Common uncertainty factors*

Steffen Henzel†　　Malte Rengel‡

May 15, 2012

Preliminary

Abstract

Uncertainty about the future course of economic variables appears in almost all economic areas and is an important driving force behind business cycle fluctuations. As uncertainty is inherent in the movements of literally hundreds of economic variables, it is unclear how many distinct (fundamental) types of uncertainty actually exist. We construct a large data set covering measures of all types of economic uncertainty. We then unravel the fundamental shocks driving the dynamics of economic uncertainty in the U.S. That is, we use a dynamic factor model to reduce the dimension of the data and identify the underlying common factors. It turns out that the stochastic dimension of uncertainty is small as there appear to be two fundamental factors. The first factor represents uncertainty related to (domestic) business cycle movements, whereas the second factor contains oil price uncertainty. Finally, we evaluate the importance of each uncertainty factor for business cycle fluctuations.

JEL classifications: C53; E31; E37
Keywords: Uncertainty, dynamic factor model

*We would like to thank Kai Carstensen and Helmut Herwartz for very valuable comments and suggestions. Financial support from the *German Research Foundation* (Grant No. CA 833/2) is gratefully acknowledged.
†Ifo Institute – Leibniz Institute for Economic Research at the University of Munich, Email: `Henzel@ifo.de`
‡Institute for Statistics and Econometrics, University of Kiel, Email: `rengel@stat-econ.uni-kiel.de`

1 Introduction

Uncertainty about the future course of economic variables is identified as one of the major driving forces behind business cycle fluctuations in recent research (Bloom, 2009; Alexopoulos and Cohen, 2009; Bloom et al., 2010; Gilchrist et al., 2010; Baker et al., 2012). However, many different types of uncertainty are discussed in the literature. For instance, a strand of research is concerned with the effects of inflation uncertainty (see, for instance, Friedman, 1977; Ball, 1992; Bernanke and Mishkin, 1997). Furthermore, a number of studies analyze the effects of uncertainty associated with production (Ramey and Ramey, 1995; Grier and Perry, 2000; Grier et al., 2004). Some authors model different forms of policy uncertainty shocks (Baker et al., 2012; Fernández-Villaverde et al., 2012a). Finally, literature is devoted to the effects of oil price uncertainty (see, for instance, Elder and Serletis, 2010; Jo, 2011). Moreover, shocks to second order moments of variables which can be interpreted as uncertainty are introduced into theoretical models motivated by the uncertainty during recent economic crisis (see, among others, Basu and Bundick, 2011; Fernández-Villaverde et al., 2012b,a).

However, it is unclear how many distinct types of uncertainty actually exist. Uncertainty appears in almost all economic areas (see, for instance, Gonçalves and Kilian, 2004). As uncertainty is inherent in the movements of literally hundreds of economic variables, the policy maker faces a monitoring and decision problem. That is, similar to the monitoring problem that occurs in first order moments of variables, it is important to decide which type of uncertainty a policy maker should take into account. In this study, we construct a large data set covering measures of all types of economic uncertainty. We then unravel the fundamental shocks driving the dynamics of economic uncertainty in the U.S. That is, we use a dynamic factor model to reduce the dimension of the data and identify the underlying common factors.

A large body of literature focuses on reducing the dimension of data sets covering distinct aspects of economic activity in first order moments.[1] Hypothesis about the number of fundamental shocks in the entire economy are analyzed in more detail by, among others, Sargent and Sims (1977), Stock and Watson (1999, 2002, 2005), and Giannone et al. (2004). Moreover, a number of formal tests have been developed to deal with this problem (Bai and Ng, 2007; Amengual and Watson, 2007; Onatski, 2009, 2010; Ahn and Horenstein, 2009). However, the actual quantity of fundamental shocks is debateable. While, for instance,

[1] Among others, Geweke (1977), Chamberlain and Rothschild (1983), Engle and Watson (1981), Stock and Watson (1989, 1991), Quah and Sargent (1993), Forni and Reichlin (1996), and Forni and Reichlin (1998).

Stock and Watson (2005) suggest seven fundamental factors, Giannone et al. (2004) and, similarly, Sargent and Sims (1977) argue in favor of only two. These studies argue that the first shock causes movements of the real variables while the second shock triggers the nominal side of the economy. These empirical findings provide a justification for the modeling strategy underlying New-Keynesian business cycle models. Usually, these models contain a limited number of shocks – i.e. far less than variables – that move the entire economy. More recently, these type of models have been enhanced with a small number of independent second moment shocks. In addition to the reduction of the monitoring problem a policy maker faces with respect to the uncertainty types a further contribution of our study is that we provide an empirical justification for the number of fundamental second moment shocks.

Following Giannone et al. (2004), we collect a large-scale data set consisting of about 180 variables covering all types of economic activity. To measure unobserved uncertainty, we then apply, for each time series, a simple data driven procedure known as *RiskMetrics*. Thus, we obtain a global picture of economic uncertainty. In a second step, we reduce the dimension of our large-scale data set and identify the common driving factors underlying all uncertainty measures. To account for possible dynamic interrelations between the measures we estimate a dynamic factor model as proposed in Doz et al. (2012), and Doz et al. (2011). We find that the stochastic dimension of the data set is two. It turns out that the first fundamental shock triggers uncertainty associated with the (domestic) business cycle whereas the second shock appears to initiate oil and commodity price uncertainty. These two shocks constitute two dynamic uncertainty factors that describe the bulk of the developments of uncertainty in the economy. Finally, we evaluate the importance of each uncertainty factor for the fluctuations of the economy over the business cycle.

The remainder of the paper is structured as follows. In Section 2, we lay out how we measure uncertainty and describe the large-scale data set. Results from the dynamic factor model are discussed in Section 3. In this section, we also provide an interpretation of the fundamental shocks. How the distinct shocks to uncertainty contribute to business cycle movements of first order variables is analyzed in Section 4. The paper concludes in Section 5.

2 Measuring uncertainty

2.1 A simple measure of economic uncertainty

As economic uncertainty is unobservable its measurement is a challenging task. There have been distinct measures proposed in the literature and the appropriateness of a measure depends on the purpose. A simple measure is provided by the cross sectional dispersion of individual forecasts obtained from survey data.[2] However, the validity of such a measure can be questioned because there is no direct relation to an individual forecaster's uncertainty (see, for instance, Zarnowitz and Lambros, 1987). Similarly, Lahiri et al. (1988) argue that the correlation of disagreement with the subjective probability distribution of an individual forecaster is weak.[3] Finally, disagreement is only available for a rather limited number of variables that are polled in questionnaires, and many surveys do not have a long history.

Concentrating on their longitudinal dimension, growth rates of macroeconomic and financial time series are known to incorporate time-varying conditional heteroscedasticity (Gonçalves and Kilian, 2004). An approach that accounts for this stylized fact is given by the (G)ARCH model class introduced by Engle (1982, 1983), and Bollerslev (1986).[4] Time-varying (conditional) volatility has the advantage that it provides a direct measure of uncertainty surrounding a (in-sample) forecast (Baillie et al., 1996; Grier and Perry, 1998; Karanasos et al., 2004; Bloom et al., 2007; Bloom, 2009). That is, conditional volatility is high in periods where the model implied growth rate deviates far from its realized counterpart.

However, (G)ARCH models come with the drawback that the data generating process is assumed to be 'true'. To avoid misspecification, innumerable extensions of the basic model exist to meet the specific requirements of a certain variable (see Bollerslev, 2009, for an overview). Consequently, each model has to be formulated and tested (Lundbergh and Terasvirta, 2002). Moreover, the model might suffer from structural changes which might occur, for instance,

[2]Some papers use the cross-sectional spread of industry or firm level data (Bloom, 2009).

[3]See Bomberger (1996), Giordani and Söderlind (2003) and Rich and Tracy (2010) for a further discussion. In principle, the Survey of Professional Forecasters (SPF) provides a more direct measure of uncertainty because it queries the subjective probability distributions of forecasters. However, it polls only information about GDP, GDP deflator, and CPI inflation.

[4]Another a class of models proposed by Clark (1973), Taylor (1982, 1986), and Hull and White (1987) is concerned with stochastic volatility (SV). In contrast to GARCH models, SV models involve an independent shock to the variance of the process which makes them computationally intensive. A further extension are the multivariate GARCH and SV models. They measure the simultaneous relations of different time-varying volatilities. However, these models suffer from the curse of dimensionality implying that the parameter space increases heavily with the cross sectional dimension.

during the Great Moderation (Evans, 1991).[5] Note that we want to picture economic uncertainty associated with a multitude of economic variables in a robust manner. Hence, to keep the analysis tractable, a simple data driven filter is more appropriate.

It is possible to approximate the uncertainty concerned with a specific variable as the variance of the underlying variable estimated over a rolling window (Andersen et al., 2006). Such an estimator suffers from the so-called variance-bias tradeoff. However, the bias can be reduced if we calculate the time varying variance σ_t^2 as the exponentially weighed moving average (EWMA) which results in the *RiskMetrics* procedure outlined in the following (Morgan, 1996).

$$\begin{aligned} \sigma_t^2 &= \lambda\sigma_{t-1}^2 + (1-\lambda)\epsilon_{t-1}^2 && (1) \\ &= (1-\lambda)\sum_{i=1}^{\infty}\lambda^{i-1}\epsilon_{t-i}^2, && (2) \end{aligned}$$

where ϵ_t denotes the residual of the regression relating the respective variable y_t to its P own lagged values:

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

Here, λ is the decay factor that controls the smoothness of the variance process.[6] As there are strong autoregressive patterns in macroeconomic variables such as production growth and inflation, we specify in (3) an autoregressive model for the first order moments x_t. We determine the respective lag-length P by BIC with a maximum lag length of six months. Note that our volatility measure depends on estimated residuals from (3). As the residuals represent in-sample forecast errors the approach enforces a forecasters perspective. Hence, similar to the GARCH model, we measure uncertainty surrounding a (in-sample) forecast. Finally, we note that the infinite sum on the right hand side of (2) is truncated by the sample range at $t-1$. Andersen et al. (2006) stress that this leads to distortions at the beginning of the sample; i.e. when t is small. To attenuate this drawback, we apply the adjustment factor $1/(1-\lambda^t)$.

[5] The same string of arguments applies to SV models, as well.

[6] We set $\lambda = 0.7$ which implies a half-life period of the innovation ϵ_t of approximately two months. After the first quarter 65.70%, after the second quarter 88.24% and after the third and forth quarter 95.96% and 98.62% of the innovation has disappeared. That is, the influence of the shock vanishes roughly after one year. As proposed by Morgan (1996) we use the same value for all series in the considered dataset.

2.2 The Data

To obtain a global picture of economic uncertainty, we rely on a large-scale data set which is similar to that of Giannone et al. (2004). This kind of data set is commonly applied to describe development of the U.S. economy in first order moments (e.g. Giannone et al., 2004; Stock and Watson, 2002). A detailed list of series is provided in table A.1 in the Appendix. 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, merchandize ex- and imports, business outlook. The time series cover the time span from 1970M1 to 2011M4 ($T = 496$) and, thus, extends to the recent crisis. The variables are transformed to obtain stationary series.[7] Given that uncertainty may materialize rather quickly, we use the data published on a monthly frequency.[8] During the recent crisis, the Federal Reserve has taken a number of unconventional policy measures ("quantitative easing") leading to a severe structural break and extreme outliers in monetary aggregates. Hence, we exclude the monetary base (series 117), the depository institutions reserves (series 118-119) and the loans and securities at all commercial banks (series 125).[9] 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 164 variables. For each of these variables, we then calculate a *RiskMetrics* measure and take the square root to obtain the conditional standard deviation instead of the conditional variance. We end up with a large-scale dataset containing uncertainty measures for all areas of economic activity.

3 Triggers of economic uncertainty

3.1 The dynamic factor model

In the following, we identify the fundamental types of uncertainty prevailing in the U.S. postwar economy. To this end, we reduce the dimension of the data and identify the common

[7] A description of the transformation of each single series is provided in table A.1 in the Appendix. To obtain an appropriate uncertainty measure of business outlook variables, the transformation of these variables differs slightly from the transformation proposed in Giannone et al. (2004).

[8] As a consequence, we have to exclude the real GDP (series 172) and the GDP deflator (series 173).

[9] Due to the unconventional policy measures, these variables experience a pronounced jump. Hence, calculating uncertainty measures for these series by means of the *RiskMetrics* procedure would lead to severe outliers in the dataset that are the result of an announced policy measure.

factors underlying economic uncertainty by means of a dynamic factor analysis. As macroeconomic variables are usually not perfectly synchronized over the business cycle, leads and lags in dynamics of individual uncertainty series should be considered. A dynamic factor model in comparison to the standard static factor approach enables us to exploit the correlation among variables at leads and lags rather than concentrating on contemporaneous correlation (Giannone et al., 2004). Moreover, idiosyncratic short-run dynamics of the proposed uncertainty measures may mask the underlying cross sectional co-movements. Finally, measurement error attached to each individual uncertainty variable may obscure the economic relationships in the data. Overall, we can reveal the underlying signal with greater precision because the dynamic factor model averages out idiosyncratic measurement error.

The standard approximative dynamic factor model in state-space representation can be written as

$$X_t = \lambda(L) f_t + \xi_t, \tag{4}$$

$$f_t = \Psi(L) f_{t-1} + u_t, \tag{5}$$

where $X_t = (x_{1,t}, ..., x_{n,t})'$ denotes the $n \times 1$ data vector consisting of the individual uncertainty measures (Stock and Watson, 2010). To assure non-negativity of uncertainty, the variable enters in logarithms. Thus, $x_{i,t} = \log(\sigma_{i,t})$, for $i = 1, ..., n$ and $t = 1, ..., T$. The dynamic factors $\widetilde{f}_{j,t}$, for $j = 1, ..., q$ are stacked in the $q \times 1$ vector $f_t = (\widetilde{f}_{1,t}, ..., \widetilde{f}_{q,t})'$. The corresponding fundamental shocks are denoted by the $q \times 1$ dimensional vector u_t. L indicates the lag-operator, and the lag polynomials $\lambda(L)$ and $\Psi(L)$ are of dimension $n \times q$ and $q \times q$, respectively. The stationary zero-mean idiosyncratic processes ξ_t in (4) might be cross sectionally correlated, and, further serially correlated. The dimension of the fundamental shocks u_t defines the number of dynamic factors in the data, and, hence the subspace spanned by the factors is of dimension q. A typical assumption is that the factors are orthogonal to the idiosyncratic components formalized by condition $E[\xi_t u_{t-k}] = 0$ for all k.

For estimation purpose it is useful to write the dynamic factor model in (4) and (5) in static factor state-space representation

$$X_t = \Lambda F_t + \xi_t, \tag{6}$$

$$F_t = A F_{t-1} + B u_t, \tag{7}$$

where the static factors are denoted by $F_t = (f_t, f_{t-1}, ..., f_{t-(p-1)})'$. They comprise the contemporaneous and the $p-1$ lagged dynamic factors $f_\bullet$ in stacked form.[10]

The dimension of F_t is $r \times 1$ with $r << n$ and $r = pq$. The matrix Λ of dimension $n \times r$ contains the factor loadings. The lag order for the VAR for static factors in (7) can be restricted to one as any p^{th} order VAR can be transformed into a first order VAR in companion form. In this case r has simply to be chosen large enough to capture the q contemporaneous dynamic factors and all their $p-1$ lags. The coefficient matrix A is commonly estimated unrestricted being agnostic about the way static factors are related (Giannone et al., 2004; Doz et al., 2011, 2012). The static factors in F_t contain the lagged dynamic factors f_t. To obtain a more parsimonious model we make use of the parametric structure of the model and impose zero restrictions on A. In effect, we obtain the usual companion form of the VAR in F_t:

$$A = \begin{pmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I & 0 & \dots & 0 & 0 \\ 0 & I & \dots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \dots & \dots & I & 0 \end{pmatrix}. \tag{8}$$

The block matrices $A_\bullet$ denote the coefficient matrices of dimension $q \times q$ that expresses the influence of the lagged dynamic factor and I denotes an identity matrix of dimension $q \times q$. That is, we assume that the number of fundamental shocks u_t is identical to the number of dynamic factors f_t.

We estimate the model in (6) and (7) with the quasi maximum likelihood procedure proposed by Doz et al. (2011, 2012). Doz et al. (2012) show that the factors are estimated consistently by means of an EM-algorithm based on Kalman filtering if T and n go to infinity. As our sample comprises $n = 164$ series and a large time-span $T = 496$ the estimation approach should deliver valid estimates.[11]

3.2 The dimension of uncertainty

When specifying the dynamic factor model, an important issue is the choice of the number of static factors r and fundamental shocks q which determines the subspace spanned by

[10]The terminology 'static factors' originates form the fact that F_t affects X_t only contemporary. However, F_t contains lagged dynamic factors (Stock and Watson, 2010).

[11]Alternative non-parametric procedures are based on the Fourier transformation of variables into the frequency domain (Forni et al., 2000, 2005). Such techniques allow for the estimation of common components $\lambda(L)f_t$, however, not to disentangle the factors themselves.

the dynamic factors. First, we determine the number of static factors r. We rely on the formal Bai and Ng (2002) criteria and a simple visual inspection by means of a scree plot. The quantity of static factors has to bee large enough to capture all information important for dynamic factors. The Bai and Ng (2002) criteria conditioned on eight distinct penalty functions are provided in table C.1. Almost all criteria have their minimum at the imposed upper bound of 18 static factors. While the $IC2$ hints at 15 static factors the $BIC3$ and $IC4$ hint at three. The simple scree plot displayed in figure 1 supports the impression that roughly $r = 16$ static factors might be sufficient to capture the bulk of common movements of uncertainty measures. The largest decrease in the degree of explained variance takes place until the fifth factor is incorporated. It appears that the additional explanatory content of more than 16 static factors is negligible.

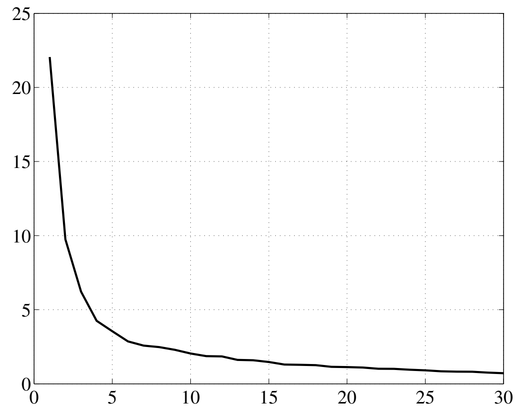
To determine the quantity of dynamic factors q we apply the three formal information criteria proposed by Bai and Ng (2007), Amengual and Watson (2007) and Hallin and Liska (2007). Results for these three procedures conditioned on several numbers of static factors are displayed in table 1.

	$r=6$	$r=7$	$r=8$	$r=9$	$r=10$	$r=11$	$r=12$	$r=13$	$r=14$	$r=15$	$r=16$
					Bai and Ng (2007)						
$\mathcal{D}_1$	3	3	3	4	3	3	3	3	3	3	3
					Amengual and Watson (2007)						
$p1$	6	7	8	8	6	5	4	3	2	1	1
$p2$	6	7	6	5	4	3	3	2	1	1	1
$p3$	6	7	8	9	10	11	12	13	14	15	16
					Hallin and Liska (2007)						
$p1$	2	2	2	2	2	2	2	2	2	2	2
$p2$	2	2	2	2	2	2	2	2	2	2	2
$p3$	1	1	1	1	1	1	1	1	1	1	1

Note: Entries denote the number of dynamic factors. Upper panel: information criterion $\mathcal{D}_1$ of Bai and Ng (2007) base on the correlation matrix of the residuals from a VAR(1) of r static factors. Test parameters are $\delta = 0.1$ and $m = 2.25$. Middle panel: criteria of Amengual and Watson (2007). Penalty functions are similar to those of the ICP measures in Bai and Ng (2002). Lower panel: criteria of Hallin and Liska (2007). Non logarithmic criteria with penalty functions $p1$ to $p3$. Results depend on initial random permutation.

Table 1: Number of dynamic factors indicated by information criteria

The statistics of Bai and Ng (2007) hint at three dynamic factors triggering the uncertainty measures. However, this information criterion is known to overestimate the number of dynamic factors (Hallin and Liska, 2007). The criteria of Amengual and Watson (2007) reason ambiguous implications conditioned on the predetermined number of static factors. For our choice of $r = 16$ the criteria based on the first two penalty functions hint at one dynamic



Explained proportion of variance by adding additional static factors.

Figure 1: Scree plot for static factors

factor, conditioned on the third penalty function unreasonable 16 dynamic factors should be incorporated. The test procedure provided by Hallin and Liska (2007) supports the choice of two dynamic factors for all three proposed penalty functions.

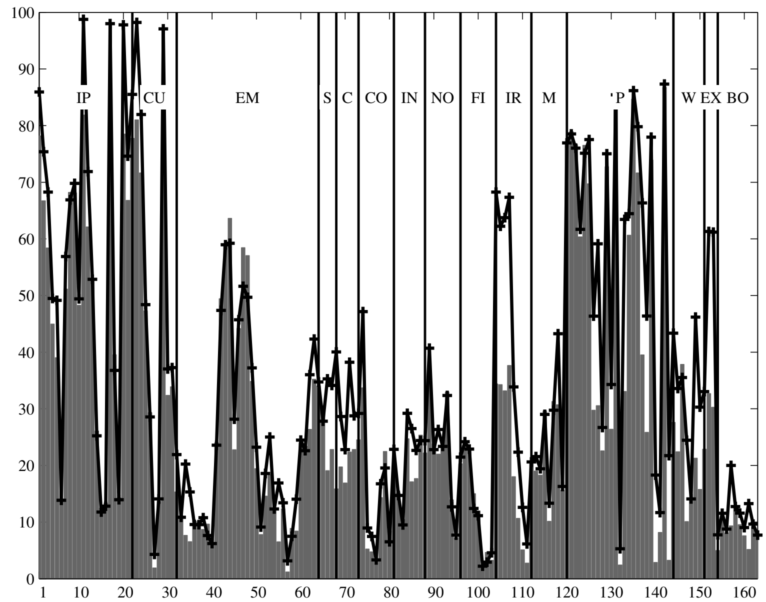
Further, we apply the iterative test procedure suggested by Onatski (2009) to determine the number of dynamic factors. Table 2 provide the p-values of test statistics. These p-values indicate a break where the null hypothesis of 3 dynamic factors is tested against 4, 5, or 6 dynamic factors. That is, the hypothesis of 3 dynamic factors cannot be rejected. Overall, these formal procedures hint at a small number of dynamic factors that hovers around $q = 2$.

	Onatski (2009)			
q_0 **vs.** q_1	$q_1 = 3$	$q_1 = 4$	$q_1 = 5$	$q_1 = 6$
$q_0 = 0$	0.0390	0.0500	0.0600	0.0700
$q_0 = 1$	0.0280	0.0390	0.0500	0.0600
$q_0 = 2$	0.0160	0.0280	0.0390	0.0500
$q_0 = 3$		0.9850	0.2160	0.2890
$q_0 = 4$			0.1200	0.2160
$q_0 = 5$				0.8030

Note: Table provides p-values of tests on number of dynamic factors q with hypotheses $H_0 : q = q_0$ vs. $H_1 : q_0 < q <= q_1$. Test parameters $\omega_j = 2\pi s_j/T$ in the discrete Fourier transformation are determined with $s_j \in \{5, ..., 40\}$. Thus, ω encloses cycles of length between 1 and 8 years.

Table 2: Number of dynamic factors indicated by iterative test procedure

To obtain an impression of the effect that the number of dynamic factors has on the explanatory power of the model in (6) and (7), we estimate it for distinct values of q. We then perform a projection of the data onto the q dynamic factors (see table A.1). Indeed, it appears that the two shocks explain uncertainty of the most important business cycle variables such as industrial production ($R^2 = 0.78$), capacity utilization ($R^2 = 0.78$), employment in the private sector ($R^2 = 0.59$), as well as consumer prices ($R^2 = 0.70$). Given that we deal with monthly data, which usually carries more noise than data collected at a lower frequency, the two-factor model seems to provide a very good description of these series. We depict the R^2 for each individual uncertainty measure in figure 2. To visualize the effect of adding a further



Note: Individual uncertainty measures in the same order as in table A.1. Grouped into different 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: R^2 from two and three dynamic factors for each uncertainty variable

dynamic factor, we compare the R^2 from a two-factor model and a three-factor model. It appears that a three-factor model does not contribute much information for most of the individual variables. There seems to be a noticeable improvement merely for short term interest rates (variables 105 to 108) where R^2 rises from roughly one third to about two thirds. Other variables where the fit is somewhat improved are uncertainty related to CPI inflation and some subgroups of CPI such as housing or services. Hence, the gain from the introduction of a third factor seems to be limited. Taken together, our results suggest that two dynamic factors are sufficient to explain most of the movements of U.S. economic uncertainty.

3.3 What are the two fundamental shocks?

We identify two dynamic factors in the data which explain the bulk of its variation. In the following, we analyze the question what the two corresponding fundamental shocks driving uncertainty in the U.S. are. To this end, we calculate the dynamic response of individual variables to these shocks. However, the shocks are, in general, not identified up to a rotation matrix (Forni et al., 2009). To note this, consider the moving average representation of F_t:

$$F_t = (I_r - AL)^{-1} B u_t. \tag{9}$$

Similarly, the impulse response function of the common component $\chi_t = \Lambda F_t$ is given by

$$\chi_t = \Lambda(I_r - AL)^{-1} B u_t = B(L) u_t \tag{10}$$

Now, consider the representation $\chi_t = C(L)\nu_t$, where $C(L) = B(L)H$ and $\nu_t = H' u_t$. Thus, there is an infinite number of rotation matrices H with $HH' = I_q$. As proposed by Giannone et al. (2004) we identify the fundamental shocks by choosing the rotation matrix H such that a target function of the following type is maximized:

$$\frac{\sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i1}^h)^2}{\sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i1}^h)^2 + \sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i2}^h)^2} \tag{11}$$

Here, c_{ij}^h denotes the response of variable i to shock j at horizon h. J_R is a selection vector that identifies a subset of variables in the dataset that enter the target function. Here, J_R identifies all variables related to output (variables 1 to 31). The denominator is simply the variance of the selected variable explained jointly by the two shocks. That is, we identify the first shock such that the fraction of the variation explained by the first shock is maximized for all production variables. Note that we leave the second shock unrestricted.

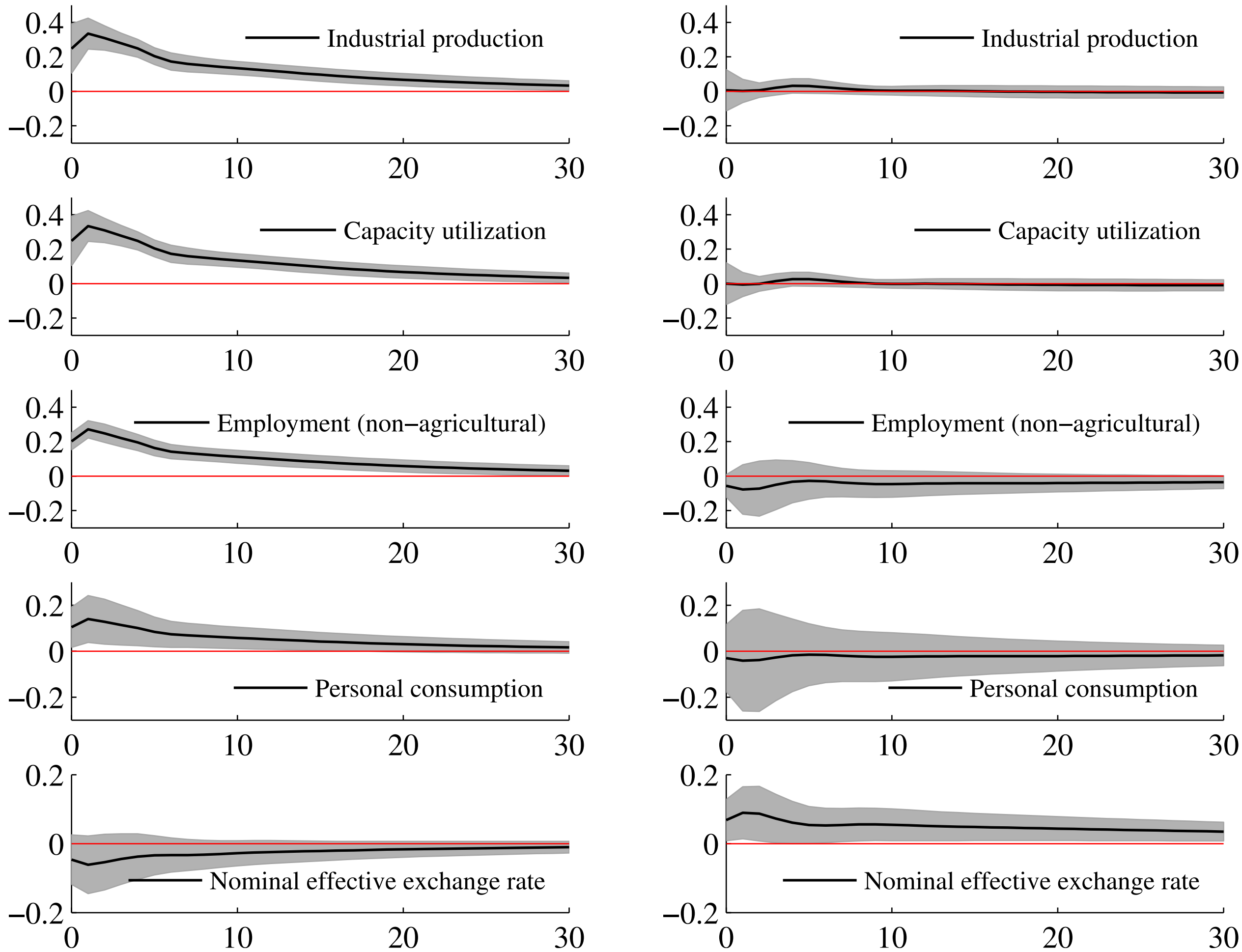
In table A.1 in Appendix A, we provide the fraction of the variance of the series which is jointly explained by the two shocks. Further, we apply a forecast error variance decomposition to analyze the influence of the single shocks. Results are provided in the latter two columns of table A.1. Results from the identification procedure are visualized in figures 3 and 4. Here, we depict impulse responses of a selection of uncertainty variables to the first and the second shock. By design, the first shock has a significant impact on industrial production uncertainty. Moreover, it drives up the variability of capacity utilization, employment, and personal consumption. Turning to nominal uncertainty variables, it turns out that the first shock induces a rise in the variability of the federal funds rate and CPI inflation uncertainty (less food and energy). Although CPI inflation uncertainty is positively affected, there is no significant reaction of uncertainty related to crude materials prices, CPI commodities, and the deflator of non-durable consumption goods. Moreover, there is no significant reaction of the nominal effective exchange rate. Overall, it appears that the first shock impacts nominal and real uncertainty variables at the same time. However, note that all of the variables that respond significantly to the first shock co-move with the business cycle of the economy. Hence, the first shock appears to trigger a general uncertainty about the domestic business cycle.

The second shock leaves production uncertainty and uncertainty related to the other real variables basically unaffected. Moreover, there is no significant reaction of CPI inflation uncertainty if the inflation measure does not include food and energy prices. Finally, uncertainty associated with the federal funds rate is unaffected as well. However, the second shock has a significant impact on a number of nominal variables. It turns out that it moves uncertainty about crude materials prices and commodities. Moreover, it significantly affects inflation uncertainty of non-durable consumption goods which comprise e.g. gasoline. Finally, it appears that exchange rate uncertainty rises after the second shock occurred. Overall, the second shock seems to affect uncertainty about variables that reflect commodity price movements and have an international origin. Hence, the second shock is interpret as an international commodity price uncertainty shock.

To verify this finding, we perform an alternative rotation where the first shock is identified as a shock to commodity price uncertainty whereas the second shock is left unrestricted. Hence, the first shock now maximizes the explanatory power for uncertainty associated with total energy production, PPI crude materials, CPI commodities, and CPI durable commodities.[12] Results are presented in table B.1 in Appendix B. A comparison of impulse response functions derived from both rotations is given in figures B.1 and B.2. It turns out that the impulse response functions are robust to the change in the identification strategy if we acknowledge that the first shock now affects commodity price uncertainty and the second shock drives business cycle uncertainty. Overall, the interpretation of both shocks remains valid for the alternative rotation strategy.

Many empirical studies that analyze the impact of uncertainty on the economy distinguish between a real production uncertainty and a nominal inflation uncertainty (See, for instance, Grier and Perry, 2000; Grier et al., 2004). However, it appears that both types of uncertainty are driven by the business cycle uncertainty shock and, thus, have an identical cause. That is, uncertainty associated with output is more or less identical to general business cycle un-

[12]Hence, J_R selects the following variables from the dataset: 16, 130, 139, 140

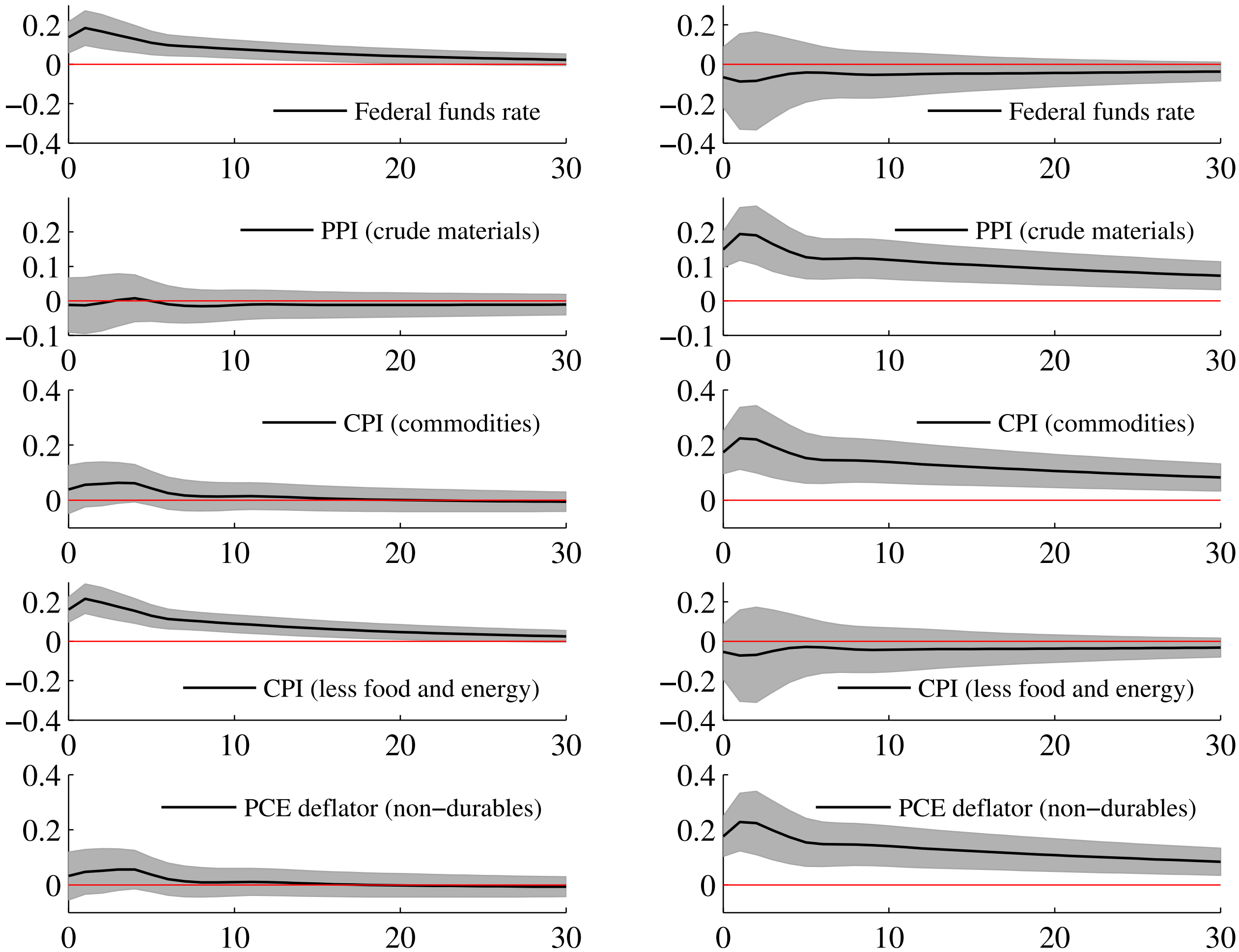


Note: Impulse responses for the first shock are depicted in the left column, and impulse responses for the second shock are depicted in the right column. Bootstrapped 90% confidence intervals for impulse responses are indicated by the shaded area.

Figure 3: Impulse response function of selected uncertainty variables

certainty. Moreover, according to table A.1, uncertainty associated with headline inflation (inflation uncertainty) can be traced back to both shocks, whereas the oil price uncertainty shock (67%) is more important than the business cycle uncertainty shock (33%). Hence, the distinction between production and inflation uncertainty seems to be rather inexpedient. That is, when analyzing the causes and consequences of increased uncertainty, it seems to be advisable to concentrate on the two distinct (orthogonal) types of uncertainty identified in our approach.

The two unobserved dynamic factors in f_t denoted by $\widetilde{f}_{j,t}$ for $j = 1, 2$ can be extracted with the help of the Kalman filter from the factor model consisting of equation (7) and the restrictions on the matrix A imposed in (8). They provide us with a concise picture of uncertainty in



Note: Impulse responses for the first shock are depicted in the left column, and impulse responses for the second shock are depicted in the right column. Bootstrapped 90% confidence intervals for impulse responses are indicated by the shaded area.

Figure 4: Impulse response function of selected uncertainty variables (ctd.)

the U.S. The first factor can be interpret as business cycle uncertainty and the second factor measures oil price uncertainty. The resulting time series are presented in figure 5.

4 How important are the uncertainty factors?

Now, we turn to the question: How much information about the business cycle is contained in the two uncertainty factors? In particular, we want to analyze whether uncertainty has the potential to impact major economic variables such as production, employment, and inflation. To this end, we make use of the large dataset of Giannone et al. (2004) which we use in section 2.2 to calculate the *RiskMetrics* uncertainty measures. Note, that for the analysis in

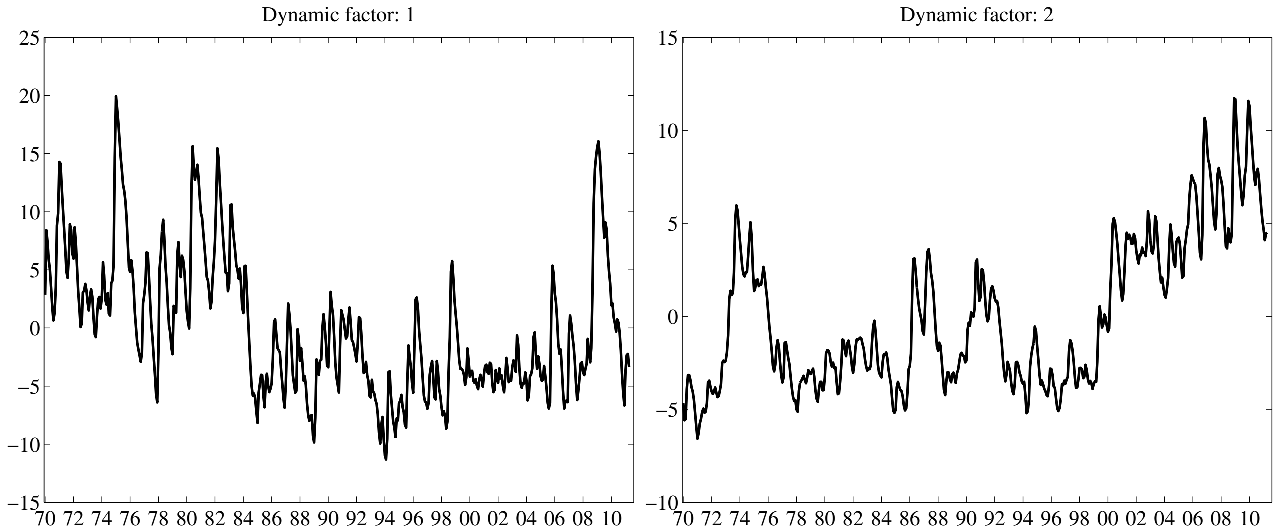


Figure 5: Dynamic uncertainty factors $\widetilde{f}_{j,t}$

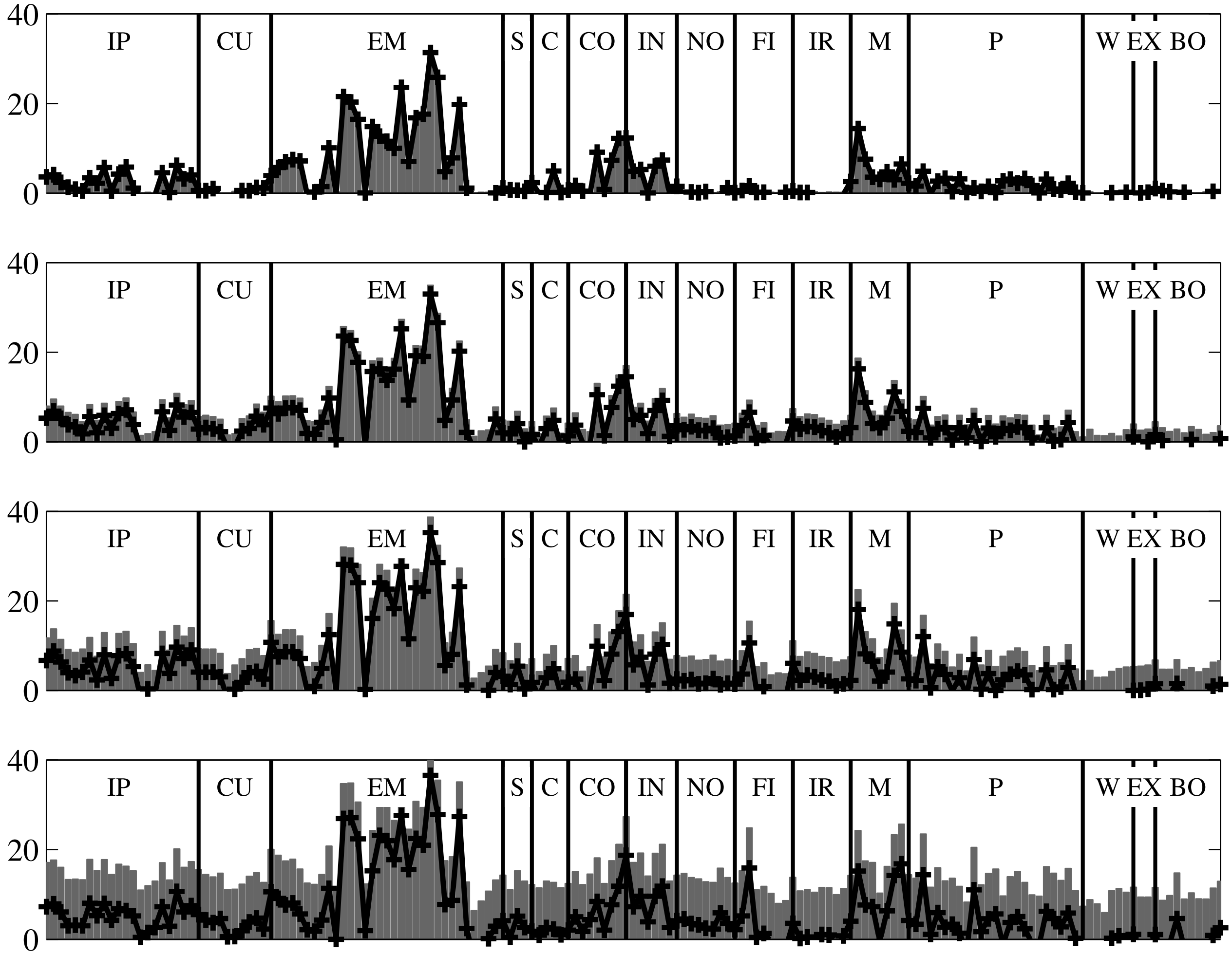
first order moments, we applied the transformations of Giannone et al. (2004) for all of the series (compare table A.1). We use this large-scale dataset to study the impact of uncertainty on the economy. To the best of our knowledge we are the first to provide such a comprehensive analysis of the relation between uncertainty and economic variables in first order moments.

To start with, we regress each variable in the dataset Y_t which consists of the first order moments of variables on (lags of) the two uncertainty factors in f_t:

$$Y_{i,t} = \mu + \sum_{l=0}^{L} \gamma_{i,l} f_{t-l} + e_t, \tag{12}$$

where $\gamma_{i,l}$ is a parameter vector of dimension 1×2 and $t = 1, ..., T$. Hence, we obtain $n = 164$ different regressions. For each of these regressions, we report the R^2 and the adjusted R^2 to account for overfitting problems. Figure 6 presents the results for a regression on contemporary uncertainty and different numbers of corresponding lags L.

Although adding lags to the regression increases the R^2, the information content of past uncertainty seems to be limited. In particular, the adjusted R^2 is virtually unaffected if more than 12 lags are included. Hence, in the following, we concentrate on the results for $L = 12$. It appears that there are considerable differences with respect to the explanatory content of the uncertainty factors across variables. For industrial production, R^2 hovers around 0.10. Considering the price variables, uncertainty accounts for about the same portion, whereas



Note: Grey bars represent R^2 from regression (6), and the solid line visualizes the adjusted R^2. The upper panel contains results when uncertainty enters only contemporary, the second panel displays results for $L = 6$, the third panel contains $L = 12$, and results for $L = 24$ are shown in the fourth panel. Individual variables are grouped into different 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).

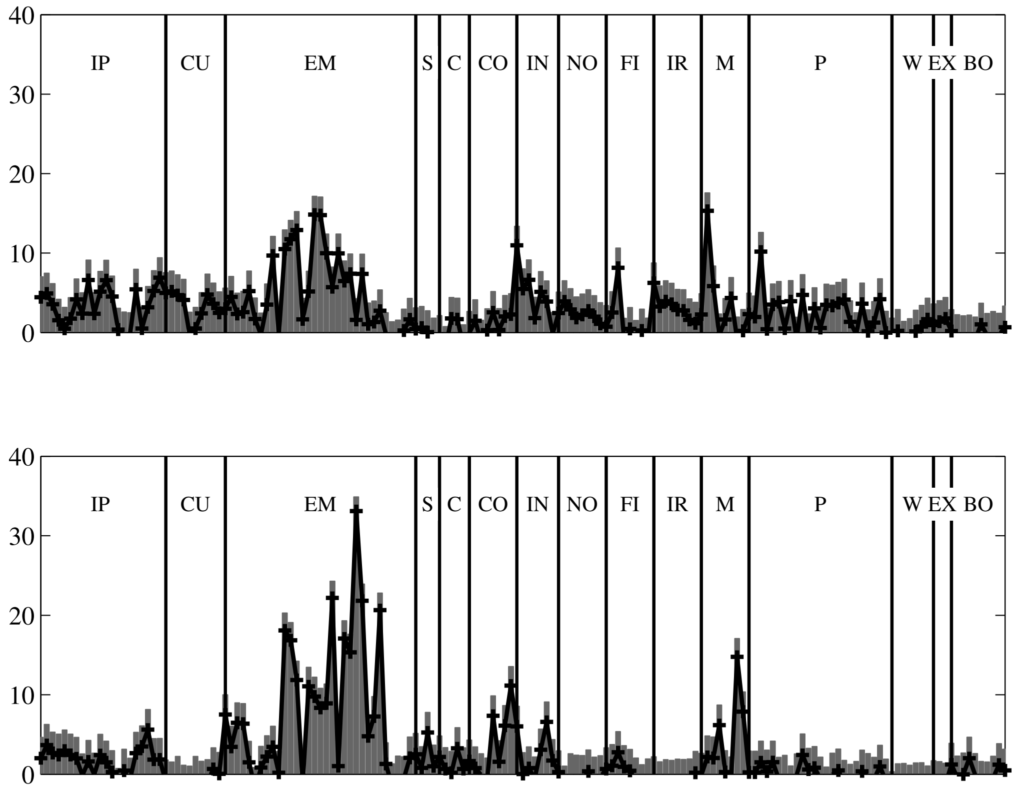
Figure 6: Information content of (lags of) uncertainty factors

uncertainty seems to have almost no explanatory content for wages ($R^2 \approx 0.03$). However, monetary variables appear to have a somewhat closer relation to uncertainty, here the R^2 amounts to 0.22 for M2. Similarly, 18% of the variation in construction can be explained by uncertainty. The largest values of the R^2 are obtained for employment. It turns out that uncertainty is able to account for up to 40% of the variation in employment in the financial sector and for 32% of total employment. The average R^2 for all employment variables is 0.18. Overall, uncertainty seems to contain valuable information for a number of important macroeconomic variables.

To get an impression which of the two uncertainty factors drives these results, we also estimate a regression where the factors enter one at a time. Results for such a regression that involves 12 lags of the respective uncertainty factor is given in figure 7.[13]

It turns out that the information content of the first factor is roughly equal for all economic time series. Overall, the R^2 is quite low. Employment variables appear to be an exception because here the first factor explains about 10% of the variation. Turning to the second factor, we observe that the results are somewhat subdivided. There appears to be a rather high R^2 for most of the employment variables, whereas for the remaining variables we obtain values that are to a considerable degree lower. Note that the monetary aggregate M2 is an

[13] Changing the number of lags does not alter the results significantly.



Note: Grey bars represent R^2 from a regression on the respective factor, and the solid line visualizes the adjusted R^2. The upper panel contains results for the first factor ($L = 12$) and the lower panel contains R^2 for the second factor. Individual variables are grouped into different 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).

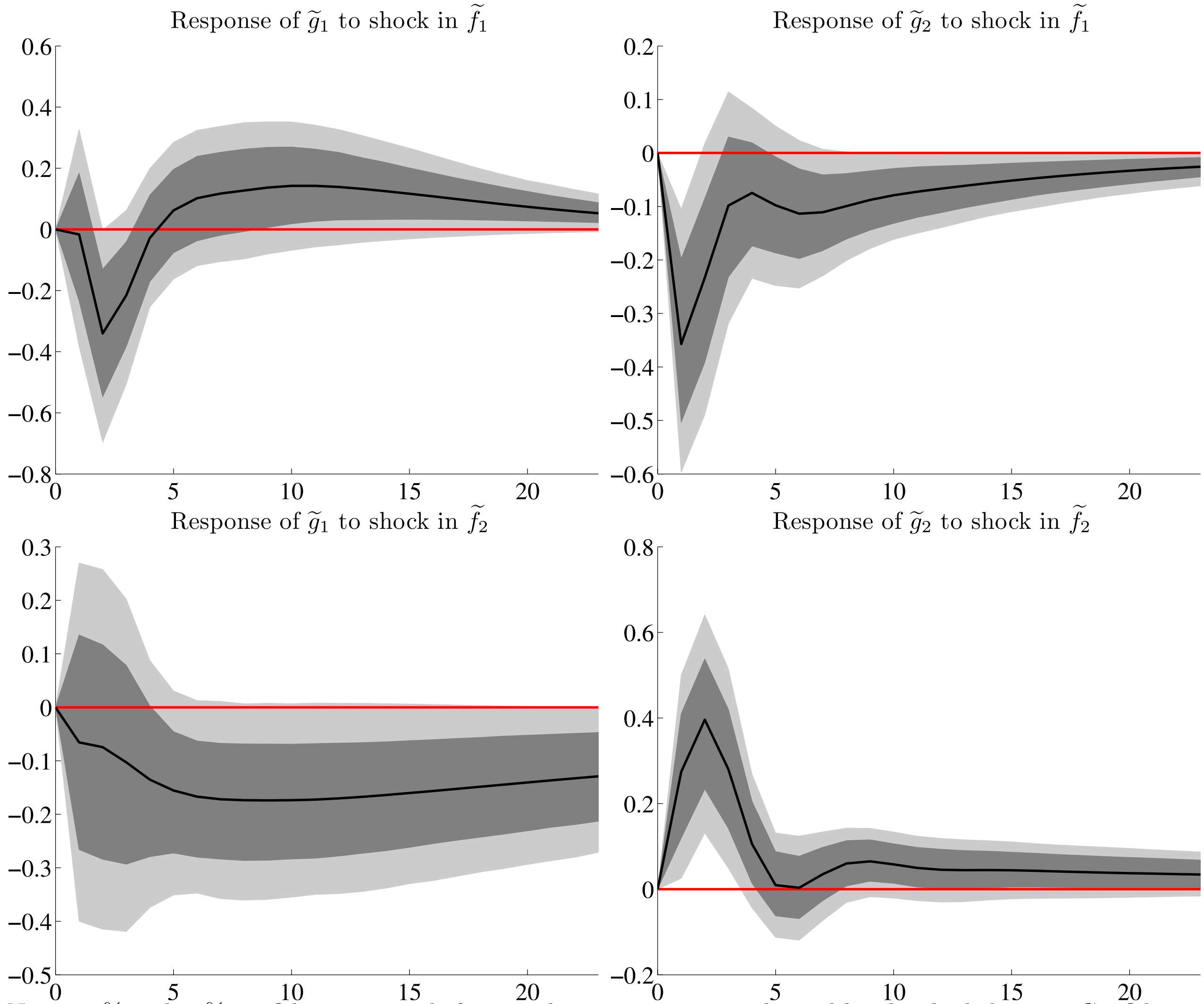
Figure 7: Information content of individual uncertainty factors

exception. Overall, our results indicate that the second factor $\widetilde{f}_2$ is somewhat more important for movements of variables in first order moments than $\widetilde{f}_1$.

As the variables in first order moments and uncertainty may be highly endogenous, we also conduct a VAR study. Moreover, the variables contained in the dataset in first order moments are highly correlated. However, modeling dynamic relationships between all variables contained in the dataset would leave us with the 'curse of dimensionality problem' inherent in standard VAR analysis. Hence, it is advisable to reduce the dimension of the dataset before estimating the VAR (Bernanke et al., 2005). To reduce the dimension of the data we simply reproduce the well known results of Giannone et al. (2004). That is, we estimate the dynamic factor model in (6) and (7) where X_t is replaced with the data in first order moments Y_t and obtain two common factors that drive the bulk of variation in the economy. According to Giannone et al. (2004), the first factor represents real economic activity, and the second factor captures the movement of nominal variables.[14] To study the dynamic relations between uncertainty and economic activity we estimate four different bivariate VARs. Each one consisting of one uncertainty factor $\widetilde{f}_j$ and one of the two factors introduced by Giannone et al. (2004) which we label $\widetilde{g}_k$, for $k = 1, 2$. According to BIC we set the lag length to 3. We analyze the effect of a sudden increase in either variable by impulse response analysis. The shocks are orthogonalized by a standard Cholesky decomposition where the respective uncertainty factor is ordered last. Figure 8 depicts the response of $\widetilde{g}_k$ to a shock in $\widetilde{f}_j$. From the upper left panel, we observe the response of real economic activity $\widetilde{g}_1$ to a shock to business cycle uncertainty $\widetilde{f}_1$. It appears that uncertainty leads to a temporary downturn of economic activity which is offset in subsequent periods. That is, the factor representing business cycle uncertainty seems to have the potential to cause an economic downturn. Moreover, the nominal factor $\widetilde{g}_2$ also declines shortly after a shock to business cycle uncertainty occurs.

In the lower part of figure 8 we present the response to a shock to oil price uncertainty ($\widetilde{f}_2$). It turns out that the point estimate for the response of real activity becomes negative and reverts to the zero line only slowly. Note that, although business cycle uncertainty appears to have a significant impact on economic activity, oil price uncertainty exerts a more sustained influence. This may also explain why we find that $\widetilde{f}_{2,t}$ has more explanatory power for variables in first order moments (see figure 7). Finally, it turns out that the nominal factor $\widetilde{g}_2$ rises temporarily following an increase in oil price uncertainty. Note that the response of $\widetilde{g}_2$ is negative when business cycle uncertainty rises. Hence, it is important to distinguish between different (fundamental) types of uncertainty to come to a well-informed policy response. Overall, the uncertainty factors we identify in this study are important

[14]The two common factors are shown in figure D.1 in the appendix.



Note: 68% and 90% confidence intervals for impulse responses are indicated by the shaded areas. Confidence intervals are derived from the bias adjusted bootstrap procedure based on 2000 replications (Kilian, 1998).

Figure 8: Impulse response function from bivariate factor VARs

drivers of economic fluctuations.

5 Conclusion

tbd.

Appendix

A Description of data

	Series	Transf.	R^2	**1**	**2**
	Industrial production				
1	Index of IP: total	3	0.78	0.99	0.01
2	Index of IP: final products and nonindustrial supplies	3	0.67	1.00	0.00
3	Index of IP: final products	3	0.58	0.99	0.01
4	Index of IP: consumer goods	3	0.45	0.99	0.01
5	Index of IP: durable consumer goods	3	0.39	0.99	0.01
6	Index of IP: nondurable consumer goods	3	0.14	0.79	0.21
7	Index of IP: business equipment	3	0.51	0.98	0.02
8	Index of IP: materials	3	0.68	1.00	0.00
9	Index of IP: materials, nonenergy, durables	3	0.68	0.95	0.05
10	Index of IP: materials, nonenergy, nondurables	3	0.48	0.86	0.14
11	Index of IP: mfg	3	0.82	1.00	0.00
12	Index of IP: mfg, durables	3	0.62	1.00	0.00
13	Index of IP: mfg, nondurables	3	0.53	0.98	0.02
14	Index of IP: mining	3	0.26	1.00	0.00
15	Index of IP: utilities	3	0.12	0.23	0.77
16	Index of IP: energy, total	3	0.13	0.88	0.12
17	Index of IP: nonenergy, total	3	0.80	1.00	0.00
18	Index of IP: motor vehicles and parts (MVP)	3	0.40	1.00	0.00
19	Index of IP: computers, comm. equip. and semiconductors (CCS)	3	0.14	0.97	0.03
20	Index of IP: nonenergy excl. CCS	3	0.79	1.00	0.00
21	Index of IP: nonenergy excl. CCS and MVP	3	0.67	0.99	0.01
	Capacity utilization				
22	Capacity utilization: total	2	0.78	1.00	0.00
23	Capacity utilization: mfg	2	0.81	0.99	0.01
24	Capacity utilization: mfg, durables	2	0.72	0.97	0.03
25	Capacity utilization: mfg, nondurables	2	0.47	0.96	0.04
26	Capacity utilization: mining	2	0.29	0.99	0.01
27	Capacity utilization: utilities	2	0.02	0.71	0.29
28	Capacity utilization: CCS	2	0.14	0.99	0.01
29	Capacity utilization: mfg excl. CCS	2	0.78	0.99	0.01
30	Purchasing Managers Index (PMI)	$0/3^{\dagger}$	0.32	0.99	0.01
31	ISM mfg index: production	$0/3^{\dagger}$	0.34	0.97	0.03
	Employment				
32	Index of help-wanted advertising	3	0.15	0.05	0.95
33	No. of unemployed in the civ. labor force (CLF)	3	0.11	0.99	0.01
34	CLF employed: total	3	0.08	0.99	0.01
35	CLF employed: nonagricultural industries	3	0.07	0.94	0.06

	Series	Transf.	R^2	1	2
36	Mean duration of unemployment	3	0.10	0.94	0.06
37	Persons unemployed less than 5 weeks	3	0.10	0.90	0.10
38	Persons unemployed 5 to 14 weeks	3	0.09	0.86	0.14
39	Persons unemployed 15 to 26 weeks	3	0.10	0.81	0.19
40	Persons unemployed 15+ weeks	3	0.06	0.98	0.02
41	Avg. weekly initial claims	3	0.24	0.98	0.02
42	Employment on nonag payrolls: total	3	0.49	0.95	0.05
43	Employment on nonag payrolls: total private	3	0.59	0.93	0.07
44	Employment on nonag payrolls: goods-producing	3	0.64	0.98	0.02
45	Employment on nonag payrolls: mining	3	0.23	0.97	0.03
46	Employment on nonag payrolls: construction	3	0.44	0.92	0.08
47	Employment on nonag payrolls: manufacturing	3	0.58	0.99	0.01
48	Employment on nonag payrolls: manufacturing,durables	3	0.57	0.99	0.01
49	Employment on nonag payrolls: manufacturing, nondurables	3	0.35	1.00	0.00
50	Employment on nonag payrolls: service-producing	3	0.19	0.99	0.01
51	Employment on nonag payrolls: utilities	3	0.08	1.00	0.00
52	Employment on nonag payrolls: retail trade	3	0.15	0.99	0.01
53	Employment on nonag payrolls: wholesale trade	3	0.18	1.00	0.00
54	Employment on nonag payrolls: financial activities	3	0.13	0.38	0.62
55	Employment on nonag payrolls: professional and business services	3	0.07	0.39	0.61
56	Employment on nonag payrolls: education and health services	3	0.12	0.68	0.32
57	Employment on nonag payrolls: leisure and hospitality	3	0.01	0.18	0.82
58	Employment on nonag payrolls: other services	3	0.09	0.94	0.06
59	Employment on nonag payrolls: government	3	0.08	0.99	0.01
60	Avg weekly hrs. of production or nonsupervisory workers (PNW): total	3	0.24	0.92	0.08
61	Avg weekly hrs. of PNW: mfg	3	0.23	0.99	0.01
62	Avg weekly overtime hrs. of PNW: mfg	3	0.26	0.99	0.01
63	ISM mfg index: employment	0/3†	0.35	0.99	0.01
	Sales				
64	Sales: mfg and trade-total (mil of chained 05$)	3	0.34	0.98	0.02
65	Sales: mfg and trade-mfg, total (mil of chained 05$)	3	0.31	0.99	0.01
66	Sales: mfg and trade-merchant wholesale (mil of chained 05$)	3	0.19	0.99	0.01
67	Sales: mfg and trade-retail trade (mil of chained 05$)	3	0.23	0.94	0.06
	Consumption				
68	Personal cons. expenditure: total (bil of chained 05$)	3	0.16	0.92	0.08
69	Personal cons. expenditure: durables (bil of chained 05$)	3	0.20	1.00	0.00
70	Personal cons. expenditure: nondurables (bil of chained 05$)	3	0.17	1.00	0.00

	Series	Transf.	R^2	1	2
71	Personal cons. expenditure: services (bil of chained 05$)	3	0.22	0.71	0.29
72	Personal cons. expenditure: durables, MVP, new autos (bil of chained 05$)	3	0.23	0.98	0.02
	Housing and construction				
73	Privately-ownedhousing, started: total (thous)	3	0.25	0.99	0.01
74	New privately-owned housing authorized: total (thous)	3	0.34	1.00	0.00
75	New 1-family houses sold: total (thous)	3	0.05	0.98	0.02
76	New 1-family houses months supply at current rate	3	0.05	0.79	0.21
77	New 1-family houses for sale at end of period (thous)	3	0.03	0.68	0.32
78	Mobile homes mfg shipments (thous)	3	0.14	0.62	0.38
79	Construction put in place: total (in mil of 05$)	3	0.22	0.95	0.05
80	Construction put in place: private (in mil of 05$)	3	0.08	1.00	0.00
	Inventories				
81	Inventories: mfg and trade: total (mil of chained 05$)	3	0.18	0.96	0.04
82	Inventories: mfg and trade: mfg (mil of chained 05$)	3	0.15	0.87	0.13
83	Inventories: mfg and trade: mfg, durables (mil of chained 05$)	3	0.10	0.98	0.02
84	Inventories: mfg and trade: mfg, nondurables (mil of chained 05$)	3	0.25	0.62	0.38
85	Inventories: mfg and trade: merchant wholesale (mil of chained 05$)	3	0.17	0.97	0.03
86	Inventories: mfg and trade: retail trade (mil of chained 05$)	3	0.18	0.96	0.04
87	ISM mfg index: inventories	$0/3^{\dagger}$	0.25	0.99	0.01
	New and unfilled orders				
88	ISM mfg index: new orders	$0/3^{\dagger}$	0.22	0.94	0.06
89	ISM mfg index: suppliers deliveries	$0/3^{\dagger}$	0.37	0.96	0.04
90	Mfg new orders: all mfg industries (in mil of current $)	3	0.24	0.92	0.08
91	Mfg new orders: mfg industries with unfilled orders (in mil of current $)	3	0.22	0.29	0.71
92	Mfg new orders: durables (in mil of current $)	3	0.25	0.88	0.12
93	Mfg new orders: nondurables (in mil of current $)	3	0.33	0.43	0.57
94	Mfg new orders: nondefense capital goods (in mil of current $)	3	0.14	0.85	0.15
95	Mfg unfilled orders: all mfg industries (in mil of current $)	3	0.07	0.29	0.71
	Financial variables				
96	NYSE composite index	3	0.20	0.91	0.09
97	S&P composite	3	0.24	0.84	0.16
98	S&P PE ratio	3	0.23	0.15	0.85
99	Nominal effective exchange rate	3	0.15	0.28	0.72
100	Spot Euro/US	3	0.12	0.43	0.57
101	Spot SZ/US	3	0.02	0.54	0.46
102	Spot Japan/US	3	0.05	0.73	0.27
103	Spot UK/US	3	0.03	0.76	0.24
104	Commercial paper outstanding (in mil of current $)*	-	-	-	-

	Series	Transf.	R^2	1	2
	Interest rates				
105	Interest rate: federal funds rate	2	0.34	0.80	0.20
106	Interest rate: U.S. 3-month Treasury (sec market)	2	0.34	0.89	0.11
107	Interest rate: U.S. 6-month Treasury (sec. market)	2	0.33	0.80	0.20
108	Interest rate: 1-year Treasury	2	0.38	0.74	0.26
109	Interest rate: 5-year Treasury (constant maturity)	2	0.18	0.92	0.08
110	Interest rate: 7-year Treasury (constant maturity)*	-	-	-	-
111	Interest rate: 10-year Treasury (constant maturity)	2	0.11	0.87	0.13
112	Bond yield: Moodys AAA corporate	2	0.05	0.97	0.03
113	Bond yield: Moodys BAA corporate	2	0.03	0.73	0.27
	Monetary variables				
114	M1 (in bil of current $)	3	0.21	0.14	0.86
115	M2 (in bil of current $)	3	0.19	0.36	0.64
116	M3 (in bil of current $)	3	0.18	0.11	0.89
117	Monetary base, adjusted 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 commercial banks: total (in mil of current $)	3	0.30	0.53	0.47
121	Loans and securities at all comm banks: securities, total (in mil of $)	3	0.10	0.68	0.32
122	Loans and securities at all comm banks: securities, U.S. govt (in mil of $)	3	0.31	0.85	0.15
123	Loans and securities at all comm banks: real estate loans (in mil of $)	3	0.31	0.01	0.99
124	Loans and securities at all comm banks: comm and Indus loans (in mil of $)	3	0.16	0.47	0.53
125	Loans and securities at all comm banks: consumer loans (in mil of $)*	-	-	-	-
126	Delinquency rate on bank-held consumer installment loans*	-	-	-	-
	Prices				
127	PPI: finished goods	4	0.77	0.12	0.88
128	PPI: finished consumer goods	4	0.79	0.09	0.91
129	PPI: intermediate materials	4	0.77	0.18	0.82
130	PPI: crude materials	4	0.60	0.01	0.99
131	PPI: finished goods excl food	4	0.77	0.02	0.98
132	Index of sensitive materials prices*	-	-	-	-
133	CPI: all items (urban)	4	0.70	0.33	0.67
134	CPI: food and beverages	4	0.30	0.91	0.09
135	CPI: housing	4	0.31	0.99	0.01
136	CPI: apparel	4	0.23	0.62	0.38
137	CPI: transportation	4	0.73	0.03	0.97
138	CPI: medical care	4	0.26	1.00	0.00
139	CPI: commodities	4	0.85	0.05	0.95
140	CPI: commodities, durables	4	0.02	0.60	0.40

	Series	Transf.	R^2	1	2
141	CPI: services	4	0.33	1.00	0.00
142	CPI: all items less food	4	0.61	0.27	0.73
143	CPI: all items less shelter	4	0.85	0.18	0.82
144	CPI: all items less medical care	4	0.72	0.35	0.65
145	CPI: all items less food and energy	4	0.40	0.90	0.10
146	Price of gold ($/oz) on the London market (recorded in the p.m.)	4	0.26	0.93	0.07
147	PCE chain weight price index: total	4	0.74	0.20	0.80
148	PCE prices: total excl food and energy	4	0.03	0.99	0.01
149	PCE prices: durables	4	0.08	0.93	0.07
150	PCE prices: nondurables	4	0.87	0.04	0.96
151	PCE prices: services	4	0.03	0.83	0.17
	Wages				
152	Avg hourly earnings: total nonagricultural (in current $)	4	0.28	0.71	0.29
153	Avg hourly earnings: construction (in current $)	4	0.22	0.89	0.11
154	Avg hourly earnings: mfg (in current $)	4	0.38	0.96	0.04
155	Avg hourly earnings: finance, insurance, and real estate (in current $)	4	0.10	0.86	0.14
156	Avg hourly earnings: professional and business services (in current $)	4	0.14	0.31	0.69
157	Avg hourly earnings: education and health services (in current $)	4	0.21	0.86	0.14
158	Avg hourly earnings: other services (in current $)	4	0.16	0.99	0.01
	Merchandize ex- and imports				
159	Total merchandize exports (FAS value) (in mil of $)	3	0.23	0.85	0.15
160	Total merchandize imports (CIF value) (in mil of $) (NSA)	3	0.33	0.99	0.01
161	Total merchandize imports (customs value) (in mil of $)	3	0.30	0.99	0.01
	Business outlook				
162	Philadelphia Fed business outlook: general activity	$0/2^\dagger$	0.05	0.61	0.39
163	Outlook: new orders	$0/2^\dagger$	0.11	0.98	0.02
164	Outlook: shipments	$0/2^\dagger$	0.08	0.99	0.01
165	Outlook: inventories	$0/2^\dagger$	0.09	0.88	0.12
166	Outlook: unfilled orders	$0/2^\dagger$	0.13	0.83	0.17
167	Outlook: prices paid	$0/2^\dagger$	0.10	0.05	0.95
168	Outlook: prices received	$0/2^\dagger$	0.08	0.77	0.23
169	Outlook employment	$0/2^\dagger$	0.05	0.99	0.01
170	Outlook: work hours	$0/2^\dagger$	0.09	0.99	0.01
171	Federal govt deficit or surplus (in mil of current $)	$0/2^\dagger$	0.08	0.01	0.99

Variables marked with an $*$ are not available for our full sample period and therefore had to be excluded from the original dataset used in Giannone et al. (2004).

Transformations applied to the data

0:	X_t
1:	$\ln(X_t)$
2:	$(1-L)X_t$, L denotes the lag-operator
3:	$(1-L)\ln(X_t)$
4:	$(1-L)(1-L^{12})\ln(X_t)$
$\cdot/\cdot^\dagger$	left hand side: transformation for first order moment analysis right hand side: transformation for second order moment analysis

Table A.1: Description of data set

Remark 1: Whenever a series has not been available in NAICS classification scheme for the whole 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 whole 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 Alternative rotation of factors (shock1 = oil)

	Series	Transf.	R^2	1	2
	Industrial production				
1	Index of IP: total	3	0.78	0.02	0.98
2	Index of IP: final products and nonindustrial supplies	3	0.67	0.01	0.99
3	Index of IP: final products	3	0.58	0.02	0.98
4	Index of IP: consumer goods	3	0.45	0.02	0.98
5	Index of IP: durable consumer goods	3	0.39	0.02	0.98
6	Index of IP: nondurable consumer goods	3	0.14	0.26	0.74
7	Index of IP: business equipment	3	0.51	0.04	0.96
8	Index of IP: materials	3	0.68	0.01	0.99
9	Index of IP: materials, nonenergy, durables	3	0.68	0.03	0.97
10	Index of IP: materials, nonenergy, nondurables	3	0.48	0.17	0.83
11	Index of IP: mfg	3	0.82	0.00	1.00
12	Index of IP: mfg, durables	3	0.62	0.00	1.00
13	Index of IP: mfg, nondurables	3	0.53	0.04	0.96
14	Index of IP: mining	3	0.26	0.01	0.99
15	Index of IP: utilities	3	0.12	0.73	0.27
16	Index of IP: energy, total	3	0.13	0.15	0.85
17	Index of IP: nonenergy, total	3	0.80	0.00	1.00
18	Index of IP: motor vehicles and parts (MVP)	3	0.40	0.01	0.99
19	Index of IP: computers, comm. equip. and semiconductors (CCS)	3	0.14	0.05	0.95
20	Index of IP: nonenergy excl. CCS	3	0.79	0.01	0.99
21	Index of IP: nonenergy excl. CCS and MVP	3	0.67	0.02	0.98
	Capacity utilization				
22	Capacity utilization: total	2	0.78	0.01	0.99
23	Capacity utilization: mfg	2	0.81	0.00	1.00
24	Capacity utilization: mfg, durables	2	0.72	0.01	0.99
25	Capacity utilization: mfg, nondurables	2	0.47	0.07	0.93
26	Capacity utilization: mining	2	0.29	0.02	0.98
27	Capacity utilization: utilities	2	0.02	0.24	0.76
28	Capacity utilization: CCS	2	0.14	0.02	0.98
29	Capacity utilization: mfg excl. CCS	2	0.78	0.00	1.00
30	Purchasing Managers Index (PMI)	$0/3^{\dagger}$	0.32	0.00	1.00
31	ISM mfg index: production	$0/3^{\dagger}$	0.34	0.05	0.95
	Employment				
32	Index of help-wanted advertising	3	0.15	0.97	0.03
33	No. of unemployed in the civ. labor force (CLF)	3	0.11	0.02	0.98
34	CLF employed: total	3	0.08	0.02	0.98
35	CLF employed: nonagricultural industries	3	0.07	0.09	0.91

	Series	Transf.	R^2	**1**	**2**
36	Mean duration of unemployment	3	0.10	0.08	0.92
37	Persons unemployed less than 5 weeks	3	0.10	0.14	0.86
38	Persons unemployed 5 to 14 weeks	3	0.09	0.18	0.82
39	Persons unemployed 15 to 26 weeks	3	0.10	0.15	0.85
40	Persons unemployed 15+ weeks	3	0.06	0.01	0.99
41	Avg. weekly initial claims	3	0.24	0.01	0.99
42	Employment on nonag payrolls: total	3	0.49	0.03	0.97
43	Employment on nonag payrolls: total private	3	0.59	0.05	0.95
44	Employment on nonag payrolls: goods-producing	3	0.64	0.01	0.99
45	Employment on nonag payrolls: mining	3	0.23	0.02	0.98
46	Employment on nonag payrolls: construction	3	0.44	0.05	0.95
47	Employment on nonag payrolls: manufacturing	3	0.58	0.00	1.00
48	Employment on nonag payrolls: manufacturing,durables	3	0.57	0.00	1.00
49	Employment on nonag payrolls: manufacturing, nondurables	3	0.35	0.01	0.99
50	Employment on nonag payrolls: service-producing	3	0.19	0.00	1.00
51	Employment on nonag payrolls: utilities	3	0.08	0.00	1.00
52	Employment on nonag payrolls: retail trade	3	0.15	0.01	0.99
53	Employment on nonag payrolls: wholesale trade	3	0.18	0.00	1.00
54	Employment on nonag payrolls: financial activities	3	0.13	0.67	0.33
55	Employment on nonag payrolls: professional and business services	3	0.07	0.66	0.34
56	Employment on nonag payrolls: education and health services	3	0.12	0.27	0.73
57	Employment on nonag payrolls: leisure and hospitality	3	0.01	0.78	0.22
58	Employment on nonag payrolls: other services	3	0.09	0.08	0.92
59	Employment on nonag payrolls: government	3	0.08	0.01	0.99
60	Avg weekly hrs. of production or nonsupervisory workers (PNW): total	3	0.24	0.05	0.95
61	Avg weekly hrs. of PNW: mfg	3	0.23	0.00	1.00
62	Avg weekly overtime hrs. of PNW: mfg	3	0.26	0.00	1.00
63	ISM mfg index: employment	$0/3^\dagger$	0.35	0.01	0.99
	Sales				
64	Sales: mfg and trade-total (mil of chained 05$)	3	0.34	0.01	0.99
65	Sales: mfg and trade-mfg, total (mil of chained 05$)	3	0.31	0.00	1.00
66	Sales: mfg and trade-merchant wholesale (mil of chained 05$)	3	0.19	0.00	1.00
67	Sales: mfg and trade-retail trade (mil of chained 05$)	3	0.23	0.09	0.91
	Consumption				
68	Personal cons. expenditure: total (bil of chained 05$)	3	0.16	0.05	0.95
69	Personal cons. expenditure: durables (bil of chained 05$)	3	0.20	0.01	0.99
70	Personal cons. expenditure: nondurables (bil of chained 05$)	3	0.17	0.00	1.00

	Series	Transf.	R^2	1	2
71	Personal cons. expenditure: services (bil of chained 05$)	3	0.22	0.24	0.76
72	Personal cons. expenditure: durables, MVP, new autos (bil of chained 05$)	3	0.23	0.04	0.96
	Housing and construction				
73	Privately-ownedhousing, started: total (thous)	3	0.25	0.02	0.98
74	New privately-owned housing authorized: total (thous)	3	0.34	0.01	0.99
75	New 1-family houses sold: total (thous)	3	0.05	0.01	0.99
76	New 1-family houses months supply at current rate	3	0.05	0.17	0.83
77	New 1-family houses for sale at end of period (thous)	3	0.03	0.27	0.73
78	Mobile homes mfg shipments (thous)	3	0.14	0.44	0.56
79	Construction put in place: total (in mil of 05$)	3	0.22	0.03	0.97
80	Construction put in place: private (in mil of 05$)	3	0.08	0.00	1.00
	Inventories				
81	Inventories: mfg and trade: total (mil of chained 05$)	3	0.18	0.06	0.94
82	Inventories: mfg and trade: mfg (mil of chained 05$)	3	0.15	0.17	0.83
83	Inventories: mfg and trade: mfg, durables (mil of chained 05$)	3	0.10	0.01	0.99
84	Inventories: mfg and trade: mfg, nondurables (mil of chained 05$)	3	0.25	0.44	0.56
85	Inventories: mfg and trade: merchant wholesale (mil of chained 05$)	3	0.17	0.01	0.99
86	Inventories: mfg and trade: retail trade (mil of chained 05$)	3	0.18	0.02	0.98
87	ISM mfg index: inventories	$0/3^{\dagger}$	0.25	0.00	1.00
	New and unfilled orders				
88	ISM mfg index: new orders	$0/3^{\dagger}$	0.22	0.09	0.91
89	ISM mfg index: suppliers deliveries	$0/3^{\dagger}$	0.37	0.03	0.97
90	Mfg new orders: all mfg industries (in mil of current $)	3	0.24	0.11	0.89
91	Mfg new orders: mfg industries with unfilled orders (in mil of current $)	3	0.22	0.76	0.24
92	Mfg new orders: durables (in mil of current $)	3	0.25	0.16	0.84
93	Mfg new orders: nondurables (in mil of current $)	3	0.33	0.62	0.38
94	Mfg new orders: nondefense capital goods (in mil of current $)	3	0.14	0.19	0.81
95	Mfg unfilled orders: all mfg industries (in mil of current $)	3	0.07	0.75	0.25
	Financial variables				
96	NYSE composite index	3	0.20	0.12	0.88
97	S&P composite	3	0.24	0.20	0.80
98	S&P PE ratio	3	0.23	0.89	0.11
99	Nominal effective exchange rate	3	0.15	0.67	0.33
100	Spot Euro/US	3	0.12	0.52	0.48
101	Spot SZ/US	3	0.02	0.41	0.59
102	Spot Japan/US	3	0.05	0.22	0.78
103	Spot UK/US	3	0.03	0.20	0.80
104	Commercial paper outstanding (in mil of current $)*	-	-	-	-

	Series	Transf.	R^2	1	2
	Interest rates				
105	Interest rate: federal funds rate	2	0.34	0.16	0.84
106	Interest rate: U.S. 3-month Treasury (sec market)	2	0.34	0.08	0.92
107	Interest rate: U.S. 6-month Treasury (sec. market)	2	0.33	0.16	0.84
108	Interest rate: 1-year Treasury	2	0.38	0.21	0.79
109	Interest rate: 5-year Treasury (constant maturity)	2	0.18	0.06	0.94
110	Interest rate: 7-year Treasury (constant maturity)*	-	-	-	-
111	Interest rate: 10-year Treasury (constant maturity)	2	0.11	0.10	0.90
112	Bond yield: Moodys AAA corporate	2	0.05	0.02	0.98
113	Bond yield: Moodys BAA corporate	2	0.03	0.31	0.69
	Monetary variables				
114	M1 (in bil of current $)	3	0.21	0.89	0.11
115	M2 (in bil of current $)	3	0.19	0.69	0.31
116	M3 (in bil of current $)	3	0.18	0.92	0.08
117	Monetary base, adjusted 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 commercial banks: total (in mil of current $)	3	0.30	0.52	0.48
121	Loans and securities at all comm banks: securities, total (in mil of $)	3	0.10	0.37	0.63
122	Loans and securities at all comm banks: securities, U.S. govt (in mil of $)	3	0.31	0.19	0.81
123	Loans and securities at all comm banks: real estate loans (in mil of $)	3	0.31	0.97	0.03
124	Loans and securities at all comm banks: comm and Indus loans (in mil of $)	3	0.16	0.59	0.41
125	Loans and securities at all comm banks: consumer loans (in mil of $)*	-	-	-	-
126	Delinquency rate on bank-held consumer installment loans*	-	-	-	-
	Prices				
127	PPI: finished goods	4	0.77	0.91	0.09
128	PPI: finished consumer goods	4	0.79	0.94	0.06
129	PPI: intermediate materials	4	0.77	0.85	0.15
130	PPI: crude materials	4	0.60	0.99	0.01
131	PPI: finished goods excl food	4	0.77	0.99	0.01
132	Index of sensitive materials prices*	-	-	-	-
133	CPI: all items (urban)	4	0.70	0.72	0.28
134	CPI: food and beverages	4	0.30	0.06	0.94
135	CPI: housing	4	0.31	0.02	0.98
136	CPI: apparel	4	0.23	0.33	0.67
137	CPI: transportation	4	0.73	0.98	0.02
138	CPI: medical care	4	0.26	0.00	1.00
139	CPI: commodities	4	0.85	0.97	0.03
140	CPI: commodities, durables	4	0.02	0.45	0.55

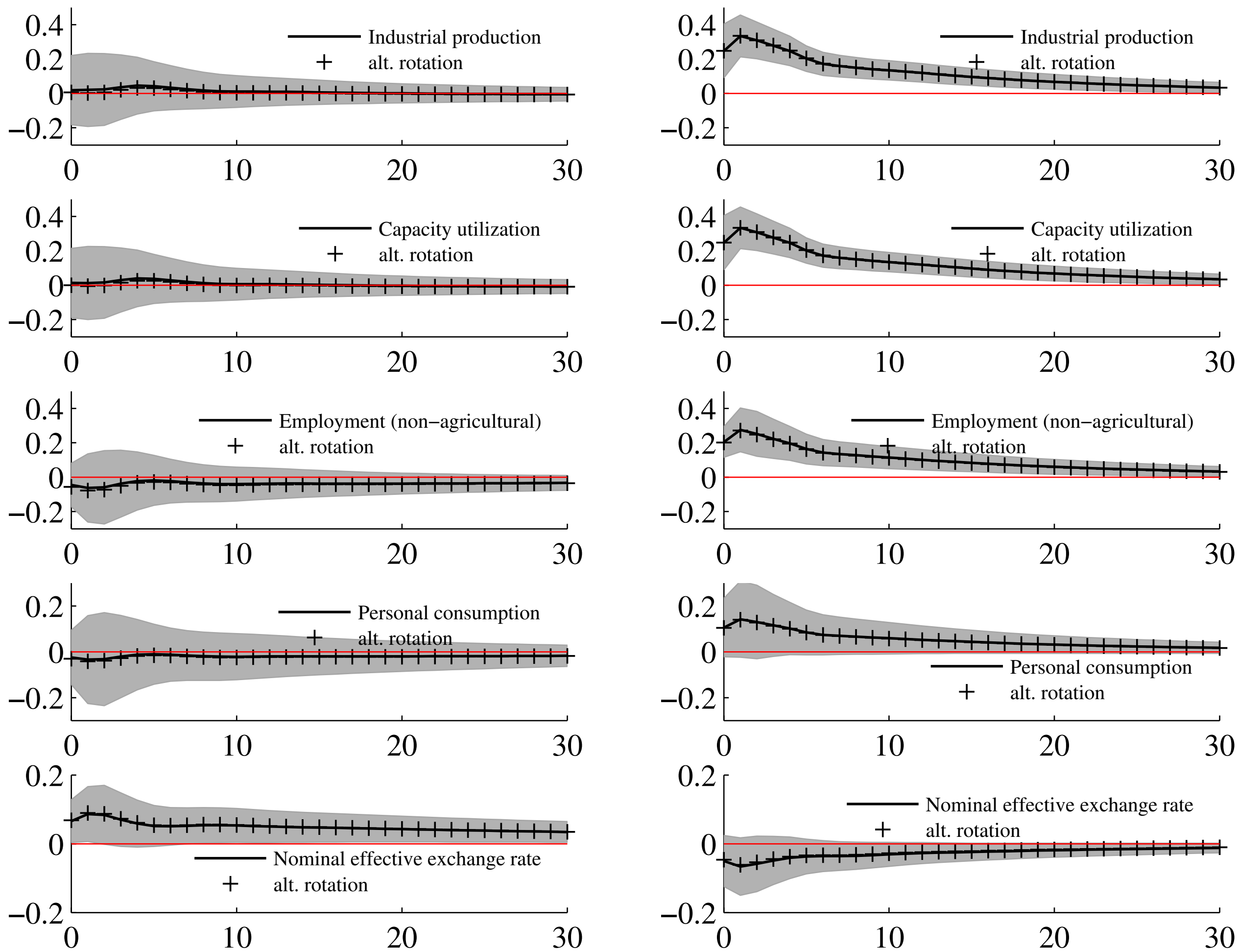
	Series	Transf.	R^2	**1**	**2**
141	CPI: services	4	0.33	0.00	1.00
142	CPI: all items less food	4	0.61	0.77	0.23
143	CPI: all items less shelter	4	0.85	0.86	0.14
144	CPI: all items less medical care	4	0.72	0.70	0.30
145	CPI: all items less food and energy	4	0.40	0.07	0.93
146	Price of gold ($/oz) on the London market (recorded in the p.m.)	4	0.26	0.09	0.91
147	PCE chain weight price index: total	4	0.74	0.84	0.16
148	PCE prices: total excl food and energy	4	0.03	0.02	0.98
149	PCE prices: durables	4	0.08	0.10	0.90
150	PCE prices: nondurables	4	0.87	0.98	0.02
151	PCE prices: services	4	0.03	0.21	0.79
	Wages				
152	Avg hourly earnings: total nonagricultural (in current $)	4	0.28	0.24	0.76
153	Avg hourly earnings: construction (in current $)	4	0.22	0.08	0.92
154	Avg hourly earnings: mfg (in current $)	4	0.38	0.03	0.97
155	Avg hourly earnings: finance, insurance, and real estate (in current $)	4	0.10	0.11	0.89
156	Avg hourly earnings: professional and business services (in current $)	4	0.14	0.74	0.26
157	Avg hourly earnings: education and health services (in current $)	4	0.21	0.10	0.90
158	Avg hourly earnings: other services (in current $)	4	0.16	0.00	1.00
	Merchandize ex- and imports				
159	Total merchandize exports (FAS value) (in mil of $)	3	0.23	0.11	0.89
160	Total merchandize imports (CIF value) (in mil of $) (NSA)	3	0.33	0.00	1.00
161	Total merchandize imports (customs value) (in mil of $)	3	0.30	0.00	1.00
	Business outlook				
162	Philadelphia Fed business outlook: general activity	$0/2^\dagger$	0.05	0.44	0.56
163	Outlook: new orders	$0/2^\dagger$	0.11	0.04	0.96
164	Outlook: shipments	$0/2^\dagger$	0.08	0.03	0.97
165	Outlook: inventories	$0/2^\dagger$	0.09	0.09	0.91
166	Outlook: unfilled orders	$0/2^\dagger$	0.13	0.14	0.86
167	Outlook: prices paid	$0/2^\dagger$	0.10	0.97	0.03
168	Outlook: prices received	$0/2^\dagger$	0.08	0.28	0.72
169	Outlook employment	$0/2^\dagger$	0.05	0.02	0.98
170	Outlook: work hours	$0/2^\dagger$	0.09	0.00	1.00
171	Federal govt deficit or surplus (in mil of current $)	$0/2^\dagger$	0.08	0.97	0.03

Note: Variables marked with an $*$ are not available for our full sample period and therefore had to be excluded from the original dataset used in Giannone et al. (2004).

Transformations applied to the data

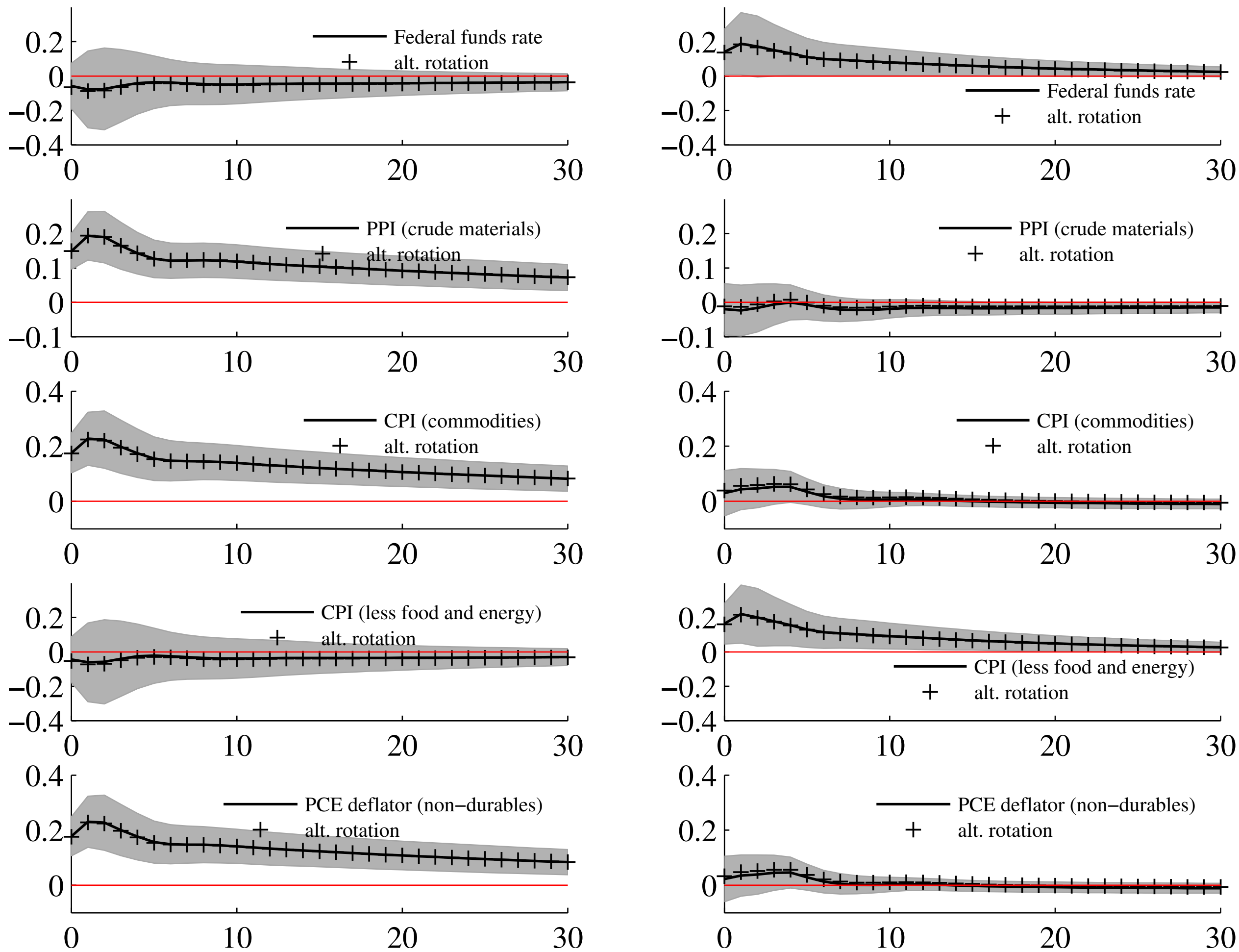
0:	X_t
1:	$\ln(X_t)$
2:	$(1-L)X_t$, L denotes the lag-operator
3:	$(1-L)\ln(X_t)$
4:	$(1-L)(1-L^{12})\ln(X_t)$
$\cdot/\cdot^\dagger$	left hand side: transformation for first order moment analysis right hand side: transformation for second order moment analysis

Table B.1: Description of data set



Note: Impulse responses for the business cycle uncertainty shock are depicted in the left column, and impulse responses for the commodity price uncertainty shock are depicted in the right column. Impulse responses from the alternative rotation are marked with a cross. Bootstrapped 90% confidence intervals for impulse responses are indicated by the shaded area.

Figure B.1: Impulse response function of selected variables for both identification strategies



Note: Impulse responses for the business cycle uncertainty shock are depicted in the left column, and impulse responses for the commodity price uncertainty shock are depicted in the right column. Impulse responses from the alternative rotation are marked with a cross. Bootstrapped 90% confidence intervals for impulse responses are indicated by the shaded area.

Figure B.2: Impulse response function of selected variables for both identification strategies (ctnd.)

C Testing for the number of static factors

r	R^2	$IC1$	$IC2$	$IC3$	$AIC1$	$BIC1$	$AIC3$	$BIC3$	$IC4$
0		-0.0020	-0.0020	-0.0020	-0.0020	-0.0020	-0.0020	-0.0020	-0.0020
1	22.0530	-0.2120	-0.2096	-0.2199	-0.2471	-0.2386	-0.2349	-0.1590	-0.1592
2	31.8023	-0.3064	-0.3017	-0.3223	-0.3767	-0.3598	-0.3522	-0.2006	-0.2011
3	38.0242	-0.3628	-0.3559	-0.3867	-0.4683	-0.4429	-0.4315	**-0.2041**	**-0.2054**
4	42.2764	-0.3947	-0.3854	-0.4265	-0.5354	-0.5015	-0.4863	-0.1831	-0.1853
5	45.2764	-0.4189	-0.4074	-0.4587	-0.5948	-0.5524	-0.5335	-0.1544	-0.1579
6	48.6831	-0.4339	-0.4201	-0.4817	-0.6450	-0.5941	-0.5714	-0.1165	-0.1215
7	51.2612	-0.4463	-0.4301	-0.5020	-0.6925	-0.6331	-0.6066	-0.0759	-0.0828
8	53.7377	-0.4592	-0.4407	-0.5229	-0.7406	-0.6728	-0.6424	-0.0360	-0.0449
9	56.0300	-0.4708	-0.4500	-0.5424	-0.7874	-0.7111	-0.6770	0.0053	-0.0060
10	58.0738	-0.4792	-0.4561	-0.5588	-0.8310	-0.7461	-0.7083	0.0498	0.0358
11	59.9405	-0.4856	-0.4601	-0.5731	-0.8725	-0.7792	-0.7375	0.0964	0.0795
12	61.7861	-0.4935	-0.4658	-0.5890	-0.9156	-0.8138	-0.7684	0.1413	0.1212
13	63.3955	-0.4974	-0.4673	-0.6008	-0.9546	-0.8443	-0.7951	0.1904	0.1668
14	64.9815	-0.5025	-0.4700	-0.6138	-0.9949	-0.8761	-0.8231	0.2382	0.2108
15	66.4498	-0.5061	**-0.4714**	-0.6254	-1.0337	-0.9064	-0.8496	0.2875	0.2561
16	67.7503	-0.5064	-0.4694	-0.6337	-1.0692	-0.9335	-0.8728	0.3401	0.3043
17	69.0278	-0.5076	-0.4683	-0.6428	-1.1056	-0.9614	-0.8970	0.3918	0.3514
18	70.2840	**-0.5098**	-0.4681	**-0.6530**	**-1.1429**	**-0.9903**	**-0.9221**	0.4425	0.3972

Note: Table provides information criteria proposed by Bai and Ng (2002) to determine the number of static factors. All criteria except the $IC4$ are taken from Bai and Ng (2002). $IC4$ is put forward in Bai and Ng (2008).

Table C.1: Information criteria for number of static factors

D Dynamic factor analysis for first order moments

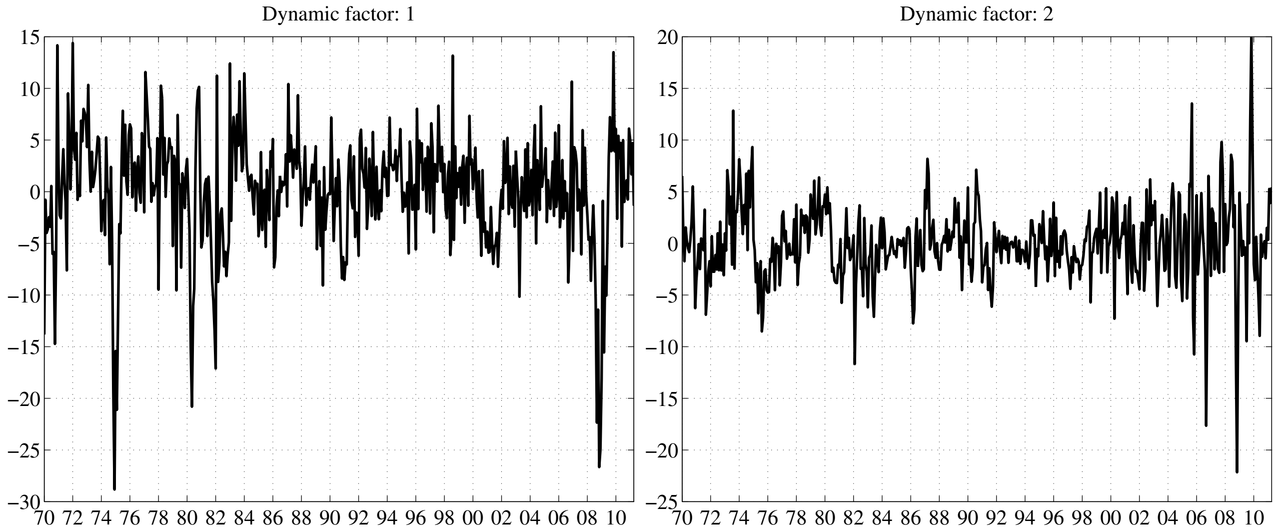


Figure D.1: Dynamic first order moments factors $\widetilde{g}_{t,k}$

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