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Identification of Macroeconomic Factors in Large Panels*

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Abstract

This paper presents a dynamic factor model in which the extracted factors and shocks are given a clear economic interpretation. The economic interpretation of the *factors* is obtained by means of a set of over-identifying loading restrictions, while the structural *shocks* are estimated following standard practices in the SVAR literature. Estimators based on the EM algorithm are developped. We apply this framework to a large panel of US monthly macroeconomic series. In particular, we identify nine macroeconomic factors and discuss the economic impact of monetary policy stocks. The results are theoretically plausible and in line with other findings in the literature.

JEL classifications: E3, E43, C51, E52, C33

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1 Introduction

In recent years, factor models have become a standard tool in applied macroeconomics and finance. In empirical macroeconomics they have been used for predictions (Bernanke & Boivin (2003), Forni et al. (2005), and Stock & Watson (2002*a*,*b*)); for structural analysis (Forni & Reichlin (1998), Forni et al. (2008), Giannone et al. (2004, 2002), Houssa (2008*a*), Bernanke et al. (2005) and Stock & Watson (2005)); and for constructing business cycle indicators (Forni et al. (2001), Kose et al. (2003), Houssa (2008*b*), and Otrok & Whiteman (1998)). Applications of factor models in finance include the arbitrage pricing theory (Chamberlain & Rothschild (1983) and Ingersoll (1984)); the measurement of risks (Campbell et al. (1997, ch. 2)); the estimation of the conditional risk-return relation in Ludvigson & Ng (2007); bond market applications (Mönch (2008), Ludvigson & Ng (2008) and Diebold et al. (2008)); and the prediction of the volatility of asset returns (Alessi et al. (2007)).

The increasing popularity of dynamic factor models (DFM) can be explained by two model features. First, factor models distinguish measurement errors and other idiosyncratic (series-specific) disturbances from structural shocks. As such, (dynamic) factor models provide a direct mapping from observed data to their theoretical and structural counterparts[1]. Second, large data sets are becoming increasingly available and classical multivariate regression models generally perform poorly in fitting them. By contrast, DFMs, exploiting the dynamic and cross-sectional structure of the panel, extract a (small) set of underlying factors. Moreover, various estimation techniques to analyze factor models in large panels have been recently developed. For instance, Stock & Watson (2002*a*,*b*) and Forni et al. (2000) propose a non-parametric estimation approach based on principal components. The former use the time domain method while the latter suggest a frequency domain estimation technique. In a related literature, Otrok & Whiteman (1998) and Kim & Nelson (1999) propose a Bayesian estimation technique whereas Doz et al. (2006, 2007) and Jungbacker & Koopman (2008) use an estimation approach based on the EM algorithm.

[1] Typically, these theoretical counterparts are defined within a DSGE model (see for example Altug (1989), Sargent (1989) and, recently, Boivin & Giannoni (2006)).

While these studies have provided important contributions to the literature on factor models, some identification issues remain, however. In particular, it is often the case that the (static) factors estimated in applied work do not necessarily have a well-defined and unambiguous economic interpretation[2]. A standard procedure amounts to inferring the economic interpretation of the factors from the dominant factor loadings. This approach, however, neglects the non-dominant (but possibly significant) loadings and hence does not necessarily generate unambiguous and well-defined interpretations of the factors.

In this paper we address this identification problem by using a procedure that *imposes* a specific and well-defined interpretation on the static factors. The economic interpretation of the extracted static factors is based on a set of overidentifying restrictions on factor loadings[3]. Furthermore, a set of standard exclusion restrictions on the impact matrix is used to identify the structural shocks. We employ the iterative maximum likelihood estimation approach as in Doz et al. (2006, 2007) and Jungbacker & Koopman (2008). The method combines the Kalman smoother and the EM algorithm.

We illustrate our approach by revisiting the large cross-section data analyzed in Bernanke et al. (2005). We aim at identifying and extracting from the data panel nine macroeconomic factors, respectively related to inflation, unemployment, economic activity, consumption, state of the business cycle, residential investments, financial markets and monetary policy. Given the identification of these factors, we assess and analyze (as in Bernanke et al. (2005)) the impact of monetary policy shocks on a number of key macroeconomic observables through impulse response analysis and variance decompositions.

Our paper is closely related to a number of recent studies. Boivin et al. (2009) and Reis & Watson (2008) impose loadings restrictions to identify a measure of

[2] *Static* factors are related to the variance-covariance matrix of the data while *dynamic* factors capture the property of their spectral density matrix. See Forni et al. (2000) for a literature review. Recent studies provide a structural interpretation to dynamic factors (shocks), see for example Giannone et al. (2004); Houssa (2008*a*) and Forni et al. (2008). The main difference between these studies and ours is that we identify (in economic and structural terms respectively) the static and dynamic factors.

[3] Alternative types of identification schemes in DFMs, among which exclusion restrictions and loading restrictions, are discussed in the literature; see for instance Stock & Watson (2005), Reis & Watson (2008), Forni & Reichlin (2001) and Kose et al. (2003).

pure inflation for the US economy. In the same way, Forni & Reichlin (2001) and Kose et al. (2003) use loading restrictions to differentiate between world, regional and country factors. Finally, Boivin & Giannoni (2006) employ loading restrictions to estimate the theoretical concepts of variables defined in DSGE model. The main difference between these studies and ours is that we employ the EM algorithm to derive closed form solutions for (linearly) restricted factor loadings. As such, we can combine various loading restrictions allowing to obtain a clear macroeconomic interpretation of the extracted factors (see sections 2 and 3).

The remainder of the paper is organized as follows. First, the methodological approach is explained in Section 2. We introduce a dynamic factor model and discuss the identification restrictions. In addition, closed-form solutions for the parameter estimates, consistent with the identification schemes and using results from Shumway & Stoffer (1982) and Wu et al. (1996), are presented. An empirical illustration is provided in Section 3. Section 4 concludes.

2 Methodology

We first introduce the DFM. More details can be found in Forni et al. (2000) and Forni & Lippi (2001). Subsequently, we employ the quasi maximum likelihood estimation approach as in Doz et al. (2006, 2007) and Jungbacker & Koopman (2008). We take this approach one step further by imposing (over-) identifying restrictions on the loadings and on the impulse response function (IRF). This allows a clear economic interpretation of the static factors and a structural identification of the shocks.

2.1 Dynamic Factor Model

Consider a panel of observable economic variables $y_{i,t}$, where i denotes the cross-section unit, $i = 1, ..., N$ while t refers to the time index, $t = 1, ..., T$. The panel of observed economic variables is transformed into stationary variables with zero mean and unit variance. These transformed variables are labeled by $x_{i,t}$. Dynamic factor models assume that a variable $x_{i,t}$ can be decomposed into two components, the *common component,* $\chi_{i,t}$, and the *idiosyncratic component* ξ_{it}:

$$x_{i,t} = \chi_{i,t} + \xi_{i,t}. \tag{1}$$

Furthermore, in exact dynamic factor models it is assumed that the idiosyncratic and common components are uncorrelated at all leads and lags and across all variables, $E(\xi_{i,t}\chi_{j,s}) = 0, \ \forall \ s,t,i,j$. The common component, $\chi_{i,t}$, is assumed to be driven by a small number r, $r << N$, of common factors $f_t = (f_{1,t} \ f_{2,t}, \cdots, f_{r,t})'$:

$$x_{i,t} = \lambda_i f_t + \xi_{i,t}, \tag{2}$$

where λ_i is a $1 \times r$ vector of factor loadings measuring the exposure of $x_{i,t}$ to the factors f_t. The idiosyncratic component, $\xi_{i,t}$, is driven by variable-specific noise. Stacking equation (2) over all cross-section units, $x_{i,t}$, $i = 1, ..., N$, gives:

$$X_t = \lambda f_t + \xi_t, \tag{3}$$

where $X_t = (x_{1,t}, \ldots, x_{N,t})'$, $\xi_t = (\xi_{1,t}, \ldots, \xi_{N,t})'$, and λ is a $N \times r$ matrix of factor loadings, $\lambda = (\lambda_1, ..., \lambda_N)'$. Equation (3) is called a *static* factor model (see for example Forni et al. (2000) and Stock & Watson (2002*b*)).

To close the model, factor dynamics have to be specified. We assume that the r-dimensional vector of common factors f_t has a VAR(p) representation:

$$\phi(L) f_t = \eta_t, \tag{4}$$

where $\phi(L) = I - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p$, with ϕ_j denoting a $r \times r$ matrix of autoregressive coefficients ($j = 1, \ldots, p$). Moreover, given the stationarity of the transformed panel, we impose stationarity on the DFM by requiring that the modulus of the roots of $\phi(L)^{-1}$ lie outside the unit circle. The q-dimensional vector of dynamic factor innovations is denoted η_t. As in Doz et al. (2006), we make additional distributional assumptions: $\eta_t \sim i.i.d\ N(0, Q)$ and $\xi_t \sim i.i.d\ N(0, R)$, with Q and R denoting (semi-) positive definite matrices[4].

Using equations (3) and (4), the model can be summarized in first order, with a $rp \times 1$ state vector F_t, $F_t = (f_t, ..., f_{t-p+1})'$, by the measurement equation:

$$X_t = \Lambda F_t + \xi_t, \tag{5}$$

and the transition equation:

$$F_t = \Phi F_{t-1} + VSu_t, \tag{6}$$

where Λ is the $N \times rp$ matrix loading, implied by λ, Φ is the $rp \times rp$ companion matrix corresponding to $\phi(L)$, $V = \left(I', 0'_{r(p-1)\times q}\right)'$, and u_t represents the structural shocks that are identified through the matrix S (see sub-section 2.2.2 below). Inverting the VAR in (6) and substituting F_t in (5) gives

$$X_t = B(L)u_t + \xi_t, \tag{7}$$

where $B(L) = \Lambda(I - \Phi L)^{-1}VS$, represents the IRF to u_t.

The state-space system, defined by equations (5) and (6), is not uniquely identified. We address the econometric identification as well as the economic interpretation of the static factors in section 2.2.1. Finally, the identification of the structural shocks u_t is discussed in section 2.2.2.

[4]Note that, by assuming *i.i.d* idiosyncratic components, (3)-(4) define an *exact* DFM as opposed to an *approximate* factor model where some correlation is allowed among idiosyncratic components. An exact factor structure is certainly a strong assumption, particularly in the case of large panel data sets where cross-sectional and serial correlations are expected to be found. As such, (3)-(4) represent a missspecified model. However, Doz et al. (2006) show that, for large N and T the exact factor model estimators are consistent quasi-maximum likelihood estimators for the approximate factor model.

2.2 Economic interpretation

Economic interpretation of the factors and shocks requires additional identification restrictions. We use two types of restrictions: (I) loading restrictions allowing for a clear macroeconomic interpretation of the (static) factors, and (II) restrictions on the impact matrix identifying the structural shocks.

2.2.1 Economic factors

We impose a set of restrictions on the loading matrix Λ, (equation (5)), and denote the restricted loading matrix by Λ^*. The linear loading restrictions take the following general form:

$$H_\Lambda vec(\Lambda^*) = \kappa_\Lambda, \tag{8}$$

where κ_Λ refers to a $\ell \times 1$ vector of ℓ linear combinations of restrictions of factor loadings defined by H_Λ, $H_\Lambda \in \mathbb{R}^{\ell \times Nr}$.

We use three types of loading restrictions, depending on the information content of the observables. In particular, economic identification is achieved by means of *(i)* unbiasedness restrictions *(ii)* one-to-one restrictions or *(iii)* exclusion restrictions.[5] The *unbiasedness restriction* implies that observable x_j is an unbiased and direct information variable for factor $f_l, l = 1, 2, \ldots, r,$:

$$\Lambda^*_{j,l} = 1, \ \Lambda^*_{j,k\neq l} = 0. \tag{9}$$

This type of restrictions is used on observables that are assumed to be a direct measure (up to some measurement error) of the underlying factor. For instance, our empirical application assumes that the observable "*CPI-u all items*" inflation is a direct measure for the inflation factor. As such, the unbiasedness restrictions imply a unit loading of "*CPI-u all items*" inflation on the inflation factor and zero loadings on all other factors. Note that these unbiasedness restrictions allow for the *econometric identification* of the DFM as the static factors are now uniquely

[5] To conform to the static factor structure of the model, *all* loadings on lagged factors are set to zero.

defined.

The *one-to-one restriction* implies a one-to-one link between an observable and a factor. Unlike unbiasedness restrictions, we allow other common factors to affect the observable as well, i.e. we do not impose $\Lambda^*_{j,k\neq l} = 0$. Formally, one-to one restrictions between observable x_j and factor l are ensured by imposing:

$$\Lambda^*_{j,l} = 1. \tag{10}$$

Finally, contemporaneous *exclusion restrictions*, i.e. the case where variable x_j is (contemporaneously) not related to the factor f_l, take the form of:

$$\Lambda^*_{j,l} = 0. \tag{11}$$

Note that this identification scheme formalizes and extends the standard informal identification procedures used in the literature. The standard approach identifies the factors from the principal factor loadings of the economic variables, disregarding the smaller loadings. Our identification procedure formalizes this approach by *(i)* imposing exclusion restrictions on the non-informative variables, which ensures that only information of relevant variables is incorporated in the factor and *(ii)* facilitating interpretation of the factors by means of the unbiasedness or one-to-one restrictions imposing a direct mapping between the observables and the static factor.

The economic interpretation of the factors is obtained by imposing at least one unbiasedness or a one-to-one restriction per factor. However, while exclusion and unbiasedness restrictions exclude some observables from the information set of a factor, we allow for feedback effects across factors. Specifically, through the VAR specification (equation (6)), we allow for dynamic interactions among factors. As such, factors can be correlated and structural shocks are eventually transmitted across all observables.

2.2.2 Structural shocks

In equation (7), structural shocks are identified. We follow the standard identification procedure in the SVAR literature by choosing an appropriate matrix S such that the implied restricted IRF, $B(L)^*$, has an economic justification. For instance, the Blanchard & Quah (1989) long-run restrictions can be obtained by choosing S such that appropriate elements of $B(1)^*$ are equal zero. Sign restrictions, recently introduced by Uhlig (2005), can also be fulfilled by choosing S such that the time path of some elements of $B(L)^*$ have an appropriate sign. Popular sign restrictions include the fact that prices cannot increase following a negative demand shock. Finally, structural identification can be obtained by imposing the Sims (1980)'s triangular representation on the matrix S. This is the approach followed in our empirical application in section 3. We first impose that the number of static factors equals the number of dynamic factors, i.e. $q = r$. This generates a structural shock to each of the static factors. Thereafter, we use the exclusion restrictions implied by the Cholesky decomposition of $Q = SS'$, with S lower triangular. The structural interpretation of the shocks is then implied by the ordering of the static factors and discussed in more detailed in section 3.

2.3 Estimation: the EM algorithm

Given the latent nature of the static factors, a standard EM algorithm is used to estimate the parameters and to extract the implied factors. Denote by $\Theta = \{\Lambda^*, R, \Phi, Q\}$ the set of parameters to be estimated with Λ^* satisfying the set of identification restrictions listed in equation (8). Conditional on the estimates of the factors, $\hat{F}$ (and matrices measuring uncertainty $\hat{P}$), the elements of Θ can be estimated by (Maximization step):

$$\begin{aligned}
\operatorname{vec}(\Lambda^*) &= \operatorname{vec}(DC^{-1}) \\
&\qquad + (C^{-1} \otimes R)\, H'_\Lambda \left[H_\Lambda (C^{-1} \otimes R)\, H'_\Lambda\right]^{-1} \left\{\kappa_\Lambda - H_\Lambda \operatorname{vec}(DC^{-1})\right\}, \\
R &= \tfrac{1}{T} G, \\
\operatorname{vec}(\Phi) &= \operatorname{vec}(BA^{-1}), \\
\Omega &= VQV' = \tfrac{1}{T}\left[C - BA^{-1}B'\right],
\end{aligned} \tag{12}$$

where the estimator for Λ^* follows from extending results in Wu et al. (1996).[6]

Conditional on the estimated parameters, Θ, the latent factors can be extracted by means of the Kalman smoother and the required moments can be computed (Expectation step). In particular, the following expectations are generated:

$$\begin{aligned}
A &= \textstyle\sum_{t=1}^T \left(\hat{P}_{t-1|T} + \hat{F}_{t-1|T}\hat{F}'_{t-1|T}\right), \\
B &= \textstyle\sum_{t=1}^T \left(\hat{F}_{t|T}\hat{F}'_{t-1|T} + \hat{P}_{\{t,t-1\}|T}\right), \\
C &= \textstyle\sum_{t=1}^T \left(\hat{F}_{t|T}\hat{F}'_{t|T} + \hat{P}_{t|T}\right), \\
D &= \textstyle\sum_{t=1}^T X_t \hat{F}'_{t|T}, \\
G &= \textstyle\sum_{t=1}^T (X_t - \Lambda^* \hat{F}_{t|T})(X_t - \Lambda^* \hat{F}_{t|T})' + \Lambda^* \hat{P}_{t|T} \Lambda^{*\prime},
\end{aligned} \tag{13}$$

with:

$$\begin{aligned}
\hat{F}_{t|T} &= E(F_t \mid \mathcal{X}_T), \\
\hat{P}_{t|T} &= E((F_t - \hat{F}_{t|T})(F_t - \hat{F}_{t|T})' \mid \mathcal{X}_T), \\
\hat{P}_{\{t,t-1\}|T} &= E((F_t - \hat{F}_{t|T})(F_{t-1} - \hat{F}_{t-1|T})' \mid \mathcal{X}_T),
\end{aligned} \tag{14}$$

[6] A derivation of the estimator is available on request.

where $E(\cdot \mid \cdot)$ denotes the conditional expectations operator implied by the Kalman smoother (as a function of Θ), see for instance de Jong & Mackinnon (1988) and de Jong (1989). $\mathcal{X}_T = \{X_1, \ldots, X_t\}$ denotes the information set. We iterate sequentially over the M-step in equation (12) and the E-step in equation (13) until convergence of the likelihood starting from different sets of initial values.[7]

In our empirical application discussed in section 3 the unrestricted model involves $1,614$ parameters to be estimated. This is computationally feasible with the EM algorithm method. Doz et al. (2006) suggest to initialize the Kalman filter by the parameters implied by principal components and then filter the factors. However, principal component analysis results in orthogonal factors and we prefer correlated factors[8]. Consequently, we suggest to entertain an oblique rotation of the orthogonal factors which is a common tool in confirmatory factor analysis as described in Lawley & Maxwell (1971). This approach does not change the initial fit but rotates the factors towards a target loading matrix which we choose to be the exactly identifying loading restrictions. The result is a set of correlated factors from which a set of implied initial parameters consistent with the identifying loading restrictions can be derived.

3 Empirical Application

We illustrate our procedure by revisiting the large data panel analyzed in Bernanke et al. (2005). This data set captures the dynamics of a wide range of macroeconomic developments in the US economy over the last decades. In particular, the sample consists of 120 time series (monthly frequency) over the period 1959:1 to 2001:8[9]. The main focus of our empirical analysis is to extract a number of factors

[7]We define convergence using a relative tolerance of 10^{-8} for the log-likelihood.

[8]The Geweke & Singleton (1981) identification scheme allows the factors to be correlated which is relevant if any macroeconomic interpretation is going to be attached to these factors.

[9]The data are already transformed by Bernanke et al. (2005) to reach stationarity; see Bernanke et al. (2005) for details on the data set and on the transformations. The final data set used contains 120 series and $T = 511$ monthly observations per series. Prior to the estimation, we de-mean the series and divide them by their standard deviation such that the resulting series have zeros mean and unit variance.

with an unambiguous (macro) economic interpretation. Moreover, we analyze the economic impact of monetary policy shocks on the US economy. We first discuss the identification of the factors. Subsequently, we analyze the extracted factors and finally, we use impulse response functions (IRFs) and variance decompositions to study the impact of monetary policy shocks on the US economy.

3.1 Identification

The identification proceeds in two steps. First, we select the number of static (and dynamic) factors, r (q), and the number of lags in the VAR of the static factors. Subsequently, restrictions are imposed to identify and interpret in macroeconomic terms the static factors and structural shocks.

3.1.1 Number of factors

Our preferred specification contains nine factors and includes six lags in the dynamics of the factors ($\widehat{r} = \widehat{q} = 9$ and $\widehat{p} = 6$). The number of dynamic factors is relatively high compared to the literature. For example, Giannone et al. (2004) argue that the number of shocks (dynamic factors) driving the US economy is equal to two (i.e. $\widehat{q} = 2$). Stock & Watson (2005) analyzing the same data set, but with a different method, argue that seven dynamic factors and nine static factors are required ($\widehat{q} = 7$ and $\widehat{r} = 9$). Bai & Ng (2007) and Hallin & Liska (2007) opt for $\widehat{q} = 4$. Bernanke et al. (2005), analyzing another large US panel, prefer a model specification with four factors ($\widehat{r} = \widehat{q} = 4$). Bork (2008) considers the same data as in Bernanke et al. (2005) and based on various information criteria finds that an exactly identified factor-augmented VAR model with $\hat{r} = 8$ explains the data well.

Part of the reported difference in the number of factors can be attributed to the fact that earlier research focussed primarily on fitting the leading statistical indicators for economic activity and inflation. As demonstrated by Stock & Watson (2005), additional factors are required to fit the other dimensions of the data panel. We follow this line of reasoning and allow for two additional factors relative to their seven dynamic factors. The motivation for introducing two more factors is based on the observation that our approach, unlike the latent factor approach, imposes a large number of overidentifying restrictions on the loading matrix. These over-identifying restrictions most likely reduce the flexibility and the fit of the factor model. This decrease in flexibility is compensated for by increasing the number of factors. The statistical performance of this restricted nine-factor model is discussed in section 3.2. Before, we provide economic identification of factors and shocks in the next sub-section.

3.1.2 Economic interpretation of factors and shocks

We identify the nine retained static factors using a relatively wide array of economic concepts or interpretations, relevant for empirical monetary policy analysis. The identification of seven out of the nine factors is motivated by small-scale macroeconomic theoretical models. Our identification procedure is also based on empirical findings in Stock & Watson (2005). In particular, we retain four (aggregate supply) factors: an *inflation factor* (π); an *economic activity factor* (y); an *hours in production factor* (hrs) functioning as a buffer to changes in demand and an *unemployment factor* (u_n). The standard aggregate demand equation motivates the identification of the following three factors: a *consumption factor* (c)*;* a *housing factor* (h) approximating (residential) investment; and a *monetary policy factor* (i)[10].

The remaining two factors have an interpretation either as additional information factors or as financial factors.[11] More precisely, we identify a *stock market factor* (s) capturing wealth or information effects and a *commodity price factor* ($pcom$)

[10]For more details we refer to Bernanke et al. (2005) for a nice exposition on the mapping between a small-scale macro model and a factor model.

[11]Information variables (or information factors) are assumed to be monitored by central banks because they may display relevant information that is not available in typical macroeconomic variables. See Leeper et al. (1996), Christiano et al. (1999) and very recently Bjørnland & Leitemo (2009) for a discussion. Generally, information variables are fast-moving variables that respond contemporaneously to all variables. Examples of fast moving variables include auction market commodity prices, stock prices, and options on financial instruments.

capturing information on nascent inflation pressures.

Insert Table 1

Table 1 offers an overview of the identification restrictions. The identification of the respective factors is obtained in two steps. First, we fix the interpretation of the factors by imposing a set of unbiasedness restrictions. In particular, we impose unbiasedness restrictions on nine observables closest to the economic interpretation of each of the factors (see shading areas in Table 1).[12] This results in an exactly identified system (along the lines of *Proposition 2* in Geweke & Singleton (1981)). This exactly identified latent factor model is labelled as the "*unrestricted model*".

Second, (over-) identifying restrictions are imposed in the form of exclusion restrictions (see Table 1). Generally, the identification scheme is based on two strategies. First, exclusion restrictions are primarily imposed on slow-moving variables while fast-moving observables are left unrestricted (except for housing starts and stock market observations).[13] This modeling choice is motivated by the idea that fast moving variables, containing a speculative component, can be considered as general and timely information variables for macroeconomic developments. Second, we differentiate between nominal, real, information, and policy factors. We define: one nominal factor (*inflation factor);* four real factors (*unemployment*, *economic activity*, *consumption*, and *hours in production factors*); three information factors (*housing, commodity price, and stock market factors);*

[12] The target observables of the factors are: the CPI-all items index (series 108) for the inflation factor (π); the Unemployment Rate all workers (series 26) for the unemployment factor (u_n); the Industrial Production-total index (series 16) for the economic activity factor (y); Personal Consumption Expenditure all items (series 49) for the consumption factor (c); Average weekly Hours of Production in manufacturing (series 47) for the hours in production factor (hrs); Housing Starts non-farm (series 54) for the housing factor (h); NAPM commodity price index (series 102) for the commodity price factor ($pcom$); The effective federal funds rate (series 77) by the monetary policy rate factor (i); and finally the NYSE stock price index (series 66) for the stock market factor (s). See appendix A for the definition and numbers assigned to each observable in the data panel.

[13] We use the definition of fast- and slow-moving variables of Bernanke et al. (2005) except housing starts and stock market returns, which we assume not to respond *contemporaneously* to some factors. This assumption helps empirically to distinguish a housing factor from a stock market factor.

and one policy factor (*monetary policy factor).* In our identification strategy, nominal factors exclude all types of real observables as (contemporaneous) information variables. In the same way, real factors exclude nominal variables. Information factors exclude all slow-moving real and nominal observables. Finally, the policy factor loads freely on all observables. Details on the restrictions per variable are listed in Table 1 and described in more detail in Appendix B.

A final set of exclusion restrictions identifies the structural shocks through a standard Cholesky decomposition of the variance-covariance matrix of disturbances in the state equation. The ordering used in the analysis is as follows: π, u_n, y, c, hrs, $pcom$, i, s. This ordering is in line with the identification of monetary policy shocks in the literature (see for example Christiano et al. (1999)).

3.2 Empirical Results

3.2.1 Identification restrictions and model performance

Our identification scheme (see section 2) involves 482 over-identifying restrictions. In this section we provide a statistical test on these restrictions. In particular, we perform an LR-test of our restricted model against the unrestricted (exactly identified) model. We complement this test by a number of measures of fit including R^2, AIC, BIC, the log-likelihood value, and IC^*_{p2}, a modified version of the Bai & Ng (2002) IC_{p2} panel information criterion (see Doz et al. (2006)). Table 2 reports the results. As expected, the over-identifying restrictions are rejected at the usual significance level. Moreover, the values of the information criteria (AIC, BIC and IC^*_{p2}) are higher for the restricted model. Interestingly, despite the statistical rejection of the model, we observe that the economic costs of the restrictions is relatively small. In particular, the cost of imposing 482 over-identifying restrictions is a decrease in overall (simple average) R^2 of approximately four percentage points, from 57.0% to 53.2%. As a result, little is lost by imposing the over-identifying restrictions and we are willing to pay the price of a slight reduction in overall R^2 for economically interpretable factors.[14]

[14] Similar drops in R-square have been reported by Reis & Watson (2008). In a related dynamic factor model they estimate a measure of pure inflation by imposing a unit loading on

Insert Table 2

The general performance (explanatory power) of the restricted nine factor model is in line with the literature. Specifically, the average R^2 of 53.2% of our model is in line with the performance of large unrestricted DFMs for the US economy (e.g. Bai & Ng (2007), Bork (2008) and Yu (2008)). Also, the value of average R^2 of our model corresponds to the value one would obtain from the Stock & Watson (2002*b*) principal components approach with six factors. These findings suggest that the over-identifying restrictions and the implied economic interpretation of the factors can be obtained without major loss in fitting the dominant dimensions of variation in the panel.

3.2.2 Implied factors

Table 3 reports the estimates of free factor loadings as well as the total variance explained by the common factors (R^2) for each of our observables. Figures 1 till 3 give a graphical representation of the estimated factor loadings for each of the nine retained factors. Overall, the statistics reported in Table 3 support the economic interpretation of the latent factors. In particular, the signs of estimated factor loadings are in line with theory. Also, the retrieved factors capture most of the variation in the key variables (with many R^2s above 90%). Figure 4 displays the factors as retrieved from the panel.

Insert Figures 4 till 3 and Table 3

Specifically, we find that the inflation factor (π) closely tracks the *CPI-u all items* inflation. Moreover, the R-squared is higher than the one based on the inflation factor identified by Bernanke et al. (2005) (96% instead of 87%).[15] The estimated factor loadings on other CPI and PPI inflation series are significantly positive and the common component captures a substantial part of the variation

each of 187 US sectoral price indices. Using t-tests they reject the null hypothesis of unit loadings on their pure inflation factor. They report that imposing these restrictions only decreases the R^2 by less than 3% for eighty percent of the 187 observables.

[15] Bernanke et al. (2005) use an exactly-identified four-factor FAVAR model.

in these series.

The unemployment factor (u_n) captures approximately 73% of the variation in the target unemployment variable, i.e. Unemployment rate all workers. Other unemployment measures load significantly and positively on this factor. Note too that this factor also contributes significantly to the variation in the payroll variables and capacity utilization. As expected, loadings are typically negative for employment, payroll and capacity utilization variables.

The economic activity factor (y) explains up to 97% of growth in industrial production (the target variable) and also fits reasonably well the different components of industrial production. Exceptions are non-durables, mining and utilities. Moreover, loadings for industrial production components are in general positive. The economic activity factor also contributes to the variation of payroll, income and employment variables. The consumption factor (c) is restricted to load only on the five personal expenditure series in addition to the fast-moving variables. The one-to-one restrictions help to extract a consumption factor that explains 67 percent in the total personal expenditure series which is significantly higher than the 6-10% reported by Bernanke et al. (2005) and Bork (2008). Note too that estimated factor loadings suggest a close link between consumption of durables and the consumption factor. Other consumption components, i.e. non-durables and services, remain largely unrelated to the consumption factor as indicated by the low R^2. The hours in production factor (hrs) explains average weekly overtime hours for production workers in manufacturing almost perfectly, $R^2 = 93\%$. Furthermore, as suggested by the loadings, this factor significantly contributes to the dynamics of capacity utilization and help-wanted ads dynamics.

The housing factor (h) explains 93% of total non-farm housing starts and authorizations while the commodity price factor ($pcom$) only captures 39% in monthly commodity price inflation as measured by movement in the NAPM commodity price index. The stock market factor (s) explains more than 97% of variation in the NYSE index. This factor also explains well price movements for the S&P500. Price earnings or dividend ratios do not load significantly on the stock market factor. The latter feature is probably explained by the fact that the stock market factor models stock *returns,* while *levels* of the price dividend and earnings ratios are included in the data set. Finally, the monetary policy factor tracks, by construction, perfectly the federal funds rate. In addition, the factor explains most of the variation in the remaining interest rate variables such as yields and spreads. Loadings for yields and spreads conform to the standard term structure literature.

3.2.3 Measuring the impact of monetary policy

We use our model to analyze the overall impact of monetary policy shocks on the US economy. To facilitate comparison with the literature we do not present the impulse response functions (IRFs) of the factors themselves. Instead, we focus on the IRFs of twenty key measures covering the US economy, as implied by the factor model (e.g. Bernanke et al. (2005)). More specifically, we analyze the federal funds rate, the yen per US dollar exchange rate, the level of industrial production, the consumer price level (CPI), monetary aggregates, the capacity utilization, the (un)employment level, the average hourly earnings, the level of consumption and consumer confidence expectations as key indicators for the macroeconomy. Additionally, we cover housing starts and two financial market indicators: the dividend yield on the S&P and the five year treasury yield.

Insert Figure 5

Figure 5 displays the IRFs of each of these variables to a 25 basis points monetary policy shock. The unit of the IRFs is the standard deviation of the respective series. Our IRFs depicted in Figure 5, are as expected and in line with the literature (see Christiano et al. (1999)). The empirical plausibility of the IRFs, therefore, suggests that the model is able to identify accurately the key macroeconomic transmission mechanisms and shocks.

Several observations can be made in this respect. First, unlike standard small-scale VAR models, we do no longer observe a price puzzle. Second, a contractionary monetary policy shock has a negative impact on output where the maximal effect is reached within one year. Third, long-run neutrality of monetary policy cannot be rejected. In particular, monetary policy shocks only have a temporary effect on production, consumption, capacity utilization, and (un)employment levels. Fourth, the impact of temporary policy shocks is initially negative on the consumption expectations but then reverses before the impact becomes neutral in the long-run. Finally, the results show a significant impact of monetary policy shocks on financial markets. Monetary policy tightening increases the bond yields with the short-term yields responding more than the long-term yields, as illustrated by the IRF of the 3 month and 5 year yield. However, given the moderate persistence of the policy shocks (see the IRF of the federal funds rate), the impact on bond yields of monetary policy shocks remains relatively small and temporary. Real estate markets, as illustrated by the IRF of the housing starts, initially respond strongly to the monetary policy shock although there is no long-run effect. Following a monetary tightening, the dividend yield tends to adjust temporarily upwards while the yen tends to depreciate against the US dollar. These IRFs match both the responses reported in Banbura et al. (2008), using a BVAR and Bernanke et al. (2005) using a FAVAR.

Insert Figure 6 and Table 4

Table 4 and Figure 6 present the variance decomposition of the selected variables at alternative forecasting horizons. This tool allows us to assess the relative importance of monetary policy shocks in the overall variation of the series. Our results are broadly in line with those reported both in Banbura et al. (2008) and Bernanke et al. (2005). In line with these studies, we observe that monetary shocks do not have an important long-run (60 month) impact on the forecast error variance of a broad selection of key macroeconomic and financial variables. Specifically, we find that a monetary policy shock explains less than 12% of the variation in industrial production, consumer prices, commodity prices, (un)employment, new orders for any forecast horizon and virtually zero for consumption and money base. Unlike Bernanke et al. (2005), however, we do not find a large significant long-run effect of monetary policy shocks on the federal funds rate and the bond yields. The estimates reported in Table 4 indicate that monetary policy shocks are only mildly persistent and only account for approximately 3% to 7% of total long-run variation in the federal funds rate and the bond yields. Banbura et al. (2008), reporting similarly small numbers, argue that this may be explained by the size of the model.[16]

4 Conclusion

This paper has proposed a methodology to identify factors within the framework of dynamic factor models. We impose an economic interpretation on the static factors through a set of over-identifying restrictions on the factor loadings. We modify the standard estimation methodology to incorporate these over-identifying loading restrictions. In particular, following Shumway & Stoffer (1982) and Wu et al. (1996), the appropriate parameter estimators and filters based on the EM algorithm are discussed.

In the empirical application the paper focuses on identifying a set of nine factors with economic interpretation. These factors represent key measures of the US economy such as inflation, unemployment, economic activity, consumption, state of the business cycle, residential investments, financial markets and monetary policy. The obtained factors are empirically plausible measures for each of the targeted key concepts, listed above. Subsequently, we use the model to assess the overall impact of monetary policy on the US economy. Our results are in line with those obtained using alternative methods on large panels, e.g. FAVARs or large BVARs.

[16] The larger the model, the more shocks can be identified and the smaller the likelihood of misspecification of the monetary policy shocks. In this model we identify nine structural shocks, which is significantly higher than the number of structural shocks identified by Bernanke et al. (2005).

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A Data description

Data are from Bernanke et al. (2005).

First column: A superscript indicates that an exactly identifying restriction has been imposed on this variable, i.e. 108[1] indicates that an identifying restriction has been imposed on this variable for the *first* factor. The second column is a mnemonic and a * indicates a "slow-moving" variable. Fourth column contains transformation codes. "level" indicates an un-transformed variable, say x_t. "ln" means $\ln x_t$ and "$\Delta \ln$" means $\ln x_t - \ln x_{t-1}$.

Real output and income

1	IPP*	1959:01–2001:08	$\Delta \ln$	Industrial production: products, total (1992 = 100,SA)
2	IPF*	1959:01–2001:08	$\Delta \ln$	Industrial production: final products (1992 = 100,SA)
3	IPC*	1959:01–2001:08	$\Delta \ln$	Industrial production: consumer goods (1992 = 100,SA)
4	IPCD*	1959:01–2001:08	$\Delta \ln$	Industrial production: durable cons. goods (1992 = 100,SA)
5	IPCN*	1959:01–2001:08	$\Delta \ln$	Industrial production: nondurable cons. goods (1992 = 100,SA)
6	IPE*	1959:01–2001:08	$\Delta \ln$	Industrial production: business equipment (1992 = 100,SA)
7	IPI*	1959:01–2001:08	$\Delta \ln$	Industrial production: intermediate products (1992 = 100,SA)
8	IPM*	1959:01–2001:08	$\Delta \ln$	Industrial production: materials (1992 = 100,SA)
9	IPMD*	1959:01–2001:08	$\Delta \ln$	Industrial production: durable goods materials (1992 = 100,SA)
10	IPMND*	1959:01–2001:08	$\Delta \ln$	Industrial production: nondur. goods materials (1992 = 100,SA)
11	IPMFG*	1959:01–2001:08	$\Delta \ln$	Industrial production: manufacturing (1992 = 100,SA)
12	IPD*	1959:01–2001:08	$\Delta \ln$	Industrial production: durable manufacturing (1992 = 100,SA)
13	IPN*	1959:01–2001:08	$\Delta \ln$	Industrial production: nondur. manufacturing (1992 = 100,SA)
14	IPMIN*	1959:01–2001:08	$\Delta \ln$	Industrial production: mining (1992 = 100,SA)
15	IPUT*	1959:01–2001:08	$\Delta \ln$	Industrial production: utilities (1992 = 100,SA)
16[3]	IP*	1959:01–2001:08	$\Delta \ln$	Industrial production: total index (1992 = 100,SA)
17	IPXMCA*	1959:01–2001:08	level	Capacity util rate: manufac., total (% of capacity,SA) (frb)
18	PMI*	1959:01–2001:08	level	Purchasing managers' index (SA)
19	PMP*	1959:01–2001:08	level	NAPM production index (percent)
20	GMPYQ*	1959:01–2001:08	$\Delta \ln$	Personal income (chained) (series #52) (bil 92$,SAAR)
21	GMYXPQ*	1959:01–2001:08	$\Delta \ln$	Personal inc. less trans. payments (chained) (#51) (bil 92$,SAAR)

(Un)employment and hours

22	LHEL*	1959:01–2001:08	Δ ln	Index of help-wanted advertising in newspapers (1967 = 100;SA)
23	LHELX*	1959:01–2001:08	ln	Employment: ratio; help-wanted ads: no. unemployed clf
24	LHEM*	1959:01–2001:08	Δ ln	Civilian labor force: employed, total (thous.,SA)
25	LHNAG*	1959:01–2001:08	Δ ln	Civilian labor force: employed, nonag. industries (thous.,SA)
26[2]	LHUR*	1959:01–2001:08	level	Unemployment rate: all workers, 16 years and over (%,SA)
27	LHU680*	1959:01–2001:08	level	Unemploy. by duration: average (mean) duration in weeks (SA)
28	LHU5*	1959:01–2001:08	level	Unemploy. by duration: pers unempl. less than 5 wks (thous.,SA)
29	LHU14*	1959:01–2001:08	level	Unemploy. by duration: pers unempl. 5 to 14 wks (thous.,SA)
30	LHU15*	1959:01–2001:08	level	Unemploy. by duration: pers unempl. 15 wks = (thous.,SA)
31	LHU26*	1959:01–2001:08	level	Unemploy. by duration: pers unempl. 15 to 26 wks (thous.,SA)
32	LPNAG*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: total (thous.,SA)
33	LP*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: total, private (thous.,SA)
34	LPGD*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: goods-producing (thous.,SA)
35	LPMI*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: mining (thous.,SA)
36	LPCC*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: contract construc. (thous.,SA)
37	LPEM*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: manufacturing (thous.,SA)
38	LPED*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: durable goods (thous.,SA)
39	LPEN*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: nondurable goods (thous.,SA)
40	LPSP*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: service-producing (thous.,SA)
41	LPTU*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: trans. and public util. (thous.,SA)
42	LPT*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: wholesale and retail (thous.,SA)
43	LPFR*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: finance, ins. and real est (thous.,SA)
44	LPS*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: services (thous.,SA)
45	LPGOV*	1959:01–2001:08	Δ ln	Employees on nonag. payrolls: government (thous.,SA)
46	LPHRM*	1959:01–2001:08	level	Avg. weekly hrs. of production wkrs.: manufacturing (sa)
47[5]	LPMOSA*	1959:01–2001:08	level	Avg. weekly hrs. of prod. wkrs.: mfg., overtime hrs. (sa)
48	PMEMP*	1959:01–2001:08	level	NAPM employment index (percent)

Consumption

49[4]	GMCQ*	1959:01–2001:08	Δ ln	Pers cons exp (chained)—total (bil 92$,SAAR)
50	GMCDQ*	1959:01–2001:08	Δ ln	Pers cons exp (chained)—tot. dur. (bil 96$,SAAR)
51	GMCNQ*	1959:01–2001:08	Δ ln	Pers cons exp (chained)—nondur. (bil 92$,SAAR)
52	GMCSQ*	1959:01–2001:08	Δ ln	Pers cons exp (chained)—services (bil 92$,SAAR)
53	GMCANQ*	1959:01–2001:08	Δ ln	Personal cons expend (chained)—new cars (bil 96$,SAAR)

Housing starts and sales

54[6]	HSFR	1959:01–2001:08	ln	Housing starts: nonfarm (1947–1958); tot. (
55	HSNE	1959:01–2001:08	ln	Housing starts: northeast (thous.u.)s.a.
56	HSMW	1959:01–2001:08	ln	Housing starts: midwest (thous.u.)s.a.
57	HSSOU	1959:01–2001:08	ln	Housing starts: south (thous.u.)s.a.
58	HSWST	1959:01–2001:08	ln	Housing starts: west (thous.u.)s.a.
59	HSBR	1959:01–2001:08	ln	Housing authorized: total new priv housing (thous.,SAAR)
60	HMOB	1959:01–2001:08	ln	Mobile homes: manufacturers' shipments (thous. of units,SAAR)

Real inventories, ordes and unfilled orders

61	MNV	1959:01–2001:08	level	NAPM inventories index (percent)
62	PMNO	1959:01–2001:08	level	NAPM new orders index (percent)
63	PMDEL	1959:01–2001:08	level	NAPM vendor deliveries index (percent)
64	MOCMQ	1959:01–2001:08	$\Delta \ln$	New orders (net)—consumer goods and materials, 1992 $ (bci)
65	MSONDQ	1959:01–2001:08	$\Delta \ln$	New orders, nondefense capital goods, in 1992 $s (bci)

Stock prices

66[9]	FSNCOM	1959:01–2001:08	$\Delta \ln$	NYSE composite (12/31/65 = 50)
67	FSPCOM	1959:01–2001:08	$\Delta \ln$	S&P's composite (1941–1943 = 10)
68	FSPIN	1959:01–2001:08	$\Delta \ln$	S&P's industrials (1941–1943 = 10)
69	FSPCAP	1959:01–2001:08	$\Delta \ln$	S&P's capital goods (1941–1943 = 10)
70	FSPUT	1959:01–2001:08	$\Delta \ln$	S&P's utilities (1941–1943 = 10)
71	FSDXP	1959:01–2001:08	level	S&P's composite common stock: dividend yield (% per annum)
72	FSPXE	1959:01–2001:08	level	S&P's composite common stock: price-earnings ratio (%,NSA)

Foreign exchange rates

73	EXRSW	1959:01–2001:08	$\Delta \ln$	Foreign exchange rate: Switzerland (swiss franc per US$)
74	EXRJAN	1959:01–2001:08	$\Delta \ln$	Foreign exchange rate: Japan (yen per US$)
75	EXRUK	1959:01–2001:08	$\Delta \ln$	Foreign exchange rate: United Kingdom (cents per pound)
76	EXRCAN	1959:01–2001:08	$\Delta \ln$	Foreign exchange rate: Canada (canadian $ per US$)

Interest rates and spreads

77[8]	FYFF	1959:01–2001:08	level	Interest rate: federal funds (effective) (% per annum,nsa)
78	FYGM3	1959:01–2001:08	level	Interest rate: us tbill,sec mkt,3-mo. (% per ann,nsa)
79	FYGM6	1959:01–2001:08	level	Interest rate: us tbill,sec mkt,6-mo. (% per ann,nsa)
80	FYGT1	1959:01–2001:08	level	Interest rate: ust const matur., 1-yr. (% per ann,nsa)
81	FYGT5	1959:01–2001:08	level	Interest rate: ust const matur., 5-yr. (% per ann,nsa)
82	FYGT10	1959:01–2001:08	level	Interest rate: ust const matur., 10-yr. (% per ann,nsa)
83	FYAAAC	1959:01–2001:08	level	Bond yield: moody's aaa corporate (% per annum)
84	FYBAAC	1959:01–2001:08	level	Bond yield: moody's baa corporate (% per annum)
85	SFYGM3	1959:01–2001:08	level	Spread fygM3—fyff
86	SFYGM6	1959:01–2001:08	level	Spread fygm6—fyff
87	SFYGT1	1959:01–2001:08	level	Spread fygt1—fyff
88	SFYGT5	1959:01–2001:08	level	Spread fygt5—fyff
89	SFYGT10	1959:01–2001:08	level	Spread fygt10—fyff
90	SFYAAAC	1959:01–2001:08	level	Spread fyaaac—fyff
91	SFYBAAC	1959:01–2001:08	level	Spread fybaac—fyff

Money and credit quantity aggregates

92	FM1	1959:01–2001:08	$\Delta \ln$	Money stock: M1 (bil$,SA)
93	FM2	1959:01–2001:08	$\Delta \ln$	Money stock: M2 (bil$,SA)
94	FM3	1959:01–2001:08	$\Delta \ln$	Money stock: M3 (bil$,SA)
95	FM2DQ	1959:01–2001:08	$\Delta \ln$	Money supply—M2 in 1992 $s (bci)
96	FMFBA	1959:01–2001:08	$\Delta \ln$	Monetary base, adj for reserve requirement changes (mil$,SA)
97	FMRRA	1959:01–2001:08	$\Delta \ln$	Depository inst reserves: total, adj for res. req chgs (mil$,SA)
98	FMRNBA	1959:01–2001:08	$\Delta \ln$	Depository inst reserves: nonbor., adj res req chgs (mil$,SA)
99	FCLNQ	1959:01–2001:08	$\Delta \ln$	Commercial and indust. loans outstanding in 1992 $s (bci)
100	FCLBMC	1959:01–2001:08	level	Wkly rp lg com. banks: net change com and ind. loans (bil$,SAAR)
101	CCINRV	1959:01–2001:08	$\Delta \ln$	Consumer credit outstanding nonrevolving g19

Price indexes

102[7]	PMCP	1959:01–2001:08	level	NAPM commodity prices index (%)
103	PWFSA*	1959:01–2001:08	$\Delta \ln$	PPI: finished goods (82 = 100,SA)
104	PWFCSA*	1959:01–2001:08	$\Delta \ln$	PPI: finished consumer goods (82 = 100,SA)
105	PWIMSA*	1959:01–2001:08	$\Delta \ln$	PPI: intermed mat. sup and components (82 = 100,SA)
106	PWCMSA*	1959:01–2001:08	$\Delta \ln$	PPI: crude materials (82 = 100,SA)
107	PSM99Q*	1959:01–2001:08	$\Delta \ln$	Index of sensitive materials prices (1990 = 100) (bci-99a)
108[1]	PUNEW*	1959:01–2001:08	$\Delta \ln$	CPI-u: all items (82–84 = 100,SA)
109	PU83*	1959:01–2001:08	$\Delta \ln$	CPI-u: apparel and upkeep (82–84 = 100,SA)
110	PU84*	1959:01–2001:08	$\Delta \ln$	CPI-u: transportation (82–84 = 100,SA)
111	PU85*	1959:01–2001:08	$\Delta \ln$	CPI-u: medical care (82–84 = 100,SA)
112	PUC*	1959:01–2001:08	$\Delta \ln$	CPI-u: commodities (82–84 = 100,SA)
113	PUCD*	1959:01–2001:08	$\Delta \ln$	CPI-u: durables (82–84 = 100,SA)
114	PUS*	1959:01–2001:08	$\Delta \ln$	CPI-u: services (82–84 = 100,SA)
115	PUXF*	1959:01–2001:08	$\Delta \ln$	CPI-u: all items less food (82–84 = 100,SA)
116	PUXHS*	1959:01–2001:08	$\Delta \ln$	CPI-u: all items less shelter (82–84 = 100,SA)
117	PUXM*	1959:01–2001:08	$\Delta \ln$	CPI-u: all items less medical care (82– 84 = 100,SA)

Average hourly earnings

118	LEHCC*	1959:01–2001:08	$\Delta \ln$	Avg hr earnings of constr wkrs: construction ($,SA)
119	LEHM*	1959:01–2001:08	$\Delta \ln$	Avg hr earnings of prod wkrs: manufacturing ($,SA)

Miscellaneous

120	HHSNTN	1959:01–2001:08	level	U. of mich. index of consumer

B Over-identifying loading restrictions

The specific set of (over-) identifying restrictions can be summarized as follows; the *inflation factor* (π) is identified by the unbiasedness restriction on CPI-u all items. Additionally, we allow other inflation measures to load on the inflation factor. With the inflation factor being a nominal factor, we exclude from the information set all real variables, e.g. industrial production.

For the four real factors we impose exclusion restrictions on nominal variables (e.g. CPI inflation). Additional exclusion restrictions limit the type of real variables acting as information variables for each of the factors. In particular, the *unemployment factor* (u_n) is identified by the unbiasedness restriction on 'Unemployment all workers'. Other (un)employment variables and measures of payroll statistics and capacity utilization are included as additional information variables. All other slow-moving variables are excluded from the information set. The *economic activity factor* (y), identified by the unbiasedness restriction on the Industrial Production (IP) total index series, uses IP variables next to employment and payroll series as additional state variables. The *hours in production factor* (hrs) measures the current over (under) production and is identified (by means of an unbiasedness restriction) through the overtime hours in production and manufacturing. As additional information variables we include variables such as capacity utilization rate, survey-based production indices (PMI, PMP) and help-wanted advertising to enter freely. We exclude (un)employment and IP growth as we consider them less informative with respect to the level of over and underproduction. The last real factor, i.e. the *consumption factor* (c) , is filtered from the observed consumption series in the panel with an unbiasedness restriction on 'Personal Consumption Expenditure' series and one-to-one restrictions on two consumption observables. Moreover, due to consumption smoothing, we do not expect strong contemporaneous correlations between production employment based statistics and consumption (growth). Therefore, we impose exclusion restrictions on production related variables.

The information and the policy factors measure particular features in the economy. More precisely, the *housing factor* (h) is included as a residential investment factor. This factor is identified through an unbiasedness restriction on the total number of housing starts and uses as additional information variables other housing starts or authorization variables. We consider the housing factor to be mainly a forward-looking variable containing all relevant information. As such, exclusion restrictions are imposed on all slow-moving variables. The *commodity price factor* ($pcom$) aims at measuring cost-push factors due to price increases of raw materials or intermediate products. It is identified by means of the NAPM commodity price index. Moreover, the commodity price factor retrieves additional information from PPI data for crude and intermediate materials and from the index of sensitive materials. The *monetary policy factor* (i) is directly measured by the effective federal funds rate. Finally, the *stock market factor* (s) is related to returns on the NYSE index and uses S&P500 stock market component indices as additional state variables. We allow all other fast-moving variables to load freely on the stock market factor allowing for direct interactions across financial markets.

Table 1: Loading restrictions.

Variable Names	π	u_n	y	c	hrs	h	$pcom$	i	s
1) IP: products, total	0	0	x	0	0	0	0	x	0
2) IP: final products	0	0	x	0	0	0	0	x	0
3) IP: consumer	0	0	x	0	0	0	0	x	0
4) IP: durable cons.	0	0	x	0	0	0	0	x	0
5) IP: nondur. cons.	0	0	x	0	0	0	0	x	0
6) IP: bus. Equip	0	0	x	0	0	0	0	x	0
7) IP: intermediate	0	0	x	0	0	0	0	x	0
8) IP: materials	0	0	x	0	0	0	0	x	0
9) IP: durable goods	0	0	x	0	0	0	0	x	0
10) IP: nondur. goods	0	0	x	0	0	0	0	x	0
11) IP: manufacturing	0	0	x	0	0	0	0	x	0
12) IP: dur. manuf	0	0	x	0	0	0	0	x	0
13) IP: nondur. manuf.	0	0	x	0	0	0	0	x	0
14) IP: mining	0	0	x	0	0	0	0	x	0
15) IP: utilities	0	0	x	0	0	0	0	x	0
16) IP: total index	0	0	1	0	0	0	0	0	0
17) Capacity util rate	0	x	x	0	x	0	0	x	0
18) Pmi	0	0	x	0	x	0	0	x	0
19) NAPM prod.	0	0	x	0	x	0	0	x	0
20) Pers. Income	0	0	x	0	0	0	0	x	0
21) Pers. Inc. - trans.	0	0	x	0	0	0	0	x	0
22) Help-wated	0	x	x	0	x	0	0	x	0
23) Empl. Help-wanted	0	x	x	0	x	0	0	x	0
24) Civ. Labor: empl.,	0	x	x	0	0	0	0	x	0
25) Civilian labor: empl.,	0	x	x	0	0	0	0	x	0
26) Unempl. Rate: all wrks	0	1	0	0	0	0	0	0	0
27) Unemp dur: mean	0	x	x	0	0	0	0	x	0
28) Unemp dur. < 5 w.	0	x	x	0	0	0	0	x	0
29) Unemp dur. 5-14 w	0	x	x	0	0	0	0	x	0
30) Unemp dur. 15+ w	0	x	x	0	0	0	0	x	0
31) Unemp dur. 15-26 w	0	x	x	0	0	0	0	x	0
32) Nonag payrl.: total	0	x	x	0	0	0	0	x	0
33) Nonag payrl.: total,	0	x	x	0	0	0	0	x	0
34) Nonag payrl.: goods	0	x	x	0	0	0	0	x	0
35) Nonag payrl.: mining	0	x	x	0	0	0	0	x	0
36) Nonag payrl.: contract	0	x	x	0	0	0	0	x	0
37) Nonag payrl.: manuf	0	x	x	0	0	0	0	x	0
38) Nonag payrl.: durable	0	x	x	0	0	0	0	x	0
39) Nonag payrl.: nondur	0	x	x	0	0	0	0	x	0
40) Nonag payrl.: service	0	x	x	0	0	0	0	x	0
41) Nonag payrl.: trans.	0	x	x	0	0	0	0	x	0
42) Nonag payrl.: sale	0	x	x	0	0	0	0	x	0
43) Nonag payrl.: finance	0	x	x	0	0	0	0	x	0
44) Nonag payrl.: services	0	x	x	0	0	0	0	x	0
45) Nonag payrl.: gov.	0	x	x	0	0	0	0	x	0
46) Avg. Wkly hrs. prod	0	0	0	0	u	0	0	x	0
47) Avg. Wkly overtime prod	0	0	0	0	1	0	0	0	0
48) NAPM Empl. Index	0	x	x	0	0	0	0	x	0
49) Pers cons exp: total	0	0	0	1	0	0	0	0	0
50) Pers cons exp: tot.	0	0	0	1	0	0	0	x	0
51) Pers cons exp: nondur.	0	0	0	1	0	0	0	x	0
52) Pers cons exp: services	0	0	0	x	0	0	0	x	0
53) Pers cons exp: new cars	0	0	0	x	0	0	0	x	0
54) Housing starts: nonfarm	0	0	0	0	0	1	0	0	0
55) Housing starts: N.E	0	x	x	0	0	x	0	x	0
56) Housing starts: M.W	0	x	x	0	0	x	0	x	0
57) Housing starts: S	0	x	x	0	0	x	0	x	0
58) Housing starts: S	0	x	x	0	0	x	0	x	0
59) Housing auth. Tot new	0	x	x	0	0	x	0	x	0
60) Mobile homes	0	x	x	0	0	x	0	x	0

The factors are denoted by the symbols $\{\pi, u_n, y, c, hrs, h, pcom, i, s\}$ and describe general inflation, unemployment, economic activity (growth), consumption growth, hours in production, residential investments, commodity price inflation, federal funds rate and stock markets returns respectively. x denotes a free factor loading that is estimated. Shading areas cover loadings that are fixed with unbiasedness restrictions.

Table 1 continued

Variable Names	π	u_n	y	c	hrs	h	$pcom$	i	s
61) NAPM inventories	x	x	x	x	x	x	x	x	x
62) NAPM new orders	x	x	x	x	x	x	x	x	x
63) NAPM vendor deliv.	x	x	x	x	x	x	x	x	x
64) New orders: cons goods	x	x	x	x	x	x	x	x	x
65) New orders: nondefense	x	x	x	x	x	x	x	x	x
66) NYSE: composite	0	0	0	0	0	0	0	0	1
67) SP500 composite	0	0	0	0	0	0	0	x	x
68) SP500 industrials	0	0	0	0	0	0	0	x	x
69) SP500 capital	0	0	0	0	0	0	0	x	x
70) SP500 utilities	0	0	0	0	0	0	0	x	x
71) SP500: dividend	x	x	x	x	x	x	x	x	x
72) SP500: price earnings	x	x	x	x	x	x	x	x	x
73) FX : Switzerland	x	x	x	x	x	x	x	x	x
74) FX : Japan	x	x	x	x	x	x	x	x	x
75) FX : U.K	x	x	x	x	x	x	x	x	x
76) FX : Canada	x	x	x	x	x	x	x	x	x
77) Federal funds	0	0	0	0	0	0	0	1	0
78) US Tbill, 3m.	x	x	x	x	x	x	x	x	x
79) US Tbill, 6m.	x	x	x	x	x	x	x	x	x
80) Tbond const 1yr.	x	x	x	x	x	x	x	x	x
81) Tbond const 5yr.	x	x	x	x	x	x	x	x	x
82) Tbond const 10yr.	x	x	x	x	x	x	x	x	x
83) Bond yield: Moody AAA	x	x	x	x	x	x	x	x	x
84) Bond yield: Moody BAA	x	x	x	x	x	x	x	x	x
85) Spread 3m – fed funds	x	x	x	x	x	x	x	x	x
86) Spread 6m – fed funds	x	x	x	x	x	x	x	x	x
87) Spread 1y – fed funds	x	x	x	x	x	x	x	x	x
88) Spread 5y – fed funds	x	x	x	x	x	x	x	x	x
89) Spread 10y – fed funds	x	x	x	x	x	x	x	x	x
90) Spread AAA – fed funds	x	x	x	x	x	x	x	x	x
91) Spread BAA – fed funds	x	x	x	x	x	x	x	x	x
92) Money stock: M1	x	x	x	x	x	x	x	x	x
93) Money stock: M2	x	x	x	x	x	x	x	x	x
94) Money stock: M3	x	x	x	x	x	x	x	x	x
95) Money supply—M2 1992	x	x	x	x	x	x	x	x	x
96) Monetary base	x	x	x	x	x	x	x	x	x
97) Depository inst reserves	x	x	x	x	x	x	x	x	x
98) Dep. Inst. Res. Nonbor.	x	x	x	x	x	x	x	x	x
99) Comm. and indust. Loans	x	x	x	x	x	x	x	x	x
100) Wkly rp lg com.	x	x	x	x	x	x	x	x	x
101) Cons credit outst.	x	x	x	x	x	x	x	x	x
102) NAPM commodity prices	0	0	0	0	0	0	1	0	0
103) PPI: finished	x	0	0	0	0	0	x	x	0
104) PPI: finished	x	0	0	0	0	0	x	x	0
105) PPI: intermed	0	0	0	0	0	0	x	x	0
106) PPI: crude	0	0	0	0	0	0	x	x	0
107) Index of sensitive mat.	0	0	0	0	0	0	x	x	0
108) CPI-U: all items	1	0	0	0	0	0	0	0	0
109) CPI-U: apparel, upkeep	x	0	0	0	0	0	0	x	0
110) CPI-U: transportation	x	0	0	0	0	0	0	x	0
111) CPI-U: medical care	x	0	0	0	0	0	0	x	0
112) CPI-U: commodities	x	0	0	0	0	0	x	x	0
113) CPI-U: durables	x	0	0	0	0	0	0	x	0
114) CPI-U: services	x	0	0	0	0	0	0	x	0
115) CPI-U: less food	x	0	0	0	0	0	0	x	0
116) CPI-U: less shelter	x	0	0	0	0	0	0	x	0
117) CPI-U: less medical	x	0	0	0	0	0	0	x	0
118) Avg hr earnings constr.	x	x	x	x	x	x	0	x	x
119) Avg hr earnings manuf.	x	x	x	x	x	x	0	x	x
120) Consumer expec. (Mich.)	x	x	x	x	x	x	x	x	x

The factors are denoted by the symbols $\{\pi, u_n, y, c, hrs, h, pcom, i, s\}$ and describe general inflation, unemployment, economic activity (growth), consumption growth, hours in production, residential investments, commodity price inflation, federal funds rate and stock markets returns respectively. x denotes a free factor loading that is estimated. Shading areas cover loadings that are fixed with unbiasedness restrictions.

Table 2: Model Performance.

	R^2	AIC	BIC	IC^*_{p2}	$Log\ Lik$	p-value for $LR\ test$
Exactly Identified Model	57.0	1.449	1.684	-0.565	-42821	–
Our (Restricted) Model	53.2	1.518	1.685	-0.475	-45413	0.0002

R^2 is a simple average of the R-squared of the 120 series; AIC denotes Akaike Information Criterion; BIC is Bayesian Information Criterion; IC^*_{p2} is a modified version of the Bai & Ng (2002) IC_{p2} information criterion; and $Log\ Lik$ is the Log-Likelihood value.

Table 3: Estimated factor loadings.

Variable Names	π	u_n	y	c	hrs	h	$pcom$	i	s	R^2
1) IP: products, total			**0.92**					−0.01		80.0
2) IP: final products			**0.87**					0.01		71.0
3) IP: consumer			**0.75**					−0.02		53.8
4) IP: durable cons.			**0.72**					0.00		47.8
5) IP: nondur. cons.			**0.43**					−0.04		17.8
6) IP: bus. Equip			**0.71**					0.01		47.4
7) IP: intermediate			**0.73**					−0.05		51.6
8) IP: materials			**0.87**					0.01		76.9
9) IP: durable goods			**0.87**					0.04		75.2
10) IP: nondur. goods			**0.40**					−0.04		16.1
11) IP: manufacturing			**1.01**					0.01		97.5
12) IP: dur. manuf			**0.97**					0.02		91.1
13) IP: nondur. manuf.			**0.70**					−0.04		47.4
14) IP: mining			**0.23**					0.03		5.1
15) IP: utilities			**0.12**					**−0.07**		2.1
16) IP: total index			1							96.5
17) Capacity util rate		**−0.74**	**0.16**		**0.25**			**0.19**		73.2
18) Pmi			**0.50**		**0.24**			**−0.11**		37.7
19) NAPM prod.			**0.54**		**0.14**			**−0.20**		42.1
20) Pers. Income			**0.31**					−0.05		10.0
21) Pers. Inc. - trans.			**0.54**					−0.05		28.6
22) Help-wated		0.03	**0.44**		−0.01			**−0.13**		21.6
23) Empl. Help-wanted		**−0.71**	0.01		**0.31**			**0.33**		68.2
24) Civ. Labor: empl..		−0.06	**0.39**					0.04		14.6
25) Civilian labor: empl.,		**−0.10**	**0.43**					0.03		18.0
26) Unempl. Rate: all wrks		1								73.1
27) Unemp dur: mean		**0.62**	**0.22**					**−0.29**		43.3
28) Unemp dur. < 5 w.		**0.71**	−0.04					**0.28**		75.8
29) Unemp dur. 5-14 w		**0.79**	−0.02					**0.11**		73.8
30) Unemp dur. 15+ w		**0.80**	**0.13**					**−0.06**		66.7
31) Unemp dur. 15-26 w		**0.82**	0.06					−0.01		70.9
32) Nonag payrl.: total		**−0.21**	**0.73**					**0.05**		55.3
33) Nonag payrl.: total,		**−0.16**	**0.76**					**0.08**		56.4
34) Nonag payrl.: goods		**−0.18**	**0.81**					**0.05**		65.4
35) Nonag payrl.: mining		**−0.11**	**0.18**					**0.17**		5.1
36) Nonag payrl.: contract		−0.04	**0.36**					−0.04		13.5
37) Nonag payrl.: manuf		**−0.18**	**0.81**					0.05		65, 9
38) Nonag payrl.: durable		**−0.18**	**0.80**					**0.07**		63, 6
39) Nonag payrl.: nondur		**−0.11**	**0.56**					−0.03		32, 9
40) Nonag payrl.: service		**−0.24**	**0.38**					0.03		20.4
41) Nonag payrl.: trans.		**−0.07**	**0.14**					0.04		2.3
42) Nonag payrl.: sale		**−0.12**	**0.42**					0.04		18, 6
43) Nonag payrl.: finance		**−0.19**	**0.21**					**0.11**		7.6
44) Nonag payrl.: services		**−0.15**	**0.33**					**0.10**		12.1
45) Nonag payrl.: gov.		**−0.25**	−0.02					**−0.13**		10.1
46) Avg. Wkly hrs. prod					**0.97**			**−0.15**		87.8
47) Avg. Wkly overtime prod					1					93.1
48) NAPM Empl. Index		**−0.53**	**0.48**					0.07		52.9
49) Pers cons exp: total				1						67.1
50) Pers cons exp: tot.				1				0.05		94.5
51) Pers cons exp: nondur.				1				**0.07**		11.4
52) Pers cons exp: services				**0.16**				**−0.09**		3.4
53) Pers cons exp: new cars				**1.04**				**0.10**		85.2
54) Housing starts: nonfarm						1				92.6
55) Housing starts: N.E						**0.48**		**−0.21**		29.8
56) Housing starts: M.W						**0.57**		**−0.38**		51.2
57) Housing starts: S						**0.94**		**0.27**		85.7
58) Housing starts: S						**0.85**		0.00		69.8
59) Housing auth. Tot new						**1.00**		0.06		95.1
60) Mobile homes						**0.61**		**0.32**		42.1

The factors are denoted by the symbols $\{\pi, u_n, y, c, hrs, h, pcom, i, s\}$ and describe general inflation, unemployment, economic activity (growth), consumption growth, hours in production, residential investments, commodity price inflation, federal funds rate and stock markets returns respectively. R^2 denotes R-squared. Coefficients in bold are statistically significant at the 5% level (the standard errors are two-sided finite difference approximations of the gradient of the likelihood function.

Table 3 continued

Variable Names	π	u_n	y	c	hrs	h	$pcom$	i	s	R^2
61) NAPM inventories	0.06	**−0.39**	**0.08**	0.00	0.01	**0.27**	**0.16**	0.04	−0.05	45.6
62) NAPM new orders	**−0.09**	**0.08**	**0.39**	−0.01	0.07	**0.26**	**0.30**	**−0.29**	0.00	60.8
63) NAPM vendor deliv.	0.04	**−0.29**	**0.15**	−0.01	**0.26**	**0.21**	**0.15**	**0.14**	**−0.09**	46.2
64) New orders: cons goods	0.00	0.08	**0.50**	**0.13**	−0.06	0.00	−0.01	**−0.07**	0.07	29.3
65) New orders: nondefense	0.04	0.01	0.06	**0.12**	0.03	0.03	0.03	−0.05	0.00	2.7
66) NYSE: composite									1	97.6
67) SP500 composite								0.00	**1.01**	100.0
68) SP500 industrials								0.00	**1.00**	98.7
69) SP500 capital								−0.02	**0.92**	83.0
70) SP500 utilities								0.01	**0.61**	36.4
71) SP500: dividend	**0.08**	**0.30**	−0.02	0.00	**−0.49**	**−0.09**	**0.32**	**0.31**	−0.03	80.7
72) SP500: price earnings	−0.06	**−0.17**	0.01	−0.01	**0.48**	0.05	**−0.30**	**−0.37**	0.00	69.8
73) FX : Switzerland	**−0.08**	−0.02	**0.17**	**0.08**	0.06	**−0.19**	**0.08**	**0.14**	**0.07**	6.0
74) FX : Japan	**−0.12**	**−0.13**	**0.09**	0.00	0.01	**−0.18**	0.06	**0.19**	−0.04	6.1
75) FX : U.K	**0.10**	−0.03	**−0.16**	−0.05	0.03	**0.13**	−0.01	**−0.15**	0.01	4.7
76) FX : Canada	−0.01	0.07	**0.13**	0.04	−0.01	−0.04	0.01	−0.02	**−0.24**	6.9
77) Federal funds								1		100.0
78) US Tbill. 3m.	**−0.06**	**0.12**	0.02	−0.01	0.03	−0.03	**0.12**	**0.96**	0.01	98, 2
79) US Tbill. 6m.	**−0.08**	**0.16**	0.01	−0.01	0.03	−0.03	**0.17**	**0.94**	0.00	98.7
80) Tbond const 1yr.	**−0.12**	**0.24**	0.01	−0.02	0.04	−0.04	**0.23**	**0.91**	0.00	99.0
81) Tbond const 5yr.	**−0.17**	**0.54**	−0.02	−0.02	**0.10**	−0.02	**0.28**	**0.76**	−0.01	100.0
82) Tbond const 10yr.	**−0.14**	**0.62**	−0.02	−0.02	**0.13**	0.00	**0.26**	**0.69**	−0.01	99.7
83) Bond yield: Moody AAA	**−0.06**	**0.65**	**−0.05**	−0.02	**0.19**	**0.07**	**0.12**	**0.65**	−0.02	100.0
84) Bond yield: Moody BAA	**−0.06**	**0.65**	**−0.05**	−0.01	**0.11**	**0.08**	**0.10**	**0.64**	0.00	99.7
85) Spread 3m − fed funds	**−0.21**	**0.38**	**0.07**	**−0.03**	**0.10**	**−0.09**	**0.39**	**−0.88**	**0.04**	80.5
86) Spread 6m − fed funds	**−0.24**	**0.47**	**0.04**	**−0.03**	**0.08**	**−0.09**	**0.50**	**−0.92**	0.01	88.7
87) Spread 1y − fed funds	**−0.38**	**0.75**	**0.02**	**−0.05**	**0.11**	**−0.12**	**0.70**	**−0.79**	0.01	90.4
88) Spread 5y − fed funds	**−0.29**	**0.93**	−0.03	−0.04	**0.18**	−0.04	**0.49**	**−0.85**	−0.01	100.0
89) Spread 10y − fed funds	**−0.21**	**0.93**	**−0.03**	**−0.03**	**0.19**	0.00	**0.40**	**−0.87**	−0.01	99.3
90) Spread AAA − fed funds	**−0.09**	**0.91**	**−0.07**	−0.02	**0.26**	**0.10**	**0.17**	**−0.85**	−0.02	100.0
91) Spread BAA − fed funds	**−0.09**	**1.00**	**−0.08**	**−0.02**	**0.17**	**0.12**	**0.15**	**−0.72**	−0.01	99.3
92) Money stock: M1	**0.17**	**0.31**	−0.05	**0.08**	**−0.21**	**0.29**	**−0.08**	**−0.13**	0.05	23.0
93) Money stock: M2	0.02	0.03	0.00	0.03	**−0.59**	**0.51**	**−0.14**	0.02	0.04	39.7
94) Money stock: M3	0.03	**−0.12**	−0.04	0.06	**−0.44**	**0.59**	−0.07	**0.18**	0.06	36.6
95) Money supply—M2 1992	**−0.53**	−0.01	0.02	0.03	**−0.44**	**0.40**	**−0.13**	0.00	0.04	53.7
96) Monetary base	**0.25**	**0.25**	−0.04	0.01	**0.14**	**0.23**	**−0.13**	−0.05	0.02	15.3
97) Depository inst reserves	0.04	**0.16**	0.02	−0.06	**−0.21**	**0.17**	**−0.09**	−0.05	0.00	9.7
98) Dep. Inst. Res. Nonbor.	**0.10**	**0.07**	**−0.15**	−0.01	**−0.16**	**0.07**	**−0.18**	**−0.09**	0.06	11.5
99) Comm. and indust. Loans	**−0.24**	**−0.22**	0.03	0.03	**0.19**	**−0.08**	**0.23**	**0.31**	0.02	20.5
100) Wkly rp lg com.	**−0.13**	0.02	0.03	−0.02	**0.34**	**−0.06**	**0.22**	**0.23**	**0.10**	15.9
101) Cons credit outst.	**−0.21**	−0.06	0.02	0.05	**−0.09**	**0.36**	**0.29**	**0.08**	−0.03	30.1
102) NAPM commodity prices							1			39.0
103) PPI: finished	**0.79**						0.03	**−0.12**		52.8
104) PPI: finished	**0.76**						0.05	**−0.17**		47.4
105) PPI: intermed							**0.28**	**0.23**		18.6
106) PPI: crude							**0.20**	−0.01		5.2
107) Index of sensitive mat.							**0.33**	**−0.14**		13.8
108) CPI-U: all items	1									95.7
109) CPI-U: apparel. upkeep	**0.44**							−0.02		17.7
110) CPI-U: transportation	**0.85**							**−0.20**		53.3
111) CPI-U: medical care	**0.23**							**0.41**		33.2
112) CPI-U: commodities	**1.02**						0.06	**−0.21**		86.1
113) CPI-U: durables	**0.58**							**0.11**		40.5
114) CPI-U: services	**0.51**							**0.33**		55.8
115) CPI-U: less food	**0.85**							**0.10**		79.8
116) CPI-U: less shelter	**1.01**							**−0.09**		88.3
117) CPI-U: less medical	**1.00**							−0.02		93.7
118) Avg hr earnings constr.	**0.10**	**−0.15**	**−0.13**	0.07	**−0.12**	0.04		0.07	−0.03	6.8
119) Avg hr earnings manuf.	**0.30**	−0.04	**0.31**	−0.03	**−0.21**	0.03		**0.11**	0.00	23.5
120) Consumer expec. (Mich.)	**−0.67**	**−0.23**	**0.12**	0.00	**0.11**	0.03	**0.23**	**−0.12**	0.02	67.7

The factors are denoted by the symbols $\{\pi, u_n, y, c, hrs, h, pcom, i, s\}$ and describe general inflation, unemployment, economic activity (growth), consumption growth, hours in production, residential investments, commodity price inflation, federal funds rate and stock markets returns respectively. R^2 denotes R-squared. Coefficients in bold are statistically significant at the 5% level (the standard errors are two-sided finite difference approximations of the gradient of the likelihood function.

Table 4: Forecast error variance due to monetary policy shocks.

Average (all variables)	π	u_n	y	c	hrs	h	$pcom$	i	s	*total*	*Idio.*
6 month	0.03	0.05	0.06	0.03	0.07	0.04	0.04	**0.05**	0.04	0.41	0.59
12 month	0.04	0.05	0.06	0.03	0.09	0.06	0.04	**0.05**	0.05	0.46	0.54
24 month	0.04	0.05	0.06	0.03	0.10	0.08	0.03	**0.05**	0.06	0.50	0.50
60 month	0.06	0.05	0.06	0.03	0.10	0.11	0.03	**0.04**	0.06	0.53	0.47

12 month horizon	π	u_n	y	c	hrs	h	$pcom$	i	s	*total*	*Idio.*
77) Federal funds rate	0.02	0.06	0.06	0.03	0.41	0.15	0.04	**0.16**	0.08	1.00	0.00
16) IP: totalindex	0.05	0.21	0.32	0.01	0.12	0.09	0.02	**0.09**	0.05	0.95	0.05
108) CPI-U: all items	0.37	0.03	0.03	0.03	0.24	0.11	0.04	**0.03**	0.01	0.91	0.09
78) US Tbill, 3m.	0.03	0.03	0.04	0.02	0.38	0.15	0.09	**0.12**	0.08	0.94	0.06
81) Tbond const 5yr.	0.06	0.02	0.00	0.01	0.31	0.12	0.34	**0.08**	0.04	1.00	0.00
96) Monetary base	0.02	0.01	0.01	0.00	0.00	0.00	0.01	**0.00**	0.00	0.06	0.94
93) Money stock: M2	0.02	0.01	0.01	0.00	0.12	0.03	0.04	**0.01**	0.03	0.25	0.75
74) FX:Japan	0.01	0.00	0.01	0.00	0.01	0.00	0.01	**0.00**	0.01	0.05	0.95
102) NAPM commodity prices	0.02	0.01	0.01	0.01	0.04	0.10	0.28	**0.05**	0.02	0.54	0.46
17) Capacity util rate	0.02	0.07	0.04	0.01	0.10	0.09	0.00	**0.10**	0.10	0.52	0.48
49) Pers cons exp: total	0.02	0.01	0.02	0.57	0.01	0.02	0.01	**0.02**	0.00	0.69	0.31
50) Pers cons exp: tot. dur	0.02	0.02	0.02	0.73	0.01	0.02	0.02	**0.02**	0.01	0.87	0.13
51) Pers cons exp: nondur.	0.01	0.01	0.01	0.35	0.01	0.01	0.01	**0.01**	0.00	0.41	0.59
26) Unempl.Rate: all wrks	0.01	0.15	0.04	0.01	0.04	0.06	0.00	**0.09**	0.06	0.45	0.55
48) NAPM Empl. Index	0.02	0.06	0.09	0.00	0.06	0.06	0.00	**0.05**	0.05	0.40	0.60
118) Avg hr earnings constr.	0.00	0.01	0.01	0.00	0.00	0.00	0.00	**0.00**	0.00	0.03	0.97
54) Housing starts: nonfarm	0.01	0.01	0.07	0.01	0.24	0.39	0.03	**0.10**	0.01	0.86	0.14
62) NAPM new orders	0.02	0.06	0.09	0.00	0.08	0.08	0.04	**0.11**	0.02	0.50	0.50
71) SP500: dividend yield	0.02	0.00	0.02	0.02	0.06	0.02	0.21	**0.04**	0.01	0.40	0.60
120) Consumer expec. (Mich.)	0.20	0.01	0.03	0.01	0.07	0.03	0.02	**0.03**	0.03	0.43	0.57

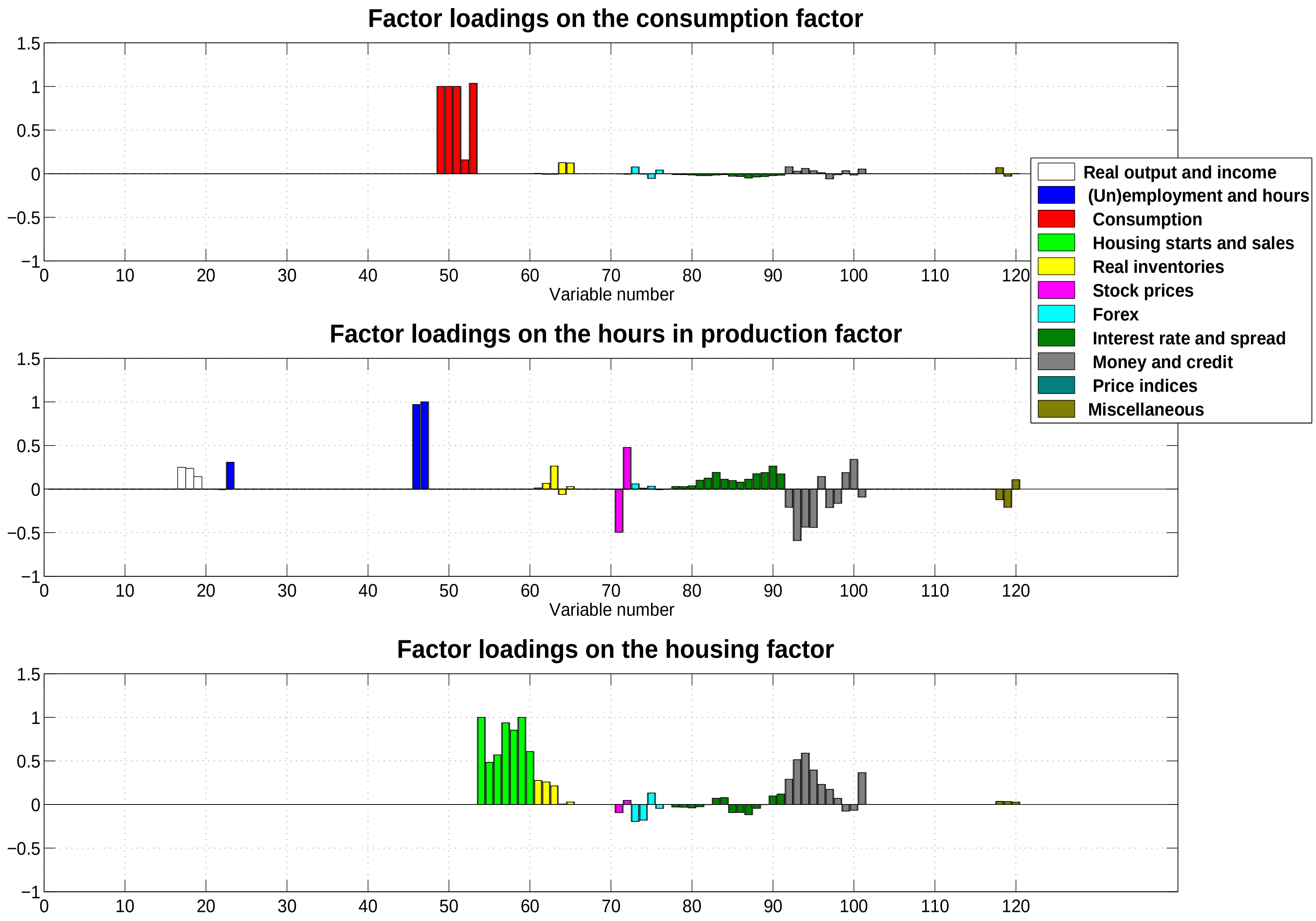
60 month horizon	π	u_n	y	c	hrs	h	$pcom$	i	s	*total*	*Idio.*
77) Federal funds rate	0.10	0.04	0.04	0.05	0.19	0.38	0.06	**0.07**	0.07	1.00	0.00
16) IP: totalindex	0.05	0.19	0.29	0.01	0.14	0.12	0.01	**0.09**	0.07	0.96	0.04
108) CPI-U: all items	0.35	0.04	0.04	0.04	0.19	0.19	0.03	**0.05**	0.03	0.94	0.06
78) US Tbill, 3m.	0.11	0.03	0.03	0.05	0.19	0.37	0.08	**0.05**	0.06	0.98	0.02
81) Tbond const 5yr.	0.16	0.02	0.02	0.05	0.19	0.37	0.14	**0.03**	0.03	1.00	0.00
96) Monetary base	0.02	0.02	0.01	0.00	0.01	0.01	0.02	**0.00**	0.01	0.10	0.90
93) Money stock: M2	0.02	0.01	0.01	0.01	0.13	0.06	0.05	**0.02**	0.05	0.35	0.65
74) FX:Japan	0.01	0.00	0.01	0.00	0.02	0.00	0.01	**0.01**	0.01	0.07	0.93
102) NAPM commodity prices	0.03	0.01	0.01	0.02	0.06	0.12	0.26	**0.05**	0.04	0.61	0.39
17) Capacity util rate	0.05	0.05	0.04	0.02	0.15	0.19	0.02	**0.11**	0.08	0.71	0.29
49) Pers cons exp: total	0.02	0.02	0.02	0.56	0.02	0.02	0.01	**0.02**	0.01	0.69	0.31
50) Pers cons exp: tot. dur	0.02	0.02	0.02	0.72	0.02	0.03	0.02	**0.03**	0.01	0.87	0.13
51) Pers cons exp: nondur.	0.01	0.01	0.01	0.35	0.01	0.01	0.01	**0.01**	0.00	0.42	0.58
26) Unempl.Rate: all wrks	0.05	0.09	0.03	0.02	0.17	0.19	0.01	**0.10**	0.06	0.72	0.28
48) NAPM Empl. Index	0.03	0.05	0.08	0.01	0.11	0.10	0.01	**0.05**	0.05	0.50	0.50
118) Avg hr earnings constr.	0.01	0.01	0.01	0.01	0.01	0.02	0.00	**0.01**	0.00	0.07	0.93
54) Housing starts: nonfarm	0.02	0.05	0.07	0.01	0.37	0.25	0.02	**0.08**	0.04	0.93	0.07
62) NAPM new orders	0.03	0.06	0.08	0.01	0.16	0.11	0.04	**0.10**	0.05	0.63	0.37
71) SP500: dividend yield	0.16	0.01	0.02	0.06	0.08	0.22	0.19	**0.03**	0.01	0.78	0.22
120) Consumer expec. (Mich.)	0.22	0.02	0.03	0.03	0.11	0.17	0.02	**0.03**	0.02	0.66	0.34

The upper panel illustrates the total fractions that the eight factors can explain of the forecast error variance on average for the panel at varying horizon. "Idio." means idiosyncratic variance. The factors are denoted by the symbols $\{\pi, u_n, y, c, hrs, h, pcom, i, s\}$ and describes general inflation, unemployment, economic activity (growth), consumption growth, hours in production, residential investments, commodity price inflation, federal funds rate and stock markets returns respectively. The middle and lower panel shows the 12 month ahead and 60 month ahead forecast error variance decomposition for key macroeconomic variables.

Figure 1: Estimated factors loadings part a

The bars represent the estimated loadings for the respective factors.

Figure 2: Estimated factors loadings part b

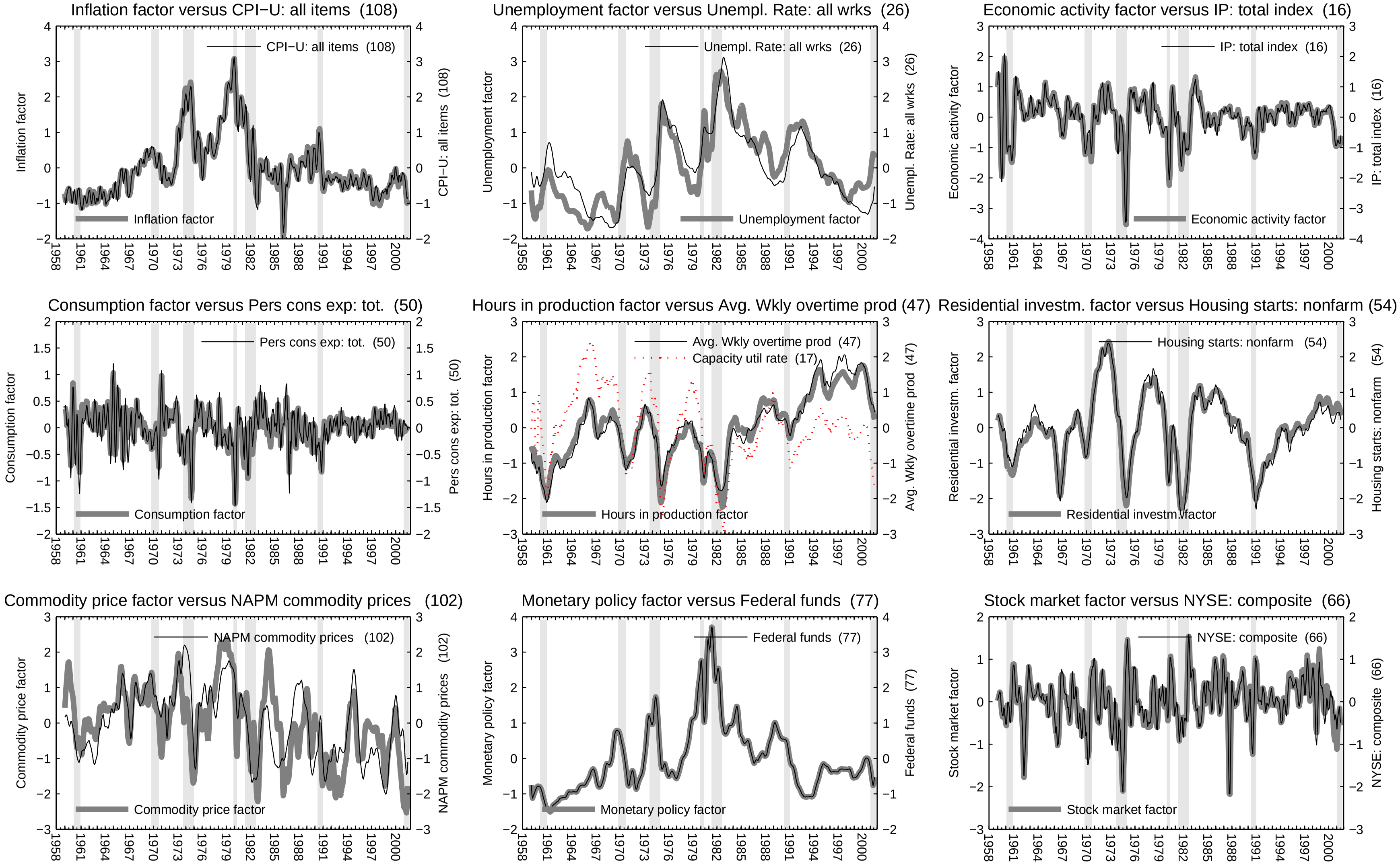


The bars represent the estimated loadings for the respective factors.

Figure 3: Estimated factors loadings part c

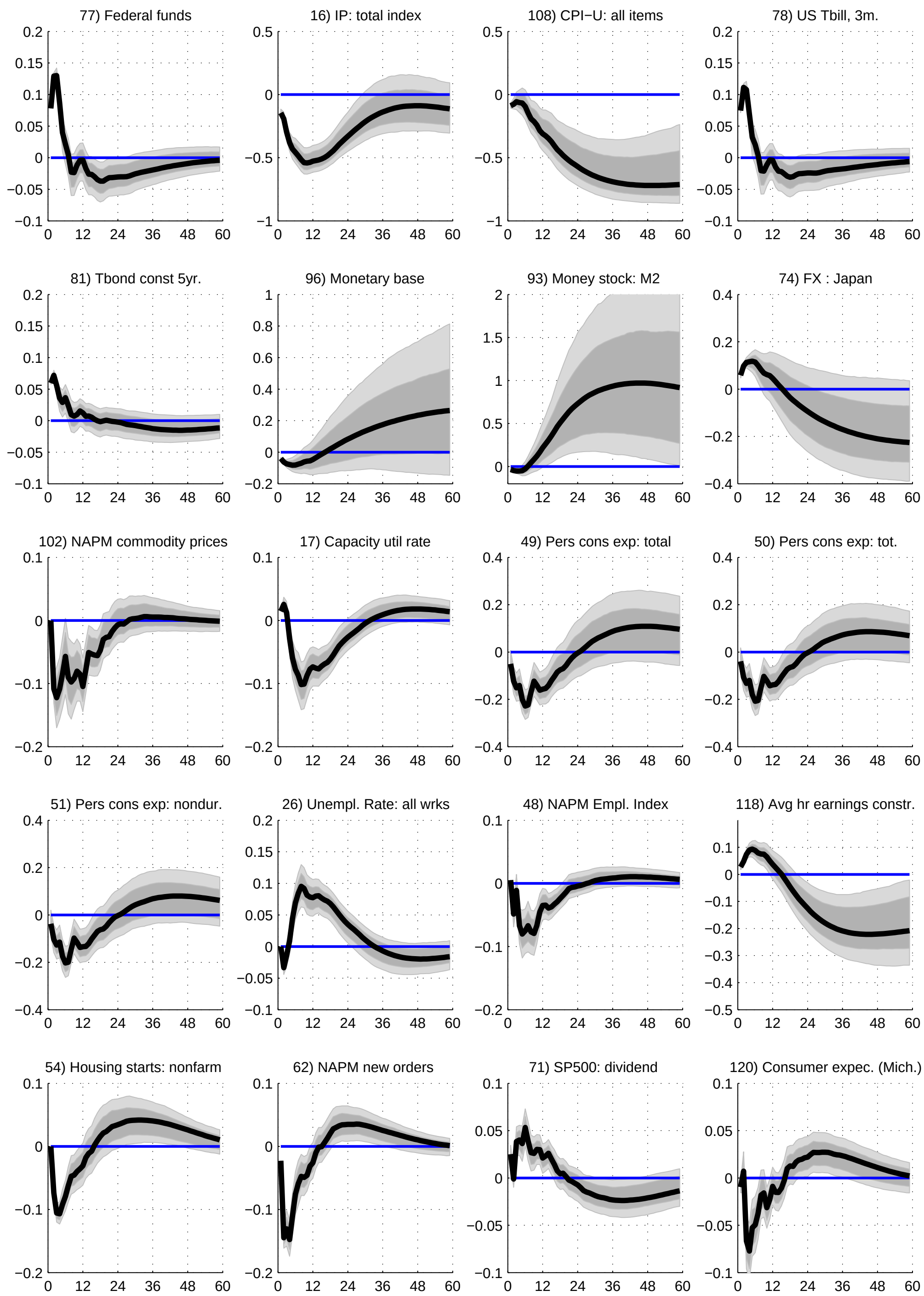
The bars represent the estimated loadings for the respective factors.

Figure 4: Time series of factors versus related observed variables



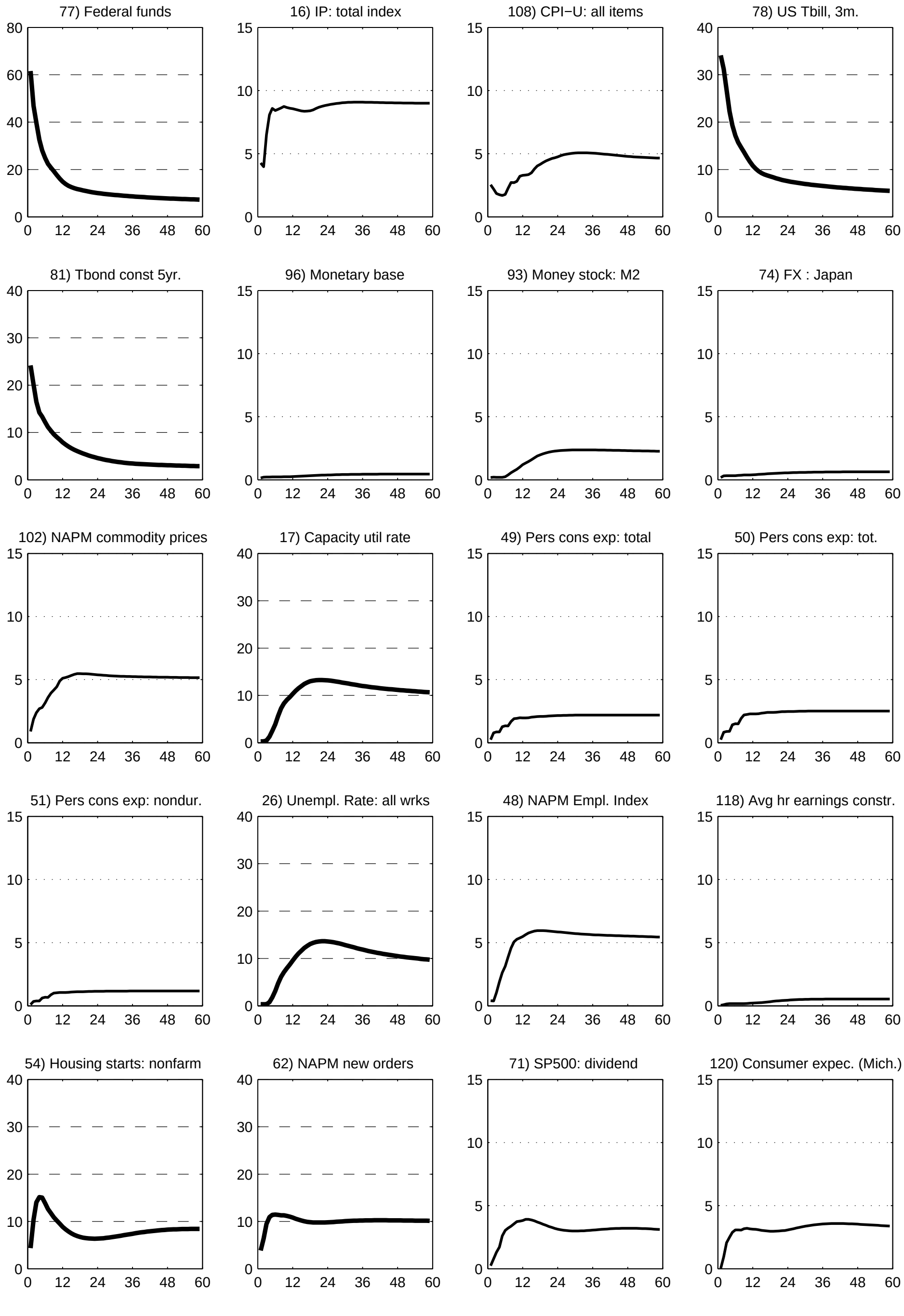
The shaded bars represent NBER-dated recessions. Numbers in parenthesis refer to the variable number in the panel; see the data appendix. To smooth series we have taken two-sided moving-averages of the original series.

Figure 5: Impulse responses to a 25 basis point monetary policy shock.



The figure illustrates the impulse responses in standard deviations of key macroeconomic variables following a 25 basis point monetary policy shock. The horizontal axis denotes the forecast horizon in months. Confidence intervals are represented by dark bands (68 percent) and light bands (90 percent)

Figure 6: Forecast error variance due to monetary policy shocks.



The figure plots the contribution of the monetary policy shock to the forecast error variance decomposition of key macroeconomic variables along the foreast horizon (the horizontal axis). Dashed gridlines indicate a larger scale compared to the dotted grid lines.