that while the fundamental shocks are orthogonal, this is not necessarily the case for the factors since they follow the vector autoregressive process in (7). However, when we calculate the variance decomposition for the VAR in the factors with respect to the elements in u_t , the first fundamental shock explains 99.80% of the forecast error variance of the first factor $f_{1,t}$ twelve months ahead. The second fundamental shock explains 99.26% of the second factor $f_{2,t}$. Our interpretation of the fundamental shocks

¹⁵The same approach is used by Kose, Otrok, and Whiteman (2003) and Kose, Otrok, and Prasad (2012) to decompose the variance of the data using a factor model. Since the factors are not restricted to be orthogonal the denominator in (16) consists of the sum of the variance proportions explained by the two factors individually which can deviate from the variance proportion explained by the two factors jointly ($\lambda_i G \mathcal{S}_f^* G' \lambda_i'$).

thus carries over to the common factors f_t . The first common factor $f_{1,t}$ is thus a measure of business cycle uncertainty while the second common factor $f_{2,t}$ provides a measure of oil and commodity price uncertainty. In figure 5 the upper panel displays our indi-



The upper panel depicts our measure of business cycle uncertainty (f_1) and the lower panel depicts oil and commodity price uncertainty (f_2). NBER recession dates are indicated by the shaded areas.

Figure 5: Indicators of macroeconomic uncertainty

cator of business cycle uncertainty along with important business cycle events. NBER dated recessions are indicated by the shaded areas. It becomes apparent that business

cycle uncertainty is countercyclical since it rises during recessions. The recession of 2001 makes an exception since it falls into a period of macroeconomic tranquility where business cycle uncertainty appears to remain low. The indicator first soars when the Bretton-Woods system collapsed in 1973. The next extraordinary peak of business cycle uncertainty is related to the bankruptcy of the Franklin National Bank in 1974 which led to a banking crisis and a period of increased macroeconomic turmoil. Moreover, the indicator peaks in 1979 when Paul Volcker became chairman of the FED. When he set the path for an anti-inflationary policy, speculations about a future recession emerged.

In the period extending from the mid-1980s, business cycle uncertainty decreases when monetary policy became less accommodating. Business cycle uncertainty thus retraces the decline of macroeconomic volatility known as the 'Great Moderation'. Business cycle uncertainty increases only moderately around the Black Monday in 1987 which marked a short period of severe turmoil and mass panic on financial markets which did not, however, root in bad economic fundamentals. Other financial market related events such as the Asian crisis and the Russian financial crisis during the late 1990s yet accelerate business cycle uncertainty. One explanation may be that these crises – other than the Black Monday – reflected a fundamental problem which led to a more widespread impact on the macroeconomy and on macroeconomic uncertainty. After a period of relative tranquility, the indicator starts to rise again beginning with the bankruptcy of Lehman Brothers in 2008 which preceded the global financial crisis.

Oil and commodity price uncertainty is displayed in the lower panel together with oil-market specific events and NBER dated recessions. Like business cycle uncertainty, oil and commodity price uncertainty peaks during recessions. The time path of oil and commodity price uncertainty may be split into two subperiods. In the first subperiod, ranging from the beginning of the 1970s until the mid-1990s the oil and commodity price uncertainty is characterized by large and persistent swings with the first peak in 1973 during the Arabian/Israel War when the political system in oil exporting countries became unstable and the OPEC cut quotas to strengthen their objectives. Oil and commodity price uncertainty accelerates again during the Iranian Revolution 1978/79 which led to a drop of Iranian oil production and peaks in 1980 during the Iran/Iraq War. The next extraordinary peak occurs in 1986 when the oil price dropped heavily. The oil demand slowed down in the aftermath of the energy crisis of 1979/80 and the decreased economic activity of oil importing countries caused a surplus in oil supply. Finally, the uncertainty about the oil production accelerates again during the first Gulf War in 1990/91. Notably, we do not observe a moderation of the level of the indicator during the 'Great Moderation' period.

By contrast, during the second subperiod beginning in the mid-1990s oil and commodity price uncertainty is characterized by an upward trending pattern. Between 1998 and 2000 the OPEC repeatedly adjusted its quotas which apparently increased the oil and commodity price uncertainty. The indicator rises sharply around 9/11 when changes in the oil production quota were no longer sufficient to stabilize the oil price. On average, oil and commodity price uncertainty remains on a higher level thereafter. It increases moderately during the second Gulf War and peaks in the mid-2000s reflecting the decrease in oil spare capacity in the aftermath of the second Gulf War. At the beginning of the global financial crisis the oil price first increased until its sudden decline accompanied by a hike in the oil and commodity price uncertainty.

To sum up, the time paths of both indicators of macroeconomic uncertainty are linked to major events that are commonly associated with economic turmoil.

4.4 How does macroeconomic uncertainty compare to familiar uncertainty measures?

Several measures have been proposed to investigate the dynamics of uncertainty and its relation to economic activity. A number of studies use stock market volatility measured by means of the option-based CBOE implied volatility index (VXO) (see, for instance, Bloom, 2009; Basu and Bundick, 2012). To obtain a long history, in the following, we use Bloom's (2009) measure which dates back to 1962. Similarly, credit spreads (SPREAD) may be used to measure the perception of risk of financial investors (Gilchrist, Yankov, and Zakrajšek, 2009; Gilchrist and Zakrajšek, 2012). Here, we focus on the 30-year Baa corporate bond spread (see also Bachmann et al., 2013). Moreover, Bachmann et al. (2013) put forward a measure (FDISP) which is derived from the dispersion of forecasts obtained from the Business Outlook Survey conducted by the Federal Reserve Bank of Philadelphia. It focuses on a specific group of respondents since it concentrates on a firm's output uncertainty. Finally, Baker et al. (2013) propose a measure of economic policy uncertainty (EPU) which is derived from the quantity of newspaper references to policy, tax rate and fiscal budget uncertainty. EPU, by design, reflects a specific type of uncertainty relating exclusively to future policy decisions.

In table 2, we assess the tightness of the relation of macroeconomic uncertainty to VXO, SPREAD, FDISP and EPU by means of canonical correlation analysis. A canonical correlation of 0.39 confirms that macroeconomic uncertainty and VXO share common dynamics. Compared to the VXO, the relation between macroeconomic uncertainty and SPREAD, as well as FDISP is somewhat closer. Finally, also

EPU bears a significant amount of co-movement with macroeconomic uncertainty.

| | VXO | SPREAD | FDISP | EPU |
|------------|------|--------|-------|------|
| f_1, f_2 | 0.39 | 0.57 | 0.51 | 0.43 |

Note: VXO: CBOE stock market volatility index (Bloom, 2009), SPREAD: Baa corporate bond spread, FDISP: Forecast dispersion measure from the Business outlook survey, Federal Reserve Bank of Philadelphia (Bachmann et al., 2013), EPU: Index of economic policy uncertainty (Baker et al., 2013). All values are significant at the 5% level. Series are quarterly averages.

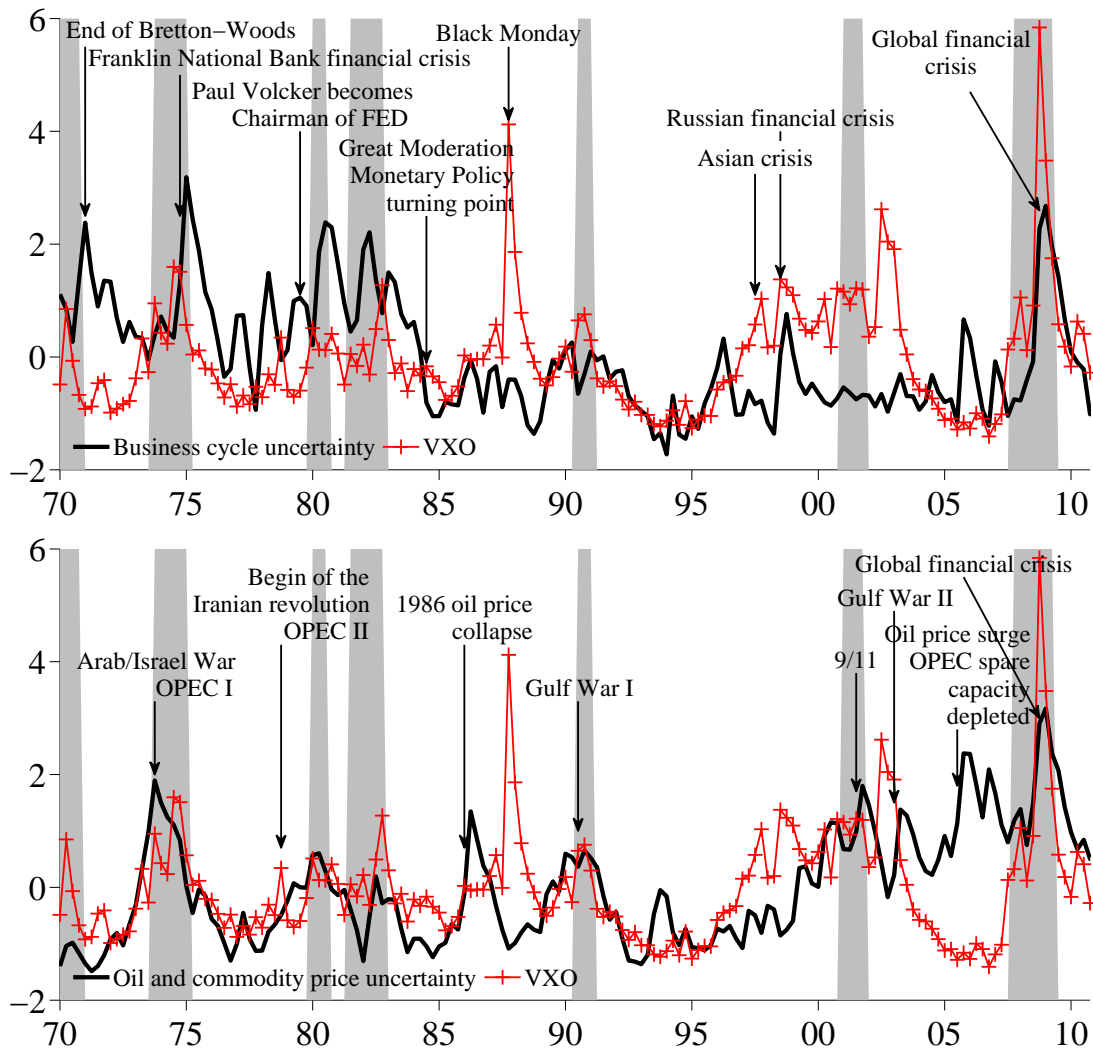
Table 2: Canonical correlations

In figure 6 we compare the dynamic patterns of the VXO to our indicators of macroeconomic uncertainty.¹⁶ To facilitate the interpretation of the graph, we calculate quarterly averages of the monthly series, and standardize all series. The upper panel displays business cycle uncertainty and the VXO. Both series increase swiftly around, for instance, the Franklin National Bank crisis, during the Russian financial crisis, and during the recent global financial crisis. Moreover, the movements appear to be synchronized during more tranquil episodes such as the early 1990s, as well. Yet the tightness of the relation among both measures varies over time. Particularly around the Black Monday we observe a jump in the VXO while there is virtually no reaction of business cycle uncertainty. A similar observation is made during the stock market crash of 2002 which apparently did not translate into uncertainty about aggregate economic outcomes. The comparison of VXO to the indicator of oil and commodity price uncertainty is provided in the lower panel of figure 6. We also observe that these two measures are synchronized during certain episodes. Particularly until the mid-1980s and during the 1990s uncertainty about oil price developments has apparently spilled over to financial markets. Financial market participants thus seem to consider turbulence on the market for oil a reason to price a firm's risk differently. The correlation appears to collapse during the mid-2000s when financial market uncertainty drops sharply which is not paralleled by oil and commodity price uncertainty. Interestingly, this coincides with a noticeable decrease in the dependence on foreign oil since its peak around 2005.¹⁷

To assess the relation to both types of macroeconomic uncertainty we regress the VXO on contemporaneous values of business cycle uncertainty and oil and commodity price uncertainty. The results are reported in the first row of table 3, and significance is indicated by the bold face estimates. First of all, we obtain a rather low R^2 which confirms the above observation that the measures have a relatively loose contempora-

¹⁶The time profiles of SPREAD, FDISP and EPU along with the indicators of macroeconomic uncertainty are displayed in figures G.1 to G.3 in the appendix.

¹⁷Data on oil dependence are obtainable from the US Energy Information Administration, <http://www.eia.gov/oog/info/twip/twiparch/110525/twipprint.html>.



Note: The upper panel depicts the business cycle uncertainty and the lower panel the oil and commodity price uncertainty. The crossed (red) line represents stock market volatility (VXO). To remove noise from the data we provide quarterly averages. To make the variables comparable all series are standardized. NBER recession dates are indicated by the shaded areas.

Figure 6: Indicators of macroeconomic uncertainty and the VXO

neous relation. However, both uncertainty factors are significant in the regression of the VXO.¹⁸ This suggests that the VXO reflects, both, business cycle uncertainty and oil and commodity price uncertainty.

¹⁸We also calculate the dynamic response of VXO, SPREAD, FDISP, and EPU to the two fundamental shocks u_1 and u_2 . We obtain essentially the same results compared to the contemporaneous regressions. Notably, the effect of business cycle uncertainty on FDISP becomes significant only after a period of 10 months. We present the results in appendix H.

| Z | α_1 | α_2 | R ² |
|--------|--------------|-------------|----------------|
| VXO | 0.19 | 0.33 | 0.15 |
| SPREAD | 0.50 | 0.26 | 0.33 |
| FDISP | -0.38 | 0.36 | 0.26 |
| EPU | 0.43 | -0.01 | 0.18 |

Note: For each alternative measure we run the following regression: $Z_t = \alpha_1 f_{1,t} + \alpha_2 f_{2,t} + d_{\text{Oct87}} + \eta_t$, where $Z_t \in \{\text{VXO}, \text{FDISP}, \text{EPU}, \text{SPREAD}\}$. VXO: CBOE stock market volatility index (Bloom, 2009), SPREAD: Baa corporate bond spread, FDISP: Forecast dispersion measure from the Business Outlook Survey, Federal Reserve Bank of Philadelphia (Bachmann et al., 2013), EPU: Index of economic policy uncertainty (Baker et al., 2013). We introduce a dummy variable d_{Oct87} that accounts for the Black Monday. All series are quarterly averages and standardized. Coefficients in bold face are significant at the 5% level.

Table 3: Regression on the uncertainty factors

Although the VXO is to some extent related to macroeconomic uncertainty, our results suggest that there are non-negligible differences between financial market uncertainty and macroeconomic uncertainty. If uncertainty is rather short-lived and limited to financial markets – for instance after the Black Monday – the fluctuations may be of limited importance from a macroeconomic perspective (Jurado et al., 2013, emphasize this point). Moreover, it has been documented that the VXO is to a large extent influenced by time-varying risk aversion of financial investors which is different from economic uncertainty (Bekaert et al., 2012). Overall, the VXO does not necessarily reflect fluctuations in macroeconomic uncertainty.

Table 3 also reveals that the SPREAD is linked positively to both types of macroeconomic uncertainty and thus delivers a result which is similar to the VXO. Yet, the SPREAD appears to be more closely related to macroeconomic uncertainty than the VXO since the R² of the regression is somewhat higher.

The dispersion of firms' forecasts appears to be negatively related to our measure of business cycle uncertainty. Bachmann et al. (2013) show that the dispersion of firms' forecasts about their business outlook serves as a proxy for the uncertainty an individual firm faces when deciding on its own future production. Thus, FDISP is interpreted as a measure of microeconomic uncertainty as opposed to uncertainty about the macroeconomic environment (Bloom et al., 2012). A negative relation to business cycle uncertainty thus suggests that firms tend to cluster their forecasts around the average forecast when they are highly uncertain about aggregate demand. By contrast, higher commodity price uncertainty comes along with higher dispersion of firms' forecasts indicated by a positive and significant coefficient in table 3. Such a result is in line with the notion that the firms' uncertainty rises whenever oil and commodity price movements

– which account for a large fraction in production cost in the manufacturing sector and therefore determine the production condition of a firm – become hard to predict.

Considering the economic policy uncertainty, we document a significantly positive contemporaneous relation to business cycle uncertainty but not to oil and commodity price uncertainty. Since uncertainty about future fiscal policy is one aspect of business cycle uncertainty this result is in line with our interpretation of the uncertainty factors.

4.5 What is the impact of macroeconomic uncertainty on economic activity?

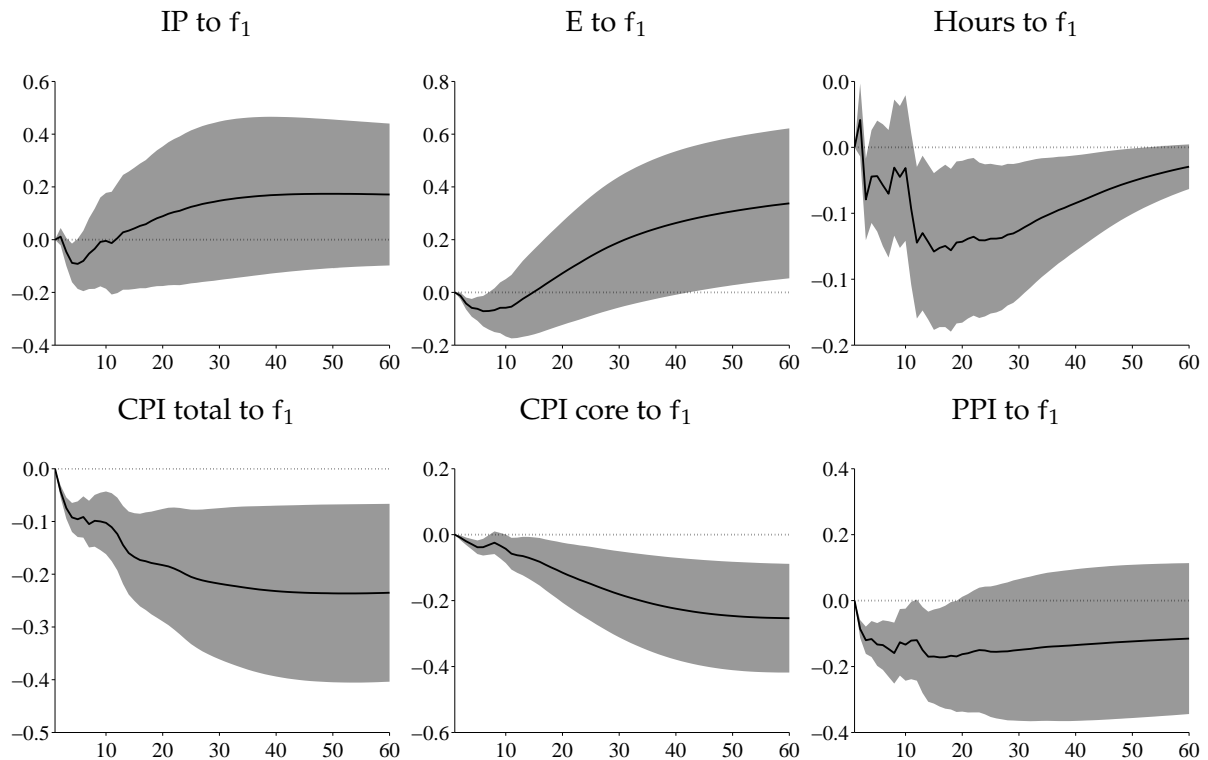
We now turn our attention to the dynamic relation between the different types of macroeconomic uncertainty and economic activity, that is, the variables in first moments. As Bachmann and Moscarini (2012) point out economic activity and macroeconomic uncertainty may be highly endogenous. To meet this concern we estimate a number of bivariate VARs. A bivariate VAR is a parsimonious way to model the joint dynamics of both variables while controlling for the interrelations among them. Each VAR consists of one uncertainty factor $f_{i,t}$, for $i = 1, 2$, and one additional variable representing economic activity. To study the response of real activity we use industrial production (IP), employment (E), and average hours (Hours). Moreover, we consider nominal variables: consumer prices (CPI total), consumer prices excluding food and energy (CPI core), and producer prices for finished goods (PPI). All variables enter in levels. We set the lag length for each VAR to 12 which is sufficient to control for the dynamic history of the variables.¹⁹ The VAR innovations are orthogonalized by means of a Cholesky decomposition where the respective uncertainty factor is ordered last.

Figure 7 collects the impulse responses for a shock to business cycle uncertainty. It appears that business cycle uncertainty leads to a short-lived drop in production activities and employment followed by a quick rebound.²⁰ The reaction of hours worked

¹⁹As a robustness check we choose the lag length for the bivariate VARs by BIC and very similar impulse responses are obtained. Moreover, our results remain qualitatively unchanged when we estimate the VARs using the variables in growth rates. These results are available upon request. Following Bloom (2009), larger VARs (covering eight or more variables) are employed in a number of papers to study the impact of a surprise increase in uncertainty. Moreover, ‘economic activity’ might not be properly reflected in a single variable such as industrial production. In appendix I, we conduct a further robustness check where we condition on a large information set. That is, we estimate factor-augmented VARs where economic activity is measured by the common factors of all 164 variables in first moments (see Bernanke, Boivin, and Elias, 2005, for details). It appears that our results also hold when we consider a broader concept of economic activity.

²⁰Recent research also discusses whether the adjustment path following an uncertainty shock is characterized by an overshoot. For instance, Bloom (2009) argues that uncertainty leads to a wait-and-see

is more prolonged. Moreover, the decrease in production and employment is small. In contrast the impact of business cycle uncertainty on prices appears to be more pronounced. We observe a persistent decline of all three price variables. Figure 8 shows

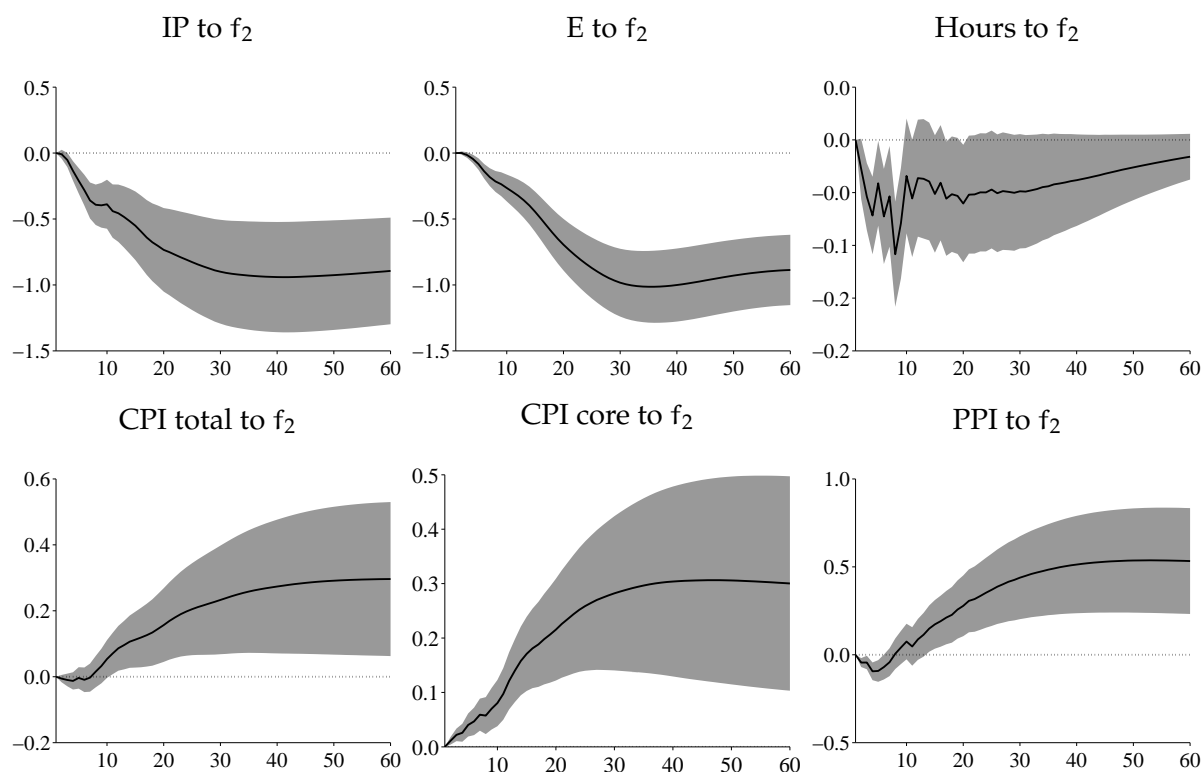


Note: The upper panel depicts the response of industrial production (IP), employment (E), and hours worked (Hours) to a surprise innovation in business cycle uncertainty. The lower panel shows impulse responses for consumer prices (CPI total), consumer prices excluding food and energy (CPI core), and producer prices of finished goods (PPI). As in Bloom (2009), Bachmann et al. (2013), and Jurado et al. (2013) we consider industrial production, employment, and average hours for the manufacturing sector. Confidence intervals are derived from the bias adjusted bootstrap procedure (Kilian, 1998). Shaded areas indicate the \pm one standard deviation confidence interval.

Figure 7: Impulse response functions for business cycle uncertainty

the response to a shock to oil and commodity price uncertainty. Here, we observe a long-lasting and pronounced decline of production and employment. Hours worked decrease as well, but by a smaller amount. The reaction of the price variables, however, goes into the opposite direction. A sudden increase in oil and commodity prices appears to be followed by a persistent hike in prices. Impulse response analysis sug-

attitude which is followed by a large rebound once the uncertainty dissolves. Results provided by Bachmann et al. (2013) and Jurado et al. (2013), for instance, suggest that whether the rebound is observed depends to a large extent on the measure (and type of uncertainty) analyzed. Indeed, we observe that a sudden increase in business cycle uncertainty is followed by a quick and sizeable rebound while this is



Note: The upper panel depicts the response of industrial production (IP), employment (E), and hours worked (H) to a surprise innovation in oil and commodity price inflation. The lower panel shows impulse responses for consumer prices (CPI total), consumer prices excluding food and energy (CPI core), and producer prices of finished goods (PPI). As in Bloom (2009), Bachmann et al. (2013), and Jurado et al. (2013) we consider industrial production, employment, and average hours for the manufacturing sector. Confidence intervals are derived from the bias adjusted bootstrap procedure (Kilian, 1998). Shaded areas indicate the \pm one standard deviation confidence interval.

Figure 8: Impulse response functions for oil and commodity price uncertainty

gests that both types of macroeconomic uncertainty induce rather different reactions of economic activity. Surprise increases in business cycle uncertainty tend to reduce production and prices and, thus, act like a standard aggregate demand shock. Leduc and Liu (2012) argue in favor of this hypothesis using a consumer survey based indicator of uncertainty. While we confirm their findings for business cycle uncertainty, we do not for oil and commodity price uncertainty. Surprise increases in the latter lead to a drop in real activity but, yet, they are accompanied by price increases. Oil and commodity price uncertainty thus acts more like an aggregate supply shock. Due to their fundamentally different impact on economic activity we conclude that it is important to distinguish between both types of macroeconomic uncertainty.

not the case when we consider oil and commodity price inflation.

The shares of the forecast error variance explained by the two types of macroeconomic uncertainty are shown in table 4. While surprise increases in business cycle uncertainty explain a small but non-negligible share of the variation of nominal variables, it appears to be of minor importance for real activity. This result is in line with Bachmann and Bayer (2013) who argue that uncertainty about future production is unlikely to be of importance for business cycle fluctuations.²¹ However, uncertainty which develops endogenously may still act as an amplifier of recessions (see, for instance, Bachmann and Moscarini, 2012, on this point). In addition, we document that a sudden increase in oil and commodity price uncertainty explains a relatively large part of the fluctuations of real activity. Particularly employment – in opposition to hours – appears to be affected quite persistently which probably reflects the fact that the adjustment of labor is more sluggish during and after a recession. Oil and commodity price uncertainty is also of importance for the dynamics of the price variables although to a lesser extent. Taken together, we document a non-negligible impact of macroeconomic uncertainty on real activity and prices.

| Horizon | Business cycle uncertainty | | | | | | Oil and commodity price uncertainty | | | | | |
|---------|----------------------------|------|-------|-----------|----------|------|-------------------------------------|-------|------|-----------|----------|-------|
| | IP | E | Hours | CPI total | CPI core | PPI | IP | E | H | CPI total | CPI core | PPI |
| 12 | 0.10 | 0.28 | 0.89 | 3.47 | 0.96 | 1.88 | 4.78 | 5.42 | 2.15 | 0.80 | 3.30 | 0.62 |
| 24 | 0.17 | 0.31 | 3.17 | 4.44 | 2.14 | 1.76 | 10.56 | 21.03 | 2.85 | 2.94 | 7.82 | 3.65 |
| 36 | 0.37 | 1.09 | 4.59 | 4.82 | 3.57 | 1.54 | 15.03 | 35.31 | 3.67 | 4.65 | 9.76 | 7.15 |
| 60 | 0.66 | 2.90 | 5.28 | 5.12 | 5.60 | 1.28 | 18.99 | 43.68 | 4.31 | 6.33 | 10.60 | 10.89 |

Note: Figures represent the share of the forecast error variance (%) due to business cycle uncertainty (left panel) and oil and commodity price uncertainty (right panel). The numbers are obtained from bivariate VARs with 12 lags consisting of one type of macroeconomic uncertainty and one measure of economic activity. The rows contain the results for different forecast horizons.

Table 4: Forecast error variance explained by macroeconomic uncertainty

5 Summary and conclusion

Economic uncertainty has recently been identified as a possible cause of business cycle fluctuations. However, almost all variables of an economy may be subject to time varying uncertainty. As a consequence, numerous individual uncertainty measures may be

²¹Bachmann and Bayer (2013) concentrate on production uncertainty arising from shocks to TFP. In a nutshell, they introduce this type of uncertainty into a heterogeneous firm model with fixed capital adjustment costs where uncertainty shocks lead to a wait-and-see behavior. The authors demonstrate that, in such a model, uncertainty shocks (firm-specific and aggregate) alone are unlikely to be a major cause for business cycle fluctuations.

obtained which entails a monitoring problem for the policy maker and the researcher alike. In the present paper, we unravel the fundamental factors governing the uncertainty about macroeconomic outcomes by means of a dynamic factor model. We interpret the common dynamics in the individual uncertainty measures as macroeconomic uncertainty.

First, we document that only a small number of fundamental factors account for the movements of macroeconomic uncertainty. Our results suggest that only two shocks are responsible for the common dynamics, and that further shocks explain variable-specific rather than macroeconomic uncertainty. Such a finding greatly reduces the monitoring problem for the policy maker and the researcher. Second, we demonstrate that the first fundamental factor is related to uncertainty surrounding variables which are closely linked to aggregate demand and is thus interpreted as ‘business cycle uncertainty’ while the second type of uncertainty reflects ‘oil and commodity price uncertainty’. Third, we analyze to what extent alternative measures applied in the literature reflect macroeconomic uncertainty. Both types of macroeconomic uncertainty come along with an increase in financial market uncertainty as measured by the VXO and the spread for Baa rated corporate bonds. However, measures such as the VXO or SPREAD should be interpreted carefully since they react to various types of uncertainty. In particular, they may indicate uncertainty which is unrelated to macroeconomic fundamentals. The dispersion of firms’ forecasts – a measure of firm-specific uncertainty – is negatively related to business cycle uncertainty while it appears to increase when oil and commodity price uncertainty mounts. Economic policy uncertainty is positively related to business cycle uncertainty only. Fourth, we document that macroeconomic uncertainty has a non-negligible impact on economic activity. Changes of the two types of uncertainty lead to quite different responses of economic indicators. A sudden increase in business cycle uncertainty leads to a (minor) slowdown in real activity which is accompanied by a price decrease. By contrast, an unexpected increase in oil and commodity price uncertainty generates a decline of economic activity which is accompanied by price increases. For a well-informed policy response to rising macroeconomic uncertainty it is thus essential to distinguish between the different fundamental types of uncertainty.

References

- Ahn, S. C. and A. R. Horenstein (2013). Eigenvalue ratio test for the number of factors. *Econometrica* 81(3), 1203–1227.
- Alexopoulos, M. and J. Cohen (2009). Uncertain times, uncertain measures. University of Toronto Working Paper 352.
- Andersen, T. G., T. Bollerslev, P. F. Christoffersen, and F. X. Diebold (2006). *Volatility and correlation forecasting*, Volume 1 of *Handbook of Economic Forecasting*, Chapter 15, pp. 777–878. Elsevier.
- Arellano, C., Y. Bai, and P. Kehoe (2012). Financial markets and fluctuations in uncertainty. Federal Reserve Bank of Minneapolis, March 2012, Staff Report.
- Bachmann, R. and C. Bayer (2013). ‘Wait-and-see’ business cycles? *Journal of Monetary Economics* forthcoming. former version circulated under the title: Uncertainty business cycles - Really?
- Bachmann, R., S. Elstner, and E. R. Sims (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics* 5(2), 217–49.
- Bachmann, R. and G. Moscarini (2012). Business cycles and endogenous uncertainty. Yale University, Manuscript.
- Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica* 70(1), pp. 191–221.
- Bai, J. and S. Ng (2008). Large dimensional factor analysis. *Foundations and Trends in Econometrics* 3(2), 89–163.
- Baillie, R. T., C.-F. Chung, and M. A. Tieslau (1996). Analysing inflation by the Fractionally Integrated ARFIMA-GARCH model. *Journal of Applied Econometrics* 11(1), 23–40.
- Baker, S. R., N. Bloom, and S. J. Davis (2013). Measuring economic policy uncertainty. Stanford University, Manuscript.
- Ball, L. (1992). Why does high inflation raise inflation uncertainty? *Journal of Monetary Economics* 29, 371–388.

- Bañbura, M. and M. Modugno (2012). Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. *Journal of Applied Econometrics*, 1–27. doi:10.1002/jae.2306.
- Basu, S. and B. Bundick (2012, September). Uncertainty shocks in a model of effective demand. NBER Working Paper 18420.
- Bekaert, G., M. Hoerova, and M. Lo Duca (2012). Risk, uncertainty and monetary policy. Columbia University, Manuscript.
- Bernanke, B. and F. Mishkin (1997). Inflation targeting: A new framework for monetary policy? *The Journal of Economic Perspectives* 2, 97–116.
- Bernanke, B. S., J. Boivin, and P. Eliasch (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics* 120(1), 387–422.
- Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica* 77(3), 623–686.
- Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2012). Really uncertain business cycles. NBER Working Paper 18245.
- Bollerslev, T. (2009). Glossary to ARCH (GARCH). In *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*. Tim Bollerslev, Jeffrey R. Russell, and Mark W. Watson.
- Born, B. and J. Pfeifer (2011). Policy risk and the business cycle. Bonn University, Discussion Paper 06-2011.
- Burns, A. F. and W. C. Mitchell (1946). *Measuring business cycles*. NBER.
- D’Amico, S. and A. Orphanides (2008). Uncertainty and disagreement in economic forecasting. *Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System* 56, 1–40.
- DeJong, D. N., R. Liesenfeld, G. V. Moura, J.-F. Richard, and H. Dharmarajan (2013). Efficient likelihood evaluation of state-space representations. *The Review of Economic Studies* 80(2), 538–567.
- Doz, C., D. Giannone, and L. Reichlin (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics* 164(1), 188–205.

- Doz, C., D. Giannone, and L. Reichlin (2012). A quasi-maximum likelihood approach for large, approximate dynamic factor models. *The Review of Economics and Statistics* 94(4), 1014–1024.
- Elder, J. and A. Serletis (2010). Oil price uncertainty. *Journal of Money, Credit and Banking* 42(6), 1137–1159.
- Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2012). Fiscal volatility shocks and economic activity. University of Pennsylvania, manuscript.
- Fernández-Villaverde, J. and J. F. Rubio-Ramírez (2010). Macroeconomics and volatility: Data, models, and estimation. NBER Working Paper 16618.
- Fernández-Villaverde, J., P. Guerrón-Quintana, and J. F. Rubio-Ramírez (2010). Fortune or virtue: Time-variant volatilities versus parameter drifting in U.S. data. NBER Working Paper 15928.
- Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramírez, and M. Uribe (2011). Risk matters: The real effects of volatility shocks. *American Economic Review* 101(6), 2530–61.
- Forni, M. and L. Gambetti (2010). The dynamic effects of monetary policy: A structural factor model. *Journal of Monetary Economics* 57(2), 203–216.
- Forni, M., D. Giannone, M. Lippi, and L. Reichlin (2007). Opening the black box - structural factor models with large gross-sections. European Central Bank, Working Paper 702.
- Forni, M., D. Giannone, M. Lippi, and L. Reichlin (2009). Opening the black box: Structural factor models with large cross sections. *Econometric Theory* 25(05), 1319–1347.
- Forni, M. and L. Reichlin (1998). Let's get real: A factor analytical approach to disaggregated business cycle dynamics. *Review of Economic Studies* 65(3), 453–73.
- Friedman, M. (1977). Nobel lecture: Inflation and unemployment. *The Journal of Political Economy* 85(3), 451–472.
- Giannone, D., L. Reichlin, and L. Sala (2002). Tracking Greenspan: Systematic and un-systematic monetary policy revisited. CEPR Discussion Paper 3550.

- Giannone, D., L. Reichlin, and L. Sala (2004). Monetary policy in real time. *NBER Macroeconomics Annual* 19, 161–224.
- Gilchrist, S., J. W. Sim, and E. Zakrajšek (2010). Uncertainty, financial frictions, and investment dynamics. Boston University, manuscript.
- Gilchrist, S., V. Yankov, and E. Zakrajšek (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of Monetary Economics* 56(4), 471–492.
- Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American Economic Review* 102(4), 1692–1720.
- Giordani, P. and P. Söderlind (2003). Inflation forecast uncertainty. *European Economic Review* 47, 1037–1059.
- Gonçalves, S. and L. Kilian (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics* 123, 89–120.
- Grier, K., O. Henry, N. Olekalns, and K. Shields (2004). The asymmetric effects of uncertainty on inflation and output growth. *Journal of Applied Econometrics* 19, 551–565.
- Grier, K. and M. Perry (2000). The effects of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence. *Journal of Applied Econometrics* 15, 45–58.
- Grier, K. B. and M. J. Perry (1998). On inflation and inflation uncertainty in the G7 countries. *Journal of International Money and Finance* 17(4), 671–689.
- Jo, S. (2011). The effects of oil price uncertainty on the macroeconomy. University of California, San Diego, manuscript.
- Jurado, K., S. C. Ludvigson, and S. Ng (2013). Measuring uncertainty. New York University, manuscript.
- Karanasos, M., M. Kranassou, and S. Fountas (2004). Analyzing US inflation by a GARCH model with simultaneous feedback. *WSEAS Transaction on Information Science and Applications* 1, 767–772.
- Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *The Review of Economics and Statistics* 80, 218–230.

- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the Crude Oil market. *American Economic Review* 99(3), 1053–1069.
- Knotek II, E. S. and S. Khan (2011). How do households respond to uncertainty shocks? *Economic Review (Q II)*. Federal Reserve Bank of Kansas City.
- Kose, M. A., C. Otrok, and E. Prasad (2012). Global business cycles: Convergence or decoupling? *International Economic Review* 53(2), 511–538.
- Kose, M. A., C. Otrok, and C. H. Whiteman (2003). International business cycles: World, region, and country-specific factors. *American Economic Review* 93(4), 1216–1239.
- Lahiri, K., C. Teigland, and M. Zaporowski (1988). Interest rates and the subjective probability distribution of inflation forecasts. *Journal of Money, Credit and Banking* 20(2), 233–248.
- Leduc, S. and Z. Liu (2012). Uncertainty shocks are aggregate demand shocks. Federal Reserve Bank of San Francisco, Working Paper 2012-10.
- Liesenfeld, R. and J.-F. Richard (2003). Univariate and multivariate stochastic volatility models: Estimation and diagnostics. *Journal of Empirical Finance* 10(4), 505–531.
- Lundbergh, S. and T. Teräsvirta (2002). Evaluating GARCH models. *Journal of Econometrics* 110(2), 417–435.
- Marcellino, M. and C. Schumacher (2010). Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. *Oxford Bulletin of Economics and Statistics* 72(4), 518–550.
- Morgan, J. (1996). *Riskmetrics* (4th ed.). Technical Documents, New York.
- Onatski, A. (2010). Determining the number of factors from empirical distribution of eigenvalues. *The Review of Economics and Statistics* 92(4), pp. 1004–1016.
- Ramey, G. and V. A. Ramey (1995). Cross-country evidence on the link between volatility and growth. *The American Economic Review* 85(5), pp. 1138–1151.
- Rich, R. and J. Tracy (2010). The relationship among expected inflation, disagreement, and uncertainty: Evidence from matched point and density forecasts. *The Review of Economics and Statistics* 92(1), 200–207.

- Richard, J.-F. and W. Zhang (2007). Efficient high-dimensional importance sampling. *Journal of Econometrics* 141(2), 1385 – 1411.
- Sargent, T. and C. Sims (1977). Business cycle modelling without pretending to have too much a priori economic theory. In C. Sims (Ed.), *New Methods in Business Cycle Research*. Federal Reserve Bank of Minneapolis, Minneapolis.
- Schaal, E. (2012). Uncertainty, productivity and unemployment in the great recession. Federal Reserve Bank of Minneapolis, Manuscript.
- Stock, J. H. and M. W. Watson (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics* 20(2), 147–162.
- Stock, J. H. and M. W. Watson (2005, July). Implications of dynamic factor models for VAR analysis. NBER Working Paper 11467.
- Zarnowitz, V. and L. A. Lambros (1987). Consensus and uncertainty in economic predictions. *The Journal of Political Economy* 95(3), 591–621.

Appendix

A Description and (forecast error) variance decomposition of uncertainty measures and data in growth rates

| Series | Transformation | Uncertainty | | | Growth rates | | | |
|------------------------------|--|----------------|--------------|------|----------------|--------------|------|------|
| | | R ² | FEVD - Shock | | R ² | FEVD - Shock | | |
| | | | 1 | 2 | | 1 | 2 | |
| <i>Industrial production</i> | | | | | | | | |
| 1 | Index of IP: Total | 3 | 0.78 | 1.00 | 0.00 | 0.90 | 0.89 | 0.11 |
| 2 | Index of IP: Final products and nonindustrial supplies | 3 | 0.66 | 1.00 | 0.00 | 0.83 | 0.89 | 0.11 |
| 3 | Index of IP: Final products | 3 | 0.58 | 1.00 | 0.00 | 0.75 | 0.89 | 0.11 |
| 4 | Index of IP: Consumer goods | 3 | 0.44 | 0.99 | 0.01 | 0.55 | 0.88 | 0.12 |
| 5 | Index of IP: Durable consumer goods | 3 | 0.40 | 0.99 | 0.01 | 0.55 | 0.88 | 0.12 |
| 6 | Index of IP: Nondurable consumer goods | 3 | 0.10 | 0.93 | 0.07 | 0.17 | 0.89 | 0.11 |
| 7 | Index of IP: Business equipment | 3 | 0.53 | 0.96 | 0.04 | 0.59 | 0.89 | 0.11 |
| 8 | Index of IP: Materials | 3 | 0.68 | 1.00 | 0.00 | 0.70 | 0.89 | 0.11 |
| 9 | Index of IP: Materials, nonenergy, durables | 3 | 0.70 | 0.92 | 0.08 | 0.78 | 0.89 | 0.11 |
| 10 | Index of IP: Materials, nonenergy, nondurables | 3 | 0.47 | 0.85 | 0.15 | 0.42 | 0.89 | 0.11 |
| 11 | Index of IP: Mfg | 3 | 0.82 | 1.00 | 0.00 | 0.99 | 0.89 | 0.11 |
| 12 | Index of IP: Mfg, durables | 3 | 0.63 | 1.00 | 0.00 | 0.84 | 0.89 | 0.11 |
| 13 | Index of IP: Mfg, nondurables | 3 | 0.53 | 0.98 | 0.02 | 0.57 | 0.89 | 0.11 |
| 14 | Index of IP: Mining | 3 | 0.27 | 0.99 | 0.01 | 0.05 | 0.87 | 0.13 |
| 15 | Index of IP: Utilities | 3 | 0.15 | 0.16 | 0.84 | 0.01 | 0.08 | 0.92 |
| 16 | Index of IP: Energy, total | 3 | 0.17 | 0.74 | 0.26 | 0.02 | 0.72 | 0.28 |
| 17 | Index of IP: Nonenergy, total | 3 | 0.80 | 0.99 | 0.01 | 0.99 | 0.89 | 0.11 |
| 18 | Index of IP: Motor vehicles and parts (MVP) | 3 | 0.40 | 1.00 | 0.00 | 0.29 | 0.86 | 0.14 |
| 19 | Index of IP: Computers, comm. equip. and semiconductors (CCS) | 3 | 0.13 | 0.99 | 0.01 | 0.25 | 0.73 | 0.27 |
| 20 | Index of IP: Nonenergy excl CCS | 3 | 0.78 | 1.00 | 0.00 | 0.98 | 0.89 | 0.11 |
| 21 | Index of IP: Nonenergy excl CCS and MVP | 3 | 0.66 | 1.00 | 0.00 | 0.86 | 0.89 | 0.11 |
| <i>Capacity utilization</i> | | | | | | | | |
| 22 | Capacity utilization: Total | 2 | 0.77 | 1.00 | 0.00 | 0.87 | 0.89 | 0.11 |
| 23 | Capacity utilization: Mfg | 2 | 0.81 | 0.99 | 0.01 | 0.96 | 0.89 | 0.11 |
| 24 | Capacity utilization: Mfg, durables | 2 | 0.72 | 0.97 | 0.03 | 0.87 | 0.89 | 0.11 |
| 25 | Capacity utilization: Mfg, nondurables | 2 | 0.47 | 0.94 | 0.06 | 0.56 | 0.89 | 0.11 |
| 26 | Capacity utilization: Mining | 2 | 0.31 | 0.98 | 0.02 | 0.06 | 0.88 | 0.12 |
| 27 | Capacity utilization: Utilities | 2 | 0.04 | 0.26 | 0.74 | 0.01 | 0.03 | 0.97 |
| 28 | Capacity utilization: Computers, comm. equip. and semiconductors | 2 | 0.13 | 1.00 | 0.00 | 0.22 | 0.73 | 0.27 |
| 29 | Capacity utilization: Mfg excl CCS | 2 | 0.78 | 0.99 | 0.01 | 0.95 | 0.89 | 0.11 |
| 30 | Purchasing managers index (PMI) | 0/3 | 0.32 | 0.99 | 0.01 | 0.33 | 0.81 | 0.19 |
| 31 | ISM mfg index: Production | 0/3 | 0.33 | 0.97 | 0.03 | 0.37 | 0.89 | 0.11 |
| <i>Employment</i> | | | | | | | | |
| 32 | Index of help-wanted advertising | 3 | 0.12 | 0.03 | 0.97 | 0.21 | 0.89 | 0.11 |
| 33 | No. of unemployed in the civ. Labor force (CLF) | 3 | 0.12 | 0.93 | 0.07 | 0.24 | 0.87 | 0.13 |
| 34 | CLF employed: Total | 3 | 0.07 | 1.00 | 0.00 | 0.20 | 0.78 | 0.22 |
| 35 | CLF employed: Nonagricultural industries | 3 | 0.06 | 0.94 | 0.06 | 0.20 | 0.76 | 0.24 |

| Series | Transformation | Uncertainty | | | Growth rates | | | |
|--------------------|---|----------------|--------------|------|----------------|--------------|------|------|
| | | R ² | FEVD - Shock | | R ² | FEVD - Shock | | |
| | | | 1 | 2 | | 1 | 2 | |
| 36 | Mean duration of unemployment | 3 | 0.10 | 0.94 | 0.06 | 0.01 | 0.72 | 0.28 |
| 37 | Persons unemployed less than 5 weeks | 3 | 0.10 | 0.86 | 0.14 | 0.02 | 0.78 | 0.22 |
| 38 | Persons unemployed 5 to 14 weeks | 3 | 0.08 | 0.90 | 0.10 | 0.10 | 0.89 | 0.11 |
| 39 | Persons unemployed 15 to 26 weeks | 3 | 0.11 | 0.67 | 0.33 | 0.08 | 0.89 | 0.11 |
| 40 | Persons unemployed 15+ weeks | 3 | 0.06 | 1.00 | 0.00 | 0.14 | 0.89 | 0.11 |
| 41 | Avg weekly initial claims | 3 | 0.24 | 1.00 | 0.00 | 0.21 | 0.77 | 0.23 |
| 42 | Employment on nonag. payrolls: Total | 3 | 0.50 | 0.91 | 0.09 | 0.46 | 0.79 | 0.21 |
| 43 | Employment on nonag. payrolls: Total private | 3 | 0.59 | 0.91 | 0.09 | 0.49 | 0.81 | 0.19 |
| 44 | Employment on nonag. payrolls: Goods-producing | 3 | 0.64 | 0.96 | 0.04 | 0.54 | 0.84 | 0.16 |
| 45 | Employment on nonag. payrolls: Mining | 3 | 0.22 | 0.95 | 0.05 | 0.03 | 0.02 | 0.98 |
| 46 | Employment on nonag. payrolls: Construction | 3 | 0.43 | 0.91 | 0.09 | 0.28 | 0.88 | 0.12 |
| 47 | Employment on nonag. payrolls: Manufacturing | 3 | 0.59 | 0.98 | 0.02 | 0.52 | 0.84 | 0.16 |
| 48 | Employment on nonag. payrolls: Manufacturing, durables | 3 | 0.58 | 0.98 | 0.02 | 0.49 | 0.86 | 0.14 |
| 49 | Employment on nonag. payrolls: Manufacturing, nondurables | 3 | 0.34 | 0.99 | 0.01 | 0.36 | 0.77 | 0.23 |
| 50 | Employment on nonag. payrolls: Service-producing | 3 | 0.20 | 1.00 | 0.00 | 0.26 | 0.57 | 0.43 |
| 51 | Employment on nonag. payrolls: Utilities | 3 | 0.08 | 0.99 | 0.01 | 0.06 | 0.04 | 0.96 |
| 52 | Employment on nonag. payrolls: Retail trade | 3 | 0.15 | 1.00 | 0.00 | 0.27 | 0.66 | 0.34 |
| 53 | Employment on nonag. payrolls: Wholesale trade | 3 | 0.19 | 0.98 | 0.02 | 0.30 | 0.41 | 0.59 |
| 54 | Employment on nonag. payrolls: Financial activities | 3 | 0.09 | 0.36 | 0.64 | 0.15 | 0.25 | 0.75 |
| 55 | Employment on nonag. payrolls: Professional and bus. services | 3 | 0.07 | 0.31 | 0.69 | 0.29 | 0.64 | 0.36 |
| 56 | Employment on nonag. payrolls: education and health services | 3 | 0.11 | 0.72 | 0.28 | 0.07 | 0.26 | 0.74 |
| 57 | Employment on nonag. payrolls: Lesiure and hospitality | 3 | 0.01 | 0.16 | 0.84 | 0.13 | 0.74 | 0.26 |
| 58 | Employment on nonag. payrolls: Other services | 3 | 0.08 | 0.97 | 0.03 | 0.19 | 0.17 | 0.83 |
| 59 | Employment on nonag. payrolls: Government | 3 | 0.09 | 0.99 | 0.01 | 0.00 | 0.14 | 0.86 |
| 60 | Avg weekly hrs. of production or nonsupervisory workers | 3 | 0.24 | 0.89 | 0.11 | 0.18 | 0.89 | 0.11 |
| 61 | Avg weekly hrs. of PNW: Mfg | 3 | 0.24 | 0.97 | 0.03 | 0.24 | 0.89 | 0.11 |
| 62 | Avg weekly overtime hrs. of PNW: Mfg | 3 | 0.27 | 0.97 | 0.03 | 0.16 | 0.89 | 0.11 |
| 63 | ISM mfg index: Employment | 0/3 | 0.35 | 1.00 | 0.00 | 0.26 | 0.63 | 0.37 |
| <i>Sales</i> | | | | | | | | |
| 64 | Sales: Mfg and trade-total (mil of chained 96\$) | 3 | 0.34 | 0.98 | 0.02 | 0.33 | 0.80 | 0.20 |
| 65 | Sales: Mfg and trade-mfg, total (mil of chained 96\$) | 3 | 0.31 | 1.00 | 0.00 | 0.29 | 0.87 | 0.13 |
| 66 | Sales: Mfg and trade-merchant wholesale (mil of chained 96\$) | 3 | 0.19 | 0.97 | 0.03 | 0.14 | 0.81 | 0.19 |
| 67 | Sales: Mfg and trade-retail trade (mil of chained 96\$) | 3 | 0.23 | 0.92 | 0.08 | 0.09 | 0.48 | 0.52 |
| <i>Consumption</i> | | | | | | | | |
| 68 | Personal cons. expenditure: Total (bil chained 96\$) | 3 | 0.15 | 0.98 | 0.02 | 0.14 | 0.24 | 0.76 |
| 69 | Personal cons. expenditure: Durables (bil of chained 96\$) | 3 | 0.20 | 0.99 | 0.01 | 0.06 | 0.59 | 0.41 |
| 70 | Personal cons. expenditure: Nondurables (bil of chained 96\$) | 3 | 0.17 | 1.00 | 0.00 | 0.04 | 0.82 | 0.18 |

| Series | Transformation | Uncertainty | | | | Growth rates | | |
|---------------------------------|---|----------------|--------------|------|----------------|--------------|------|------|
| | | R ² | FEVD - Shock | | R ² | FEVD - Shock | | |
| | | | 1 | 2 | | 1 | 2 | |
| 71 | Personal cons. expenditure: Services (bil of chained 96\$) | 3 | 0.20 | 0.73 | 0.27 | 0.02 | 0.64 | 0.36 |
| 72 | Personal cons. expenditure: Durables (bil of chained 96\$) | 3 | 0.23 | 0.98 | 0.02 | 0.03 | 0.54 | 0.46 |
| <i>Housing and construction</i> | | | | | | | | |
| 73 | Privately-owned housing, started: Total (thous) | 3 | 0.24 | 0.99 | 0.01 | 0.05 | 0.87 | 0.13 |
| 74 | New privately-owned housing authorized: Total (thous) | 3 | 0.34 | 1.00 | 0.00 | 0.03 | 0.84 | 0.16 |
| 75 | New 1-family houses sold: Total (thous) | 3 | 0.05 | 0.94 | 0.06 | 0.00 | 0.11 | 0.89 |
| 76 | New 1-family houses-months supply at current rate | 3 | 0.05 | 0.65 | 0.35 | 0.01 | 0.20 | 0.80 |
| 77 | New 1-family houses for sale at end of period (thous) | 3 | 0.04 | 0.59 | 0.41 | 0.10 | 0.88 | 0.12 |
| 78 | Mobile homes-mfg shipments (thous) | 3 | 0.16 | 0.48 | 0.52 | 0.01 | 0.64 | 0.36 |
| 79 | Construction put in place: Total (mil of 96\$) | 3 | 0.23 | 0.90 | 0.10 | 0.11 | 0.82 | 0.18 |
| 80 | Construction put in place: Private (mil of 96\$) | 3 | 0.09 | 0.88 | 0.12 | 0.15 | 0.86 | 0.14 |
| <i>Inventories</i> | | | | | | | | |
| 81 | Inventories: Mfg, Total (mil of chained 96\$) | 3 | 0.19 | 0.96 | 0.04 | 0.06 | 0.33 | 0.67 |
| 82 | Inventories: Mfg (mil of chained 96\$) | 3 | 0.15 | 0.86 | 0.14 | 0.05 | 0.02 | 0.98 |
| 83 | Inventories: Mfg, durables (mil of chained 96\$) | 3 | 0.10 | 0.99 | 0.01 | 0.03 | 0.04 | 0.96 |
| 84 | Inventories: Mfg, nondurables (mil of chained 96\$) | 3 | 0.24 | 0.55 | 0.45 | 0.03 | 0.09 | 0.91 |
| 85 | Inventories: Merchant wholesale (mil of chained 96\$) | 3 | 0.19 | 0.86 | 0.14 | 0.01 | 0.14 | 0.86 |
| 86 | Inventories: Retail trade (mil of chained 96\$) | 3 | 0.17 | 0.97 | 0.03 | 0.08 | 0.87 | 0.13 |
| 87 | ISM mfg index: Inventories | 0/3 | 0.29 | 0.84 | 0.16 | 0.12 | 0.16 | 0.84 |
| <i>New and unfilled orders</i> | | | | | | | | |
| 88 | ISM mfg index: New orders | 0/3 | 0.22 | 0.93 | 0.07 | 0.39 | 0.89 | 0.11 |
| 89 | ISM mfg index: Suppliers deliveries | 0/3 | 0.37 | 0.92 | 0.08 | 0.10 | 0.52 | 0.48 |
| 90 | Mfg new orders: All mfg industries (mil of current \$) | 3 | 0.26 | 0.85 | 0.15 | 0.21 | 0.66 | 0.34 |
| 91 | Mfg new orders: Mfg ind. with unfilled orders (mil of current \$) | 3 | 0.21 | 0.22 | 0.78 | 0.08 | 0.86 | 0.14 |
| 92 | Mfg new orders: Durables (mil of current \$) | 3 | 0.25 | 0.84 | 0.16 | 0.14 | 0.89 | 0.11 |
| 93 | Mfg new orders: Nondurables (mil of current \$) | 3 | 0.32 | 0.35 | 0.65 | 0.32 | 0.17 | 0.83 |
| 94 | Mfg new orders: Nondefense capital goods (mil of current \$) | 3 | 0.12 | 0.90 | 0.10 | 0.02 | 0.86 | 0.14 |
| 95 | Mfg unfilled orders: All mfg industries (mil of current \$) | 3 | 0.09 | 0.17 | 0.83 | 0.14 | 0.19 | 0.81 |
| <i>Financial variables</i> | | | | | | | | |
| 96 | NYSE composite index | 3 | 0.20 | 0.92 | 0.08 | 0.01 | 0.02 | 0.98 |
| 97 | S&P composite | 3 | 0.22 | 0.84 | 0.16 | 0.01 | 0.24 | 0.76 |
| 98 | S&P P/E ratio | 3 | 0.11 | 0.17 | 0.83 | 0.01 | 0.67 | 0.33 |
| 99 | Nominal effective exchange rate | 3 | 0.21 | 0.18 | 0.82 | 0.00 | 0.13 | 0.87 |
| 100 | Spot Euro/US | 3 | 0.17 | 0.27 | 0.73 | 0.00 | 0.39 | 0.61 |
| 101 | Spot SZ/US | 3 | 0.05 | 0.21 | 0.79 | 0.00 | 0.68 | 0.32 |
| 102 | Spot Japan/US | 3 | 0.08 | 0.38 | 0.62 | 0.00 | 0.08 | 0.92 |
| 103 | Spot UK/US | 3 | 0.04 | 0.56 | 0.44 | 0.01 | 0.03 | 0.97 |
| 104 | Commercial paper outstanding (mil of current \$)* | - | - | - | - | - | - | - |

| Series | Transformation | Uncertainty | | | Growth rates | | | |
|---------------------------|---|----------------|--------------|------|----------------|--------------|------|------|
| | | R ² | FEVD - Shock | | R ² | FEVD - Shock | | |
| | | | 1 | 2 | | 1 | 2 | |
| <i>Interest rates</i> | | | | | | | | |
| 105 | Interest rate: Federal funds rate | 2 | 0.29 | 0.88 | 0.12 | 0.11 | 0.72 | 0.28 |
| 106 | Interest rate: U.S. 3-mo Treasury (sec. market) | 2 | 0.30 | 0.96 | 0.04 | 0.08 | 0.55 | 0.45 |
| 107 | Interest rate: U.S. 6-mo Treasury (sec. market) | 2 | 0.27 | 0.88 | 0.12 | 0.10 | 0.54 | 0.46 |
| 108 | Interest rate: 1-year Treasury | 2 | 0.31 | 0.81 | 0.19 | 0.09 | 0.52 | 0.48 |
| 109 | Interest rate: 5-year Treasury (constant maturity) | 2 | 0.17 | 0.91 | 0.09 | 0.08 | 0.22 | 0.78 |
| 110 | Interest rate: 7-year Treasury (constant maturity) | 2 | 0.11 | 0.91 | 0.09 | 0.08 | 0.15 | 0.85 |
| 111 | Interest rate: 10-year Treasury (constant maturity) | 2 | 0.10 | 0.89 | 0.11 | 0.08 | 0.13 | 0.87 |
| 112 | Bond yield: Moodys AAA corporate | 2 | 0.05 | 1.00 | 0.00 | 0.09 | 0.07 | 0.93 |
| 113 | Bond yield: Moodys BAA corporate | 2 | 0.05 | 0.49 | 0.51 | 0.05 | 0.02 | 0.98 |
| <i>Monetary variables</i> | | | | | | | | |
| 114 | M1 (bil of current \$) | 3 | 0.21 | 0.09 | 0.91 | 0.02 | 0.39 | 0.61 |
| 115 | M2 (bil of current \$) | 3 | 0.13 | 0.37 | 0.63 | 0.00 | 0.76 | 0.24 |
| 116 | M3 (bil of current \$) | 3 | 0.12 | 0.09 | 0.91 | 0.01 | 0.89 | 0.11 |
| 117 | Monetary base, adj. for reserve requirement (rr) changes (bil of \$)* | - | - | - | - | - | - | - |
| 118 | Depository institutions reserves: total (adj. for rr changes)* | - | - | - | - | - | - | - |
| 119 | Depository institutions: nonborrowed (adj. for rr changes)* | - | - | - | - | - | - | - |
| 120 | Loans and securities at all comm banks: Total (mil of current \$) | 3 | 0.24 | 0.52 | 0.48 | 0.06 | 0.40 | 0.60 |
| 121 | Loans and securities at all comm banks: Securities, total (mil of \$) | 3 | 0.10 | 0.64 | 0.36 | 0.01 | 0.74 | 0.26 |
| 122 | Loans and securities at all comm banks: Securities, U.S. govt (mil of \$) | 3 | 0.28 | 0.86 | 0.14 | 0.01 | 0.17 | 0.83 |
| 123 | Loans and securities at all comm banks: Real estate loans (mil of \$) | 3 | 0.23 | 0.03 | 0.97 | 0.03 | 0.32 | 0.68 |
| 124 | Loans and securities at all comm banks: Comm and Ind loans (mil of \$) | 3 | 0.19 | 0.32 | 0.68 | 0.10 | 0.02 | 0.98 |
| 125 | Loans and securities comm banks: consumer loans (mil of \$)* | - | - | - | - | - | - | - |
| 126 | Delinquency rate on bank-held consumer installment loans* | - | - | - | - | - | - | - |
| <i>Prices</i> | | | | | | | | |
| 127 | PPI: Finished goods (1982 = 100 for all PPI data) | 3 | 0.73 | 0.10 | 0.90 | 0.54 | 0.03 | 0.97 |
| 128 | PPI: Finished consumer goods | 3 | 0.76 | 0.07 | 0.93 | 0.49 | 0.02 | 0.98 |
| 129 | PPI: Intermediate materials | 3 | 0.71 | 0.09 | 0.91 | 0.52 | 0.02 | 0.98 |
| 130 | PPI: Crude materials | 3 | 0.55 | 0.02 | 0.98 | 0.17 | 0.03 | 0.97 |
| 131 | PPI: Finished goods excl food | 3 | 0.73 | 0.01 | 0.99 | 0.53 | 0.03 | 0.97 |
| 132 | Index of sensitive materials prices* | - | - | - | - | - | - | - |
| 133 | CPI: All items (urban) | 3 | 0.72 | 0.31 | 0.69 | 0.95 | 0.03 | 0.97 |
| 134 | CPI: Food and beverages | 3 | 0.20 | 0.91 | 0.09 | 0.27 | 0.03 | 0.97 |
| 135 | CPI: Housing | 3 | 0.32 | 0.99 | 0.01 | 0.53 | 0.05 | 0.95 |
| 136 | CPI: Apparel | 3 | 0.18 | 0.55 | 0.45 | 0.17 | 0.02 | 0.98 |
| 137 | CPI: Transportation | 3 | 0.71 | 0.03 | 0.97 | 0.57 | 0.02 | 0.98 |
| 138 | CPI: Medical care | 3 | 0.19 | 0.99 | 0.01 | 0.19 | 0.09 | 0.91 |
| 139 | CPI: Commodities | 3 | 0.88 | 0.06 | 0.94 | 0.79 | 0.02 | 0.98 |
| 140 | CPI: Commodities, durables | 3 | 0.06 | 0.80 | 0.20 | 0.38 | 0.04 | 0.96 |

| Series | Transformation | Uncertainty | | | Growth rates | | | |
|------------------------------------|---|----------------|--------------|------|----------------|--------------|------|------|
| | | R ² | FEVD - Shock | | R ² | FEVD - Shock | | |
| | | | 1 | 2 | | 1 | 2 | |
| 141 | CPI: Services | 3 | 0.29 | 1.00 | 0.00 | 0.46 | 0.06 | 0.94 |
| 142 | CPI: All items less food | 3 | 0.63 | 0.24 | 0.76 | 0.88 | 0.03 | 0.97 |
| 143 | CPI: All items less shelter | 3 | 0.81 | 0.18 | 0.82 | 0.88 | 0.02 | 0.98 |
| 144 | CPI: All items less medical care | 3 | 0.73 | 0.32 | 0.68 | 0.95 | 0.03 | 0.97 |
| 145 | CPI: All items less food and energy | 3 | 0.41 | 0.88 | 0.12 | 0.47 | 0.05 | 0.95 |
| 146 | Price of gold (\$/oz) on the London market (recorded in the p.m.) | 3 | 0.23 | 0.68 | 0.32 | 0.02 | 0.11 | 0.89 |
| 147 | PCE chain weight price index: Total | 3 | 0.68 | 0.24 | 0.76 | 0.87 | 0.03 | 0.97 |
| 148 | PCE prices: Total excl. food and energy | 3 | 0.07 | 1.00 | 0.00 | 0.43 | 0.05 | 0.95 |
| 149 | PCE prices: Durables | 3 | 0.06 | 0.98 | 0.02 | 0.34 | 0.04 | 0.96 |
| 150 | PCE prices: Nondurables | 3 | 0.86 | 0.02 | 0.98 | 0.71 | 0.02 | 0.98 |
| 151 | PCE prices: Services | 3 | 0.07 | 0.84 | 0.16 | 0.40 | 0.05 | 0.95 |
| <i>Wages</i> | | | | | | | | |
| 152 | Avg hourly earnings: Total nonagricultura (current \$) | 3 | 0.33 | 0.80 | 0.20 | 0.18 | 0.02 | 0.98 |
| 153 | Avg hourly earnings: Construction (current \$) | 3 | 0.23 | 0.77 | 0.23 | 0.08 | 0.34 | 0.66 |
| 154 | Avg hourly earnings: Mfg (current \$) | 3 | 0.36 | 0.92 | 0.08 | 0.14 | 0.02 | 0.98 |
| 155 | Avg hourly earnings: Finance, insurance, and real estate (current \$) | 3 | 0.13 | 0.87 | 0.13 | 0.03 | 0.05 | 0.95 |
| 156 | Avg hourly earnings: Professional and business services (current \$) | 3 | 0.07 | 0.61 | 0.39 | 0.06 | 0.17 | 0.83 |
| 157 | Avg hourly earnings: Education and health services (current \$) | 3 | 0.19 | 0.92 | 0.08 | 0.12 | 0.05 | 0.95 |
| 158 | Avg hourly earnings: Other services (current \$) | 3 | 0.15 | 1.00 | 0.00 | 0.17 | 0.05 | 0.95 |
| <i>Merchandise ex- and imports</i> | | | | | | | | |
| 159 | Total merchandise exports (FAS value) (mil of \$) | 3 | 0.21 | 0.88 | 0.12 | 0.05 | 0.39 | 0.61 |
| 160 | Total merchandise imports (CIF value) (mil of \$) (NSA) | 3 | 0.32 | 0.99 | 0.01 | 0.07 | 0.13 | 0.87 |
| 161 | Total merchandise imports (customs value) (mil of \$) | 3 | 0.30 | 1.00 | 0.00 | 0.07 | 0.15 | 0.85 |
| <i>Business outlook</i> | | | | | | | | |
| 162 | Philadelphia Fed business outlook: General activity | 0/2 | 0.10 | 0.33 | 0.67 | 0.07 | 0.64 | 0.36 |
| 163 | Outlook: New orders | 0/2 | 0.16 | 0.77 | 0.23 | 0.06 | 0.58 | 0.42 |
| 164 | Outlook: Shipments | 0/2 | 0.11 | 0.82 | 0.18 | 0.05 | 0.70 | 0.30 |
| 165 | Outlook: Inventories | 0/2 | 0.09 | 0.83 | 0.17 | 0.18 | 0.60 | 0.40 |
| 166 | Outlook: Unfilled orders | 0/2 | 0.10 | 0.97 | 0.03 | 0.06 | 0.75 | 0.25 |
| 167 | Outlook: Prices paid | 0/2 | 0.09 | 0.04 | 0.96 | 0.41 | 0.02 | 0.98 |
| 168 | Outlook: Prices received | 0/2 | 0.05 | 0.91 | 0.09 | 0.40 | 0.02 | 0.98 |
| 169 | Outlook: Employment | 0/2 | 0.05 | 0.97 | 0.03 | 0.10 | 0.84 | 0.16 |
| 170 | Outlook: Work hours | 0/2 | 0.10 | 0.97 | 0.03 | 0.08 | 0.54 | 0.46 |
| 171 | Federal govt deficit or surplus (mil of current \$) | 0 | 0.04 | 0.05 | 0.95 | 0.02 | 0.02 | 0.98 |

Note: Variables marked with a '*' are not available for the full sample period and therefore excluded from the analysis. The transformations applied to the data and determined in the column 'Transformation' are explained in greater detail below. The columns denoted by 'Uncertainty' report results for uncertainty measures while columns denoted by 'Levels' results for variables in first-order moments. The latter are, in principle, replications of the results made by Giannone et al. (2004). In the columns labeled 'R²' we report the R² of factor models based on two fundamental factors. Columns '1' and '2' display the forecast error variances (12-month-ahead) explained by the first or the second shock.

Table A.1: Description of the dataset and forecast error variance decomposition

| Transformations applied to the data | |
|-------------------------------------|--|
| 0: | X_t |
| 1: | $\ln(X_t)$ |
| 2: | $(1 - L)X_t$, L denotes the lag-operator |
| 3: | $(1 - L) \ln(X_t)$ |
| ·/· | left hand side: transformation for first moment analysis right hand side: transformation for second moment analysis |

Remark 1: Whenever a series has not been available in NAICS classification scheme for the entire sample period, missing values have been linked with data based on the SIC classification scheme.

Remark 2: Series 32 has been published only until 2010M7. It has been linked with the Help Wanted Online Index published by the Conference Board.

Remark 3: Whenever a series denoted in mil. of chained 2005 \$ has not been available for the entire sample period, missing values have been linked with data published in mil. of chained 1996 \$.

Remark 4: Series 116 has been replaced by the monetary aggregates index published by the Federal Reserve Bank of St. Louis (monetary aggregate (all), sum, comparable to old index M3).

B Estimation of the dynamic factor model

Doz et al. (2012) introduce a Quasi Maximum Likelihood estimation procedure for the so-called ‘approximating’ factor model. Idiosyncratic components ξ_t in (6) and residuals ϵ_t in (7) are assumed to be gaussian distributed and orthogonal ($E[\xi_t \epsilon'_{t-k}] = 0$, for all k). Moreover, for the purpose of estimation the idiosyncratic components are assumed to be serially and cross sectionally uncorrelated. Doz et al. (2012) show theoretically and in a Monte Carlo study that – despite these potentially misspecified correlation structure of the idiosyncratic components – the factors are estimated consistently if n and T are large.

The Quasi Maximum Likelihood estimation procedure is based on the EM-algorithm which enables us to handle the parametric structure of the model (see Doz et al., 2012; Marcellino and Schumacher, 2010). We initialize the EM algorithm with an estimate of \hat{f}_t obtained from the principal components corresponding to the r largest eigenvalues of the covariance matrix of X_t . Given this initialization we iterate between the following steps.

M-step:

- Obtain the loadings matrix $\hat{\lambda}$ by regressing X_t on \hat{f}_t .
- Estimate the idiosyncratic components from $\hat{\xi}_t = X_t - \hat{\lambda}\hat{f}_t$. Further, evaluate the corresponding covariance matrix of the idiosyncratic components denoted by $\hat{\delta}_\xi$. Restrict the off-diagonal elements to zero as proposed by Doz et al. (2012).
- Estimate the h-th order VAR in f_t using \hat{f}_t .
- Estimate the covariance of the residuals $\hat{\delta}_\epsilon$.

E-step:

- ξ_t and ϵ_t are both assumed to be normally distributed and independent from each other.
- Apply the Kalman smoother given the parameter estimates from the M-step and update the estimated factors \hat{f}_t .
- The Likelihood function is evaluated by means of the Kalman filter.

Iterate forward between the E-step and the M-step until convergence is reached.

To estimate R we apply an eigenvalue decomposition to the final estimate of the covariance matrix $\hat{\delta}_\epsilon$. Let M be a matrix containing the eigenvalues on the main diagonal and zeros elsewhere. The corresponding eigenvectors are stored in the matrix Q. Thus, R is estimated as

$$\hat{R} = QM^{\frac{1}{2}}, \quad (17)$$

and

$$\hat{u}_t = \hat{\epsilon}_t QM^{\frac{1}{2}}. \quad (18)$$

C Bootstrap procedure for impulse responses

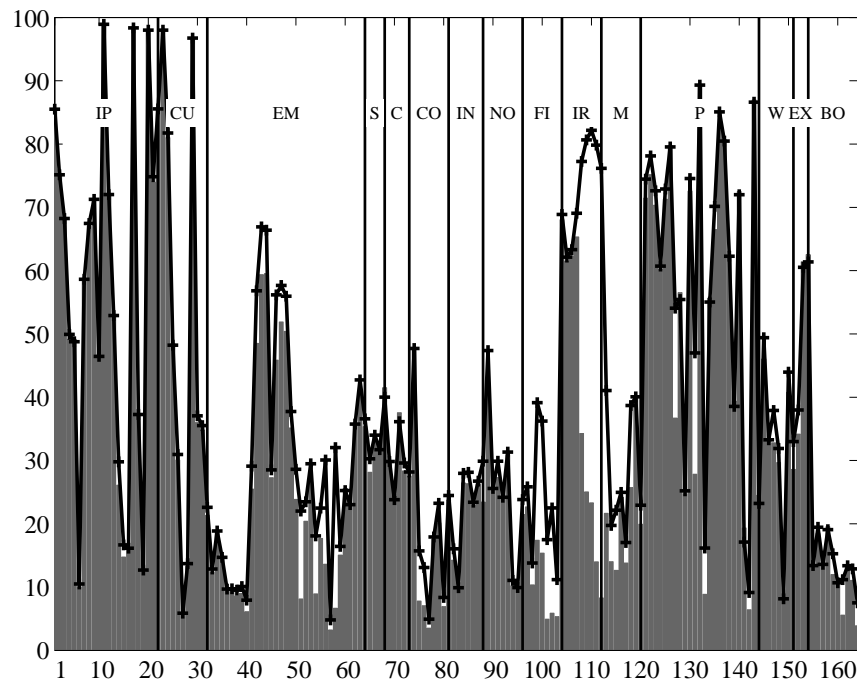
We employ a bootstrap procedure similar to that proposed by Forni, Giannone, Lippi, and Reichlin (2007) and Giannone, Reichlin, and Sala (2002) to compute the confidence

bounds for the responses of individual uncertainty measures to the fundamental shocks u_t in figures 3 and 4. Having estimated the factor model we make use of the following estimated quantities: $\hat{\lambda}$, $\hat{\xi}_t$, $\hat{\Psi}(L)$ and \hat{e}_t .

- To simulate the factors, denoted by \tilde{f}_t , we apply the residual based bootstrap and draw with replacement from centered residuals of the VAR in the factors: $\hat{e}_t - \bar{e}$, where \bar{e} is the sample average.
- The estimated parameters in $\hat{\Psi}(L)$ are then used to simulate a new dataset from $\tilde{X}_t = \hat{\lambda}\tilde{f}_t + \hat{\xi}_t$. We do not permute $\hat{\xi}_t$ because the major part of estimation uncertainty is related to the estimation of the VAR in the factors (compare Giannone et al., 2002, on this point).
- Use \tilde{X}_t and re-estimate the factor model in equations (6) and (7) in section 3 to obtain a new set of bootstrapped parameters and impulse responses.

We obtain 500 draws of each impulse response function by repeated execution of this bootstrap procedure.

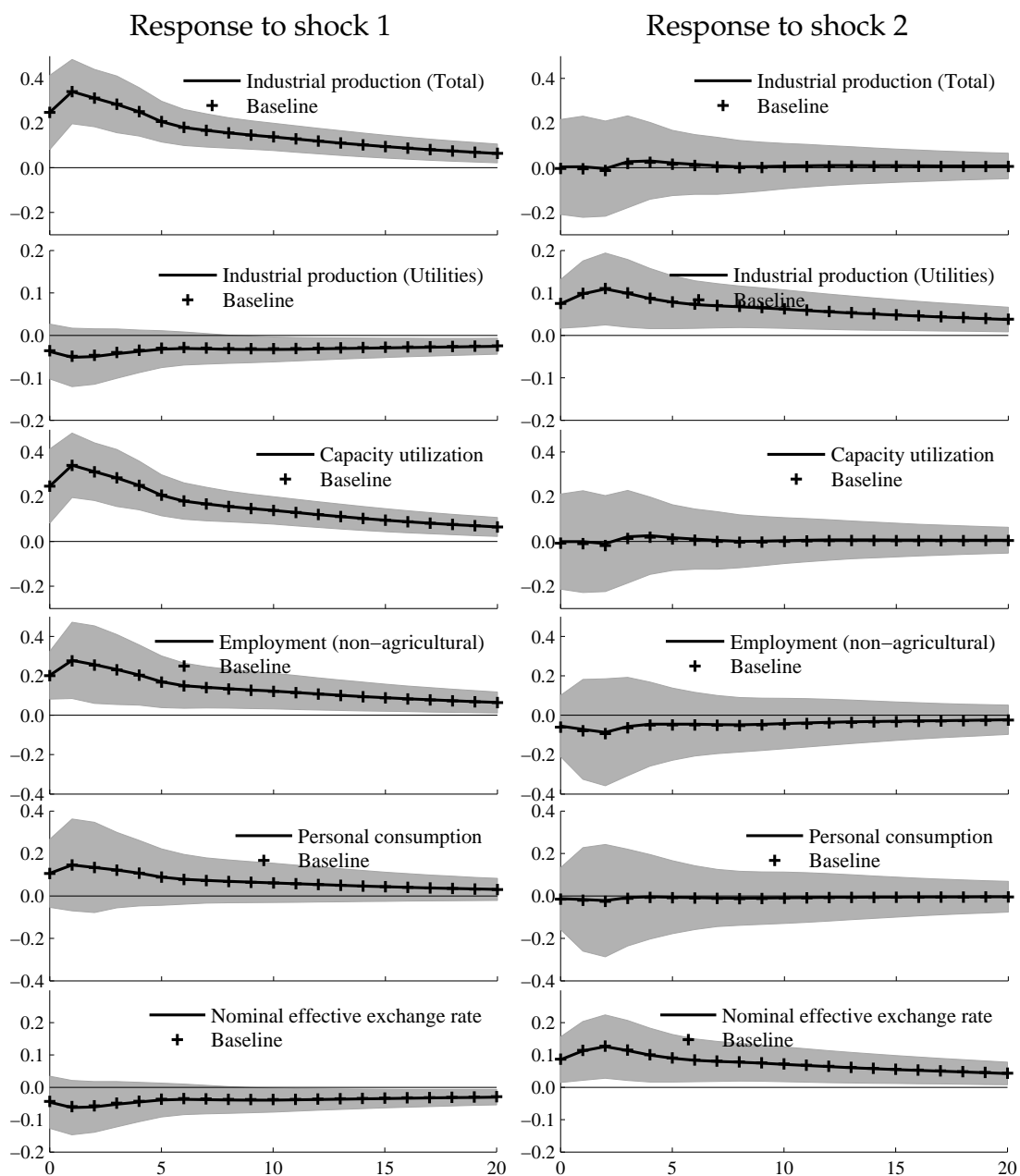
D Explained variance proportions with four fundamental shocks



Note: The figure displays on the y-axis the respective proportion of the explained variance for $r = 3$ (grey bars) and $r = 4$ (crossed line). On the x-axis it depicts the individual uncertainty measures in the same order as in table A.1. They are grouped into the following categories: IP (1-21, industrial production), CU (22-31, capacity utilization), EM (32-63, employment), S (64-67, sales), C (68-72, consumption), CO (73-80, housing and construction), IN (81-87, inventories), NO (88-95, new and unfilled orders), FI (96-104, financial variables), IR (105-113, interest rates), M (114-126, monetary variables), P (127-151, prices), W (152-158, wages), EX (159-161, merchandize ex- and imports), BO (162-167, business outlook).

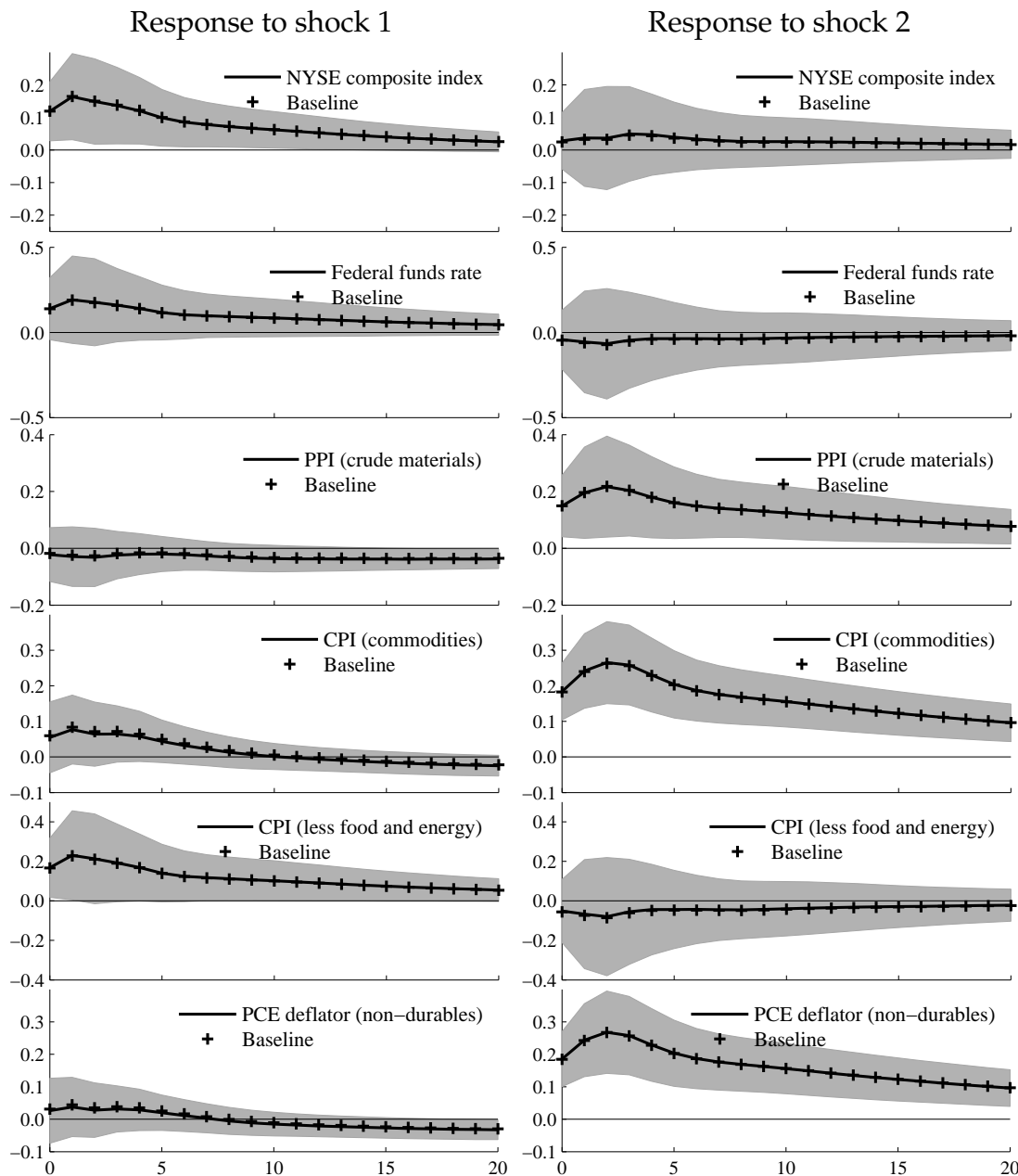
Figure D.1: Explained variance proportions for $r = 3$ and $r = 4$

E Alternative rotation of fundamental shocks



Note: Impulse responses to the first fundamental shock (left column) and to the second fundamental shock (right column) identified with the alternative rotation are indicated by the bold lines. Impulse responses from the baseline rotation are marked with crosses. Shaded areas indicate bootstrapped 90% confidence intervals.

Figure E.1: Impulse responses of individual uncertainty measures for both identification strategies (1)

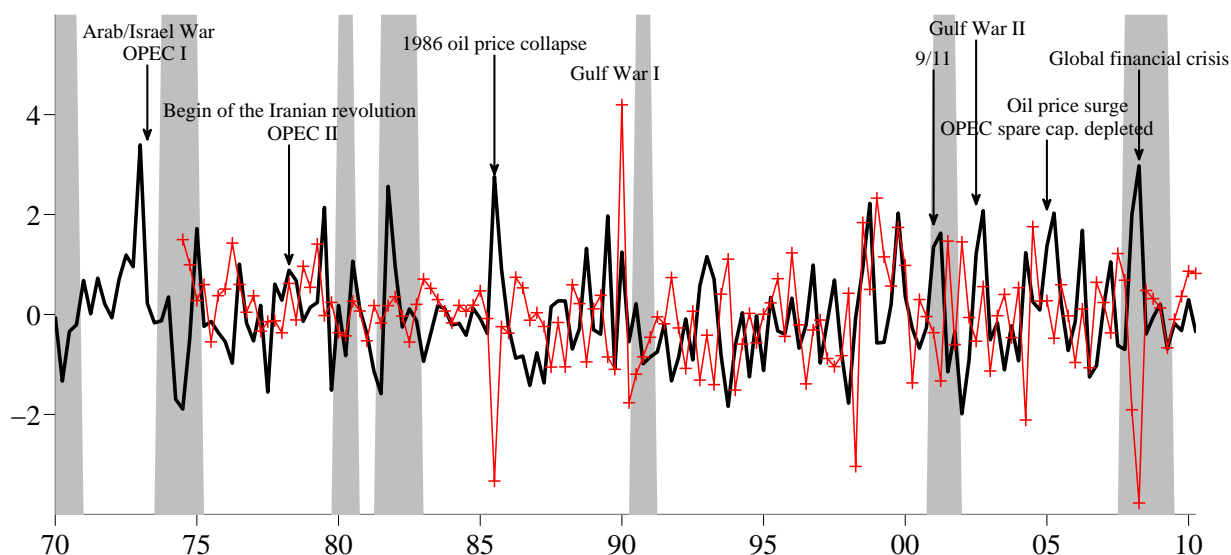


Note: Impulse responses to the first fundamental shock (left column) and to the second fundamental shock (right column) identified with the alternative rotation are indicated by the bold lines. Impulse responses from the baseline rotation are marked with crosses. Shaded areas indicate bootstrapped 90% confidence intervals.

Figure E.2: Impulse responses of individual uncertainty measures for both identification strategies (2)

F Oil and commodity price uncertainty and precautionary oil demand

In the following, we compare the oil and commodity price uncertainty shock to the precautionary oil-market specific demand shock introduced by Kilian (2009). Such a shock occurs when there is a shift in uncertainty about the availability of future oil supplies. For instance, agents may develop a precautionary demand for oil which serves as an insurance against a potential shortfall of oil supply. We may thus hypothesize that the oil and commodity price uncertainty shock is similar to Kilian's (2009) precautionary oil demand shock. In figure F.1 we depict both series.



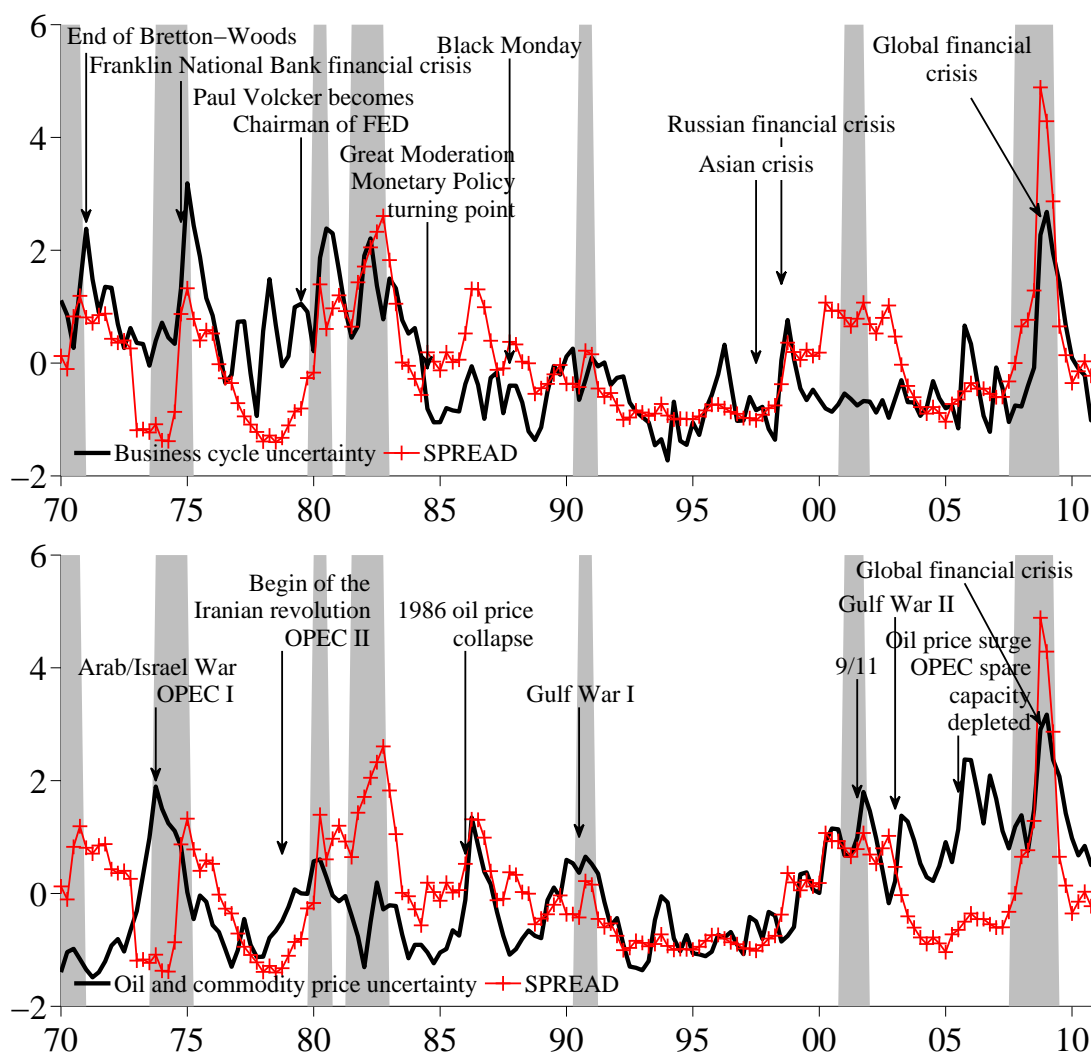
The thick black line represents the oil and commodity price uncertainty shock, and the crossed thin red line the oil-market specific demand shock of Kilian (2009). Shaded areas represent NBER recession dates. To improve the readability, the figure presents quarterly averages, and the series are standardized.

Figure F.1: Oil and commodity price uncertainty and oil-market specific demand shock

We update Kilian's (2009) precautionary oil demand shock until 2011M4. The correlation among the oil-market specific demand shock and our oil and commodity price uncertainty shock is 0.23 and significant at the one-percent level. Periods of huge precautionary demand shocks fall together with periods of large amplitudes of the commodity price uncertainty shock. However, there are episodes where both shocks operate in the opposite direction. While, for instance, both series co-move during the Gulf Wars, we observe episodes such as the global financial crisis where a large drop in oil-specific demand is accompanied by a rise in oil and commodity price uncertainty. The

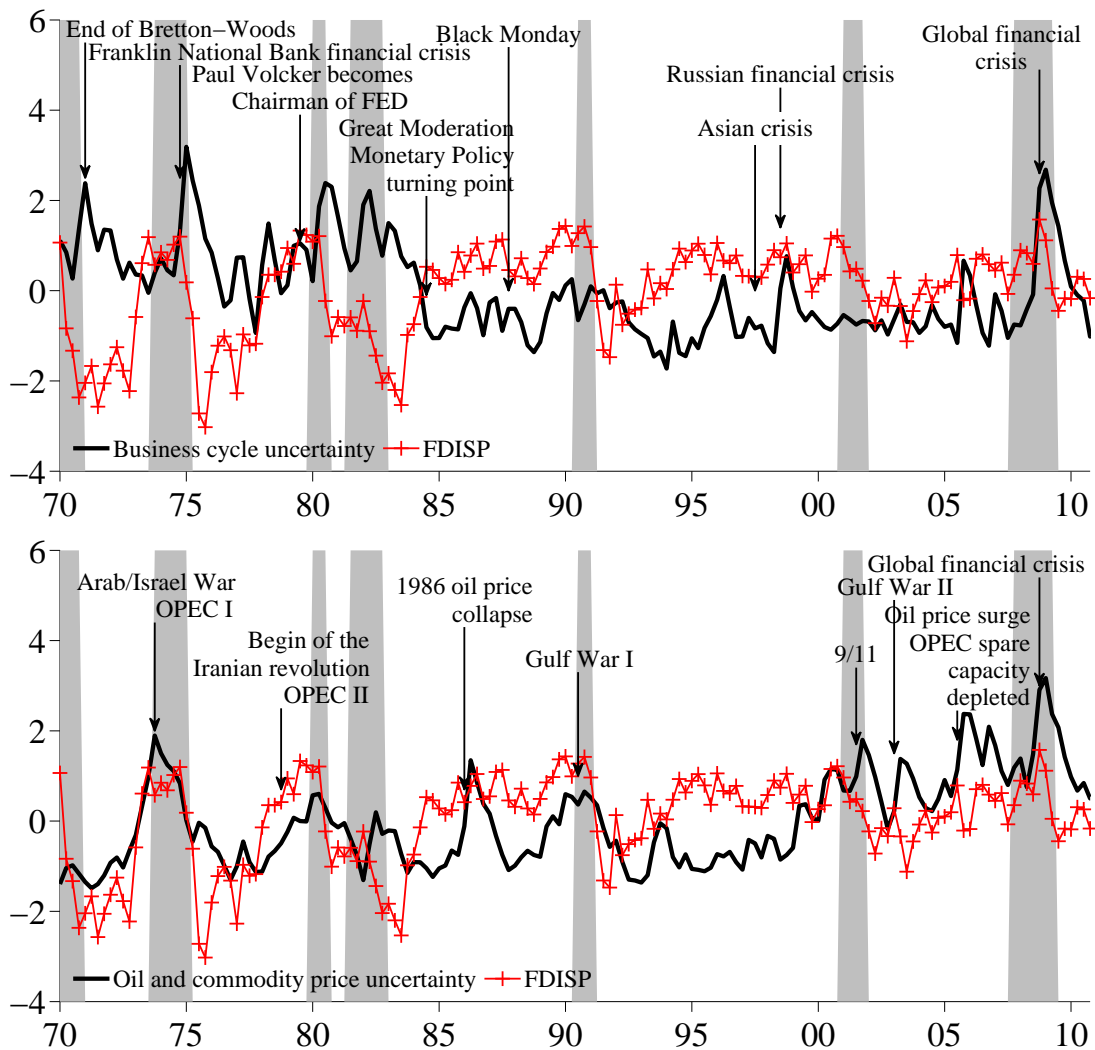
sign of the oil-market specific demand shock depends on the prevalence of an expected oil production surplus or deficit. It is, for instance, negative during a recession where there is uncertainty about an expected oil production surplus. During such periods oil and commodity price uncertainty typically increases.

G Comparison to familiar measures of uncertainty



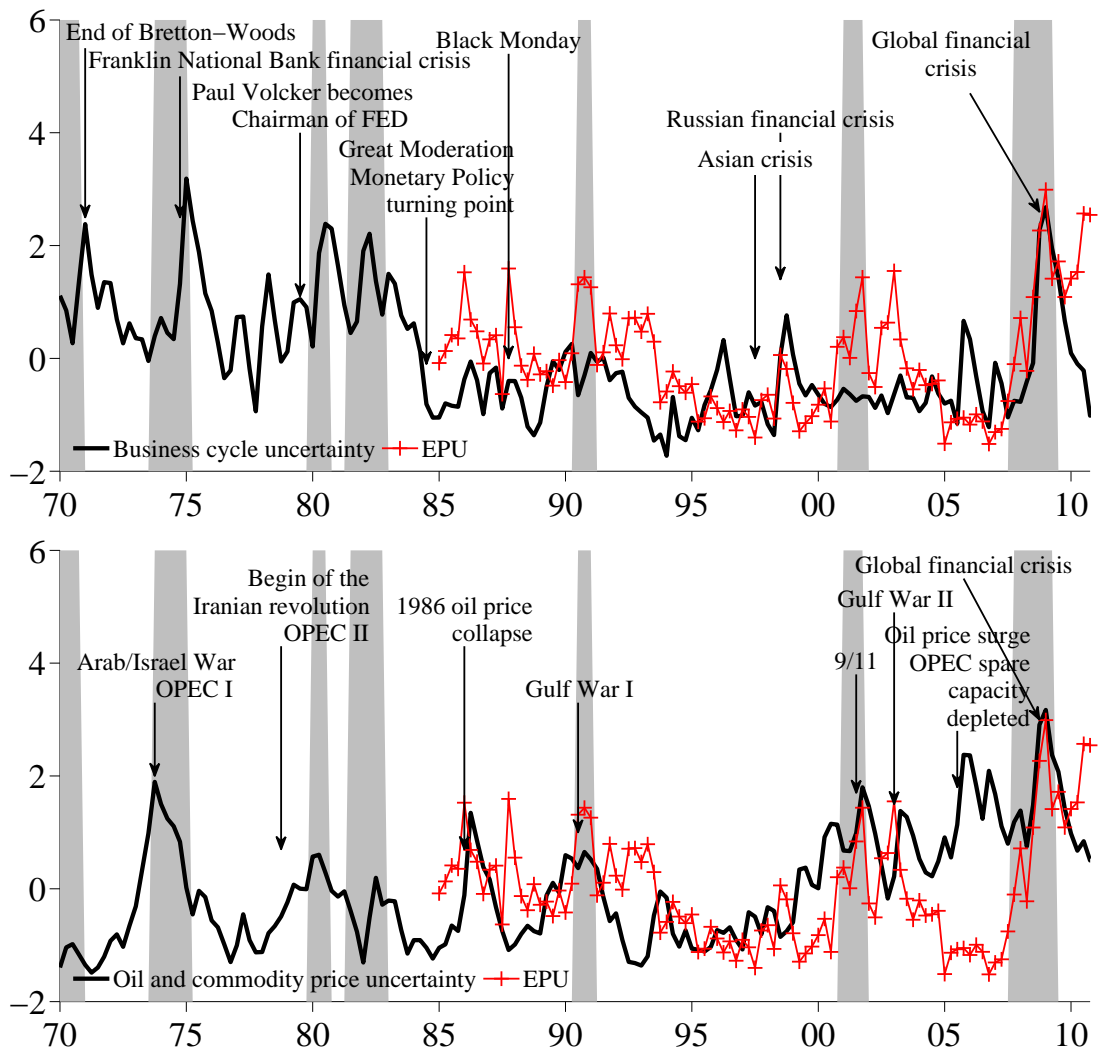
The upper panel depicts the business cycle uncertainty and the lower panel the oil and commodity price uncertainty. The crossed (red) line represents the Baa corporate bond spread (SPREAD). To remove noise from the data we depict quarterly averages. To make the variables comparable all series are demeaned and standardized by the standard deviation. NBER recession dates are indicated by the shaded areas.

Figure G.1: Indicators of macroeconomic uncertainty and SPREAD



Note: The upper panel depicts the business cycle uncertainty and the lower panel the oil and commodity price uncertainty. The crossed (red) line represents firms' forecast dispersion (FDISP). To remove noise from the data we provide quarterly averages. To make the variables comparable all series are demeaned and standardized. NBER recession dates are indicated by the shaded areas.

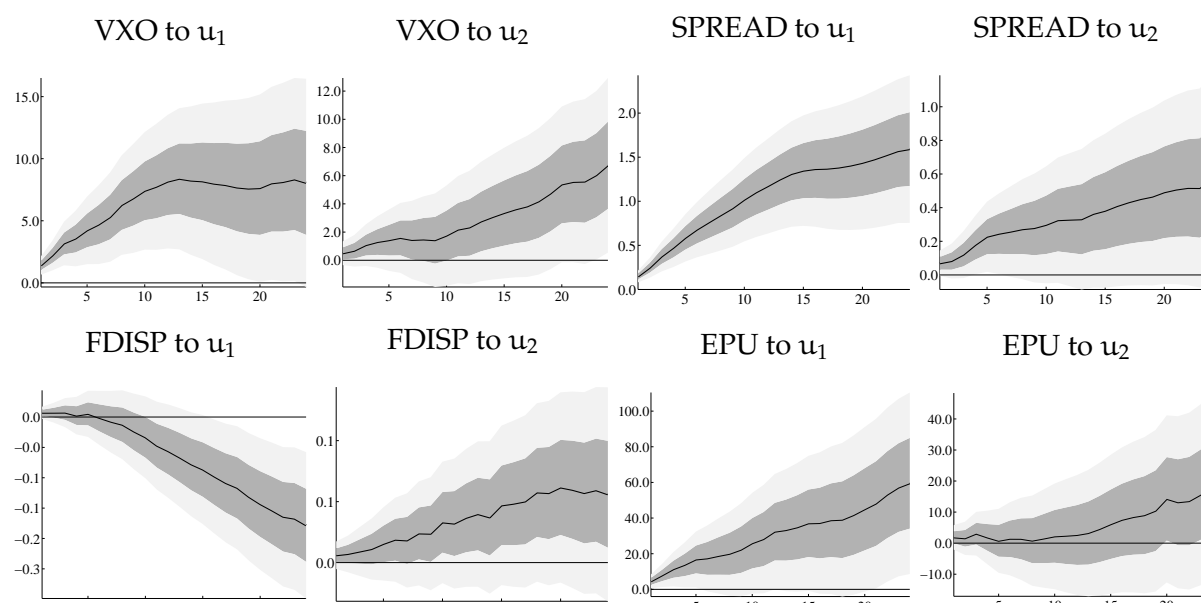
Figure G.2: Indicators of macroeconomic uncertainty FDISP



Note: The upper panel depicts the business cycle uncertainty and the lower panel the oil and commodity price uncertainty. The crossed (red) line represents economic policy uncertainty (EPU). To remove noise from the data we provide quarterly averages. To make the variables comparable all series are demeaned and standardized. NBER recession dates are indicated by the shaded areas.

Figure G.3: Indicators of macroeconomic uncertainty EPU

H Responses of familiar measures of uncertainty



Note: The upper panel depicts the response of the VXO and SPREAD to a surprise innovation in business cycle uncertainty u_1 and oil and commodity price uncertainty u_2 . The lower panel shows the responses for FDISP, and EPU to the same shocks. The response is calculated from a regression of the respective uncertainty measure on 24 lags of the two shock series u_1 and u_2 . Confidence intervals are derived from a block bootstrap using block size 10 and 20000 replications. The dark shaded area indicates the \pm one standard deviation confidence interval while light gray represents the \pm two standard deviations confidence interval.

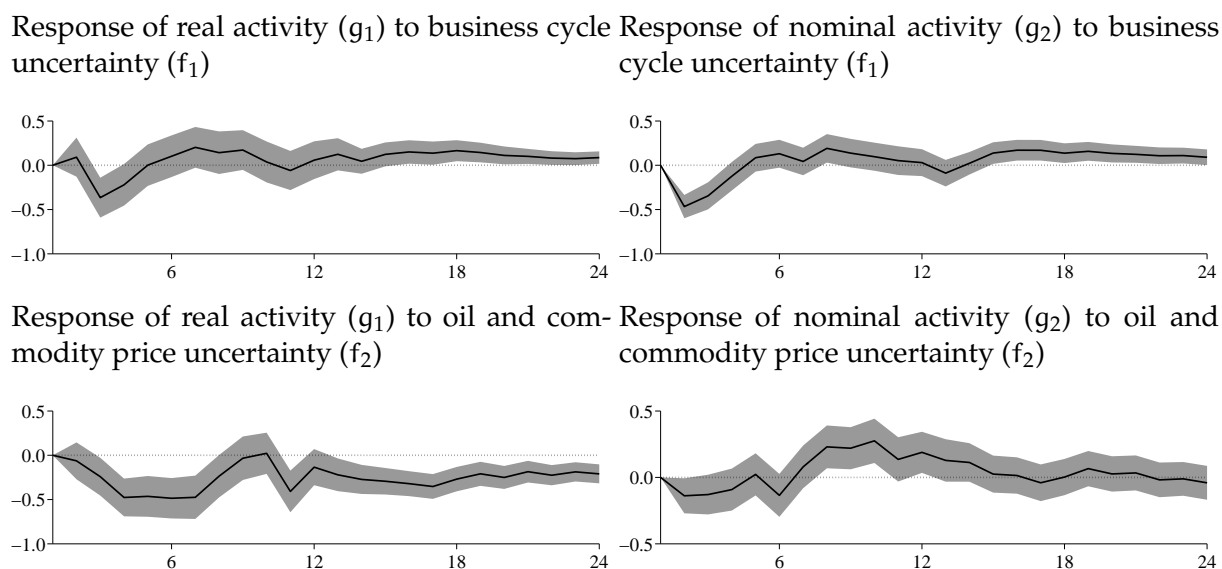
Figure H.1: Responses of familiar measures of uncertainty

I Responses to macroeconomic uncertainty in a FAVAR

As a robustness check for our results in section 4.5, we evaluate the impact of macroeconomic uncertainty on economic activity which is reflected in the common movements of many variables. To this end we set up a factor-augmented VAR (FAVAR) which helps us to overcome the so-called overparameterization problem. We consider all variables in first moments and transform them such that they are stationary (see table A.1) and estimate a factor model in the spirit of Doz et al. (2012). Following Giannone et al. (2004) we condense the information contained in all 164 variables in two common shocks. The shocks in first moments are identified such that shock 1 in first moments explains the

bulk of the variation in the output variables (series 1 to 31). The variance decomposition provided in the last two columns of table A.1 confirms the result of Giannone et al. (2004) who document that shock 1 in first moments represents real activity while shock 2 in first moments governs the nominal side of the economy. Similar to the proceeding described in section 4.3 in the main body of the text we use a rotation strategy to separately identify the two first moment factors which we label $g_{1,t}$ and $g_{2,t}$.

We estimate bivariate FAVARs using the two-step procedure proposed by Bernanke et al. (2005). Each consists of one uncertainty factor and one of the two factors introduced by Giannone et al. (2004) representing economic activity. We set the lag length to 12, and the VAR innovations are orthogonalized by means of a Cholesky decomposition where the respective uncertainty factor is ordered last. Figure I.1 depicts the response of $g_{1,t}$ and $g_{2,t}$ to a one standard deviation surprise innovation in $f_{1,t}$ and $f_{2,t}$. We observe a fall in real activity ($g_{1,t}$) for both types of uncertainty. As in section 4.5, $f_{1,t}$ precedes a decrease of the nominal factor ($g_{2,t}$) while $f_{2,t}$ tends to increase $g_{2,t}$.



Note: Confidence intervals are derived from the bias adjusted bootstrap procedure (Kilian, 1998). Shaded areas indicate the \pm one standard deviation confidence interval.

Figure I.1: Impulse response functions from bivariate FAVARs

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