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Abstract

This paper proposes a method to interpret factors which are otherwise difficult to assign economic meaning to by utilizing a threshold factor-augmented vector autoregression (FAVAR) model. We observe the frequency of the factor loadings being induced to zero when they fall below the estimated threshold to infer the economic relevance that the factors carry. The results indicate that we can link the factors to particular economic activities, such as real activity, unemployment, without any prior specification on the data set. By exploiting the flexibility of FAVAR models in structural analysis, we examine impulse response functions of the factors and individual variables to a monetary policy shock. The results suggest that the proposed method provides a useful framework for the interpretation of factors and associated shock transmission.

Key words: Factor models, FAVAR, latent threshold, MCMC, interpretation of latent factors, shrinkage estimation.

JEL classification: C11, C31, C51, C55, E50.

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1 Introduction

In this paper, we propose a threshold factor-augmented vector autoregression model as a method to interpret factors. The threshold structure induces factor loadings onto zero when factors fall below the estimated threshold level. The survival rate of factor loadings reveals the relationship between factors and macroeconomic variables. With this method, we attempt to distinguish the economic meanings of the estimated factors.

Data availability has evolved rapidly in recent years. However, using such large data sets introduce a challenge by bringing model specification and estimation problems along. Researchers might simply want to use big information sets to make use of all the relevant information available. To overcome the difficulty of using many indicators, vector autoregressions (VARs) are designed to include more than one evolving variable, as a generalization of autoregression models. VARs have been acknowledged as a means of identifying the direction and the magnitude of monetary shocks since the time they were proposed by Bernanke and Blinder (1992) and Sims (1992).

Despite VARs' common use, relatively small number of macroeconomic variables in VARs cannot capture all the necessary information and might cause omitted variable bias. Another point worth noting in VARs is the selection of the variables. There are generally different measures of the same series, e.g. output, inflation or unemployment. Even for the same country these series can differ but each might include some information that others do not. Unfortunately, VAR results heavily depend on the choice of these series. Furthermore, impulse response analysis is limited by the series added to the system and adding more variables to VARs creates degrees of freedom issues.

Employing factor models, as in Bai and Ng (2002), Stock and Watson (2002) and Bai (2003) among many others both in theoretical and empirical work, can deal with these seemingly adverse issues. Factor models beneficially adapt large information sets to the analysis by providing a convenient tool to reduce dimensions and to extract information. True specifications of the models that researchers are interested in have been successfully accomplished thanks to factor models. As factors are latent variables capturing the common fluctuations in the data, one can imagine the set of factors as the summary of the information in that particular data set. Therefore, the curse of dimensionality can be avoided in factor-augmented models.

Due to the nature of factor models, macroeconomic shocks cannot be traced back to the variables in factor models, i.e. factor models alone cannot explain the effects of, e.g. monetary policy, shocks on all macroeconomic variables. Therefore, Bernanke et al. (2005) combine factor models with VARs to be able to use both large information sets and explain the effects of monetary shocks on various indicators. This new factor augmented VAR (FAVAR) model, can be used to incorporate vast data sets in empirical exercises and to observe impulse response functions of all variables.

Despite their convenient features, economic meanings of factors have been a black box. Belviso and Milani (2006) acknowledge the interpretability problem and propose the Structural FAVAR (SFAVAR) model. Their SFAVAR model divides the large information set into subgroups of particular economic activities. Only one factor is extracted from each category. Thereby this factor is simply associated with the corresponding group. Certainly others have attempted to interpret factors by using different approaches, e.g. Del Negro and Otrok (2008), Ludvigson and Ng (2009a,b), Bork (2009).

We extend Nakajima and West (2013b)'s threshold factor model and propose a latent threshold FAVAR model to shed light on the interpretability of factors. Our adaptation is based on the following idea: the factors to be extracted from the data may not be relevant for some time periods. Therefore, some of the loadings are induced to zero for the particular time periods unless they are above a threshold level which is endogenously estimated. This strategy implicitly allows us to detect the factor loadings that are frequently or rarely shut down for specific macroeconomic variables.

Overall, we ask the following question: what if a factor loading is shut down particularly for one or more groups of macroeconomic variables throughout time and only a few (preferably one) of the factors are related to particular variables? We explore the answers to this question by observing the frequency surviving factor loadings. Our strategy clarifies the interpretation of the factors by approaching these questions from a different angle compared to Belviso and Milani (2006)'s SFAVAR approach. Our approach does *not* require a pre-specification of the data set and any subgroups within it. Moreover, the data driven shrinkage clearly defines a more sparse model.

The proposed method may seem similar to the time varying parameter FAVAR (TVP-FAVAR) where the factor loadings and some other parameters are allowed to differ over time as in Korobilis (2009), Liu et al. (2011), Baumeister et al. (2010) and Eickmeier et al. (2011a,b) among numerous others. In the time varying parameter models, the point when the loadings become sufficiently small and, hence, irrelevant is not easily identifiable since we do not have a strict measure of the threshold under which the factors become redundant. The factor loadings in this paper are also time varying in a broader perspective. However our approach concentrates more on a specific time varying loadings scheme to interpret the factors. The threshold structure enables us to observe this measure and induce the loadings to zero for irrelevant factors on associated time periods.

Estimating the model with Bayesian techniques, we use a US data set constructed by quarterly macroeconomic indicators running from 1964:Q1 to 2013:Q1. The first set of our results presents the survival rates which we observe through the frequency of shut downs in factor loadings. The factors are mainly assigned to one group of macroeconomic indicators such as unemployment, inflation/finance or real activity. The second set of findings depicts the impulse response functions. The responses of factors to monetary contraction are generally as expected. Impulse response functions of factors against shocks to factors and of individual variables against interest rate shock are in line with economic theory suggests.

The paper proceeds as follows. Section 2 introduces our model and summarizes the Bayesian estimation along with the identification restrictions. Section 3 gives the details of the data set. Section 4 presents the results for number of the factors to be used and elaborates on interpretation of the factors. Section 5 provides details of impulse response functions. Section 6 concludes and presents the future work. All other relevant information, including the details of the Bayesian estimation, the impulse response functions which are not discussed throughout the main sections, different identification restrictions and the data description are given in Appendix.

2 The Model

The model used in this paper comprises a VAR system along with a factor model. Let X_t be a $N \times 1$ vector of observed macroeconomic series. These series form an information set in factor analysis. We seek to observe the impact of the observable policy variable, $m \times 1$ vector Y_t, on the large data set of economic activity, X_t. Hence, monetary economists frequently take Y_t as Federal Funds Rate (FFR), as in this paper, but in practice this is not a restriction. We can also have several (policy) variables in Y_t. The unobserved variables are factors f_t, $k \times 1$ vector, and the time varying factor loading matrix Λ_t of dimension $N \times k$.

The model has 3 main equations: a state equation where f_t and Y_t follow a VAR(q) process, a measurement equation which illustrates how the large data set X_t is related to the latent factors f_t and the policy variables Y_t, and lastly the autoregressive process for the latent threshold factor loadings. Typical FAVAR model has first two parts. The threshold part is borrowed from Nakajima and West (2013a,b).

Assume the joint process of the factors and the policy variable can be represented in the state equation as a reduced VAR,

$$\begin{bmatrix} f_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} f_t \\ Y_t \end{bmatrix} + \varepsilon_t, \quad \text{for } t = 1, \dots, T, \tag{1}$$

where $\varepsilon_t \sim \mathcal{N}(0, \Sigma)$ and $\Phi(L) = \Phi_1 L + \Phi_2 L^2 + \cdots + \Phi_q L^q$ is a lag polynomial of order q with each Φ_j is $K \times K$ matrix for $j = 1, \dots, q$ satisfying stationarity requirements, where $K = k + m$.

The state equation cannot be estimated by itself since the factors are unobservable. A small number of factors, $k << N$, are extracted from the data as the representatives of the common fluctuations and used in the state equation to interact with Y_t. Therefore we need the following measurement equation,

$$X_t = c_t + \Lambda_t f_t + \gamma Y_t + e_t, \quad \text{for } t = 1, \dots, T, \tag{2}$$

where e_t is $N \times 1$ vector of idiosyncratic components such that $e_t \sim \mathcal{N}(0, \Omega_t)$ where Ω_t is $N \times N$ diagonal time varying covariance matrix and $E(e_t \,|\, F_t, Y_t) = 0$ with $E(e_{jt}, e_{lt}) = 0$ for all $j, l = 1, \dots, N$ and $j \neq l$. We assume that the diagonal elements of matrix Ω_t follow a stochastic volatility process, that is, $\Omega_t = \text{diag}\{e^{h_{1,t}}, \dots, e^{h_{N,t}}\}$ is in the form of

$$h_t = \mu_h + \alpha_h(h_{t-1} - \mu_h) + v_{ht}$$

with $v_{ht} \sim \mathcal{N}(0, V_h)$ where both α_h and V_h are $N \times N$ diagonal matrices and $h_t = (h_{1,t}, \dots, h_{N,t})'$. The time varying intercept follows a stationary autoregressive process

$$c_t = \mu_c + \alpha_c(c_{t-1} - \mu_c) + v_{ct}$$

with $v_{ct} \sim \mathcal{N}(0, V_c)$ where both α_c and V_c are $N \times N$ diagonal matrices. The time varying intercept and variance help us capturing the changes in the data over time, especially when the time varying parameters tend to create unstable results, e.g. as in the Great Moderation or Great Recession period.

Factors are representatives of the variations in the data. However their relevance might depend on the particular time periods and therefore change over time. Hence, the factor loadings in our model are *not* left unrestricted but instead represented by a threshold structure. Intuitively, the idea is to examine the relative importance of the factors in each time period. This specific representation enables us to observe if factor loadings are below a threshold and therefore should be induced to zero for the associated time periods.

To exploit the above insight, we stack all the non-zero elements in the loadings matrix Λ_t.[1] Let us denote each non-zero element of Λ_t as λ_{jt}. Then the threshold structure on the factor loadings is,

$$\lambda_{jt} = \beta_{jt} \mathbb{1}(|\beta_{jt}| \geq \delta_j), \quad \text{for } j = 1, \dots, p,$$

where $p = (N - k + 1)k$ is the number of the non-zero loadings, $\mathbb{1}(\cdot)$ denotes the indicator function, $\delta_j \geq 0$ is the latent threshold for $j = 1, \dots, p$ and it is to be estimated. The latent time varying parameter vector $\beta_t = (\beta_{1t}, \dots, \beta_{pt})$ follows a stationary VAR(1) model

$$\beta_t = \mu_\beta + \alpha_\beta(\beta_{t-1} - \mu_\beta) + v_{\beta t}, \tag{3}$$

[1] The zero elements are due to the identification restrictions, which are explained in Section 2.2.

where $v_{\beta t} \sim \mathcal{N}(0, V_\beta)$, μ_β is $p \times 1$, α_β and V_β are both $p \times p$ diagonal matrices. The AR coefficient of β_{jt} satisfies the stationarity of AR(1) processes for each factor loading, i.e. $|\alpha_{\beta j}| < 1$. Suffice it to say, we assume that the errors of different equations are jointly normal and independent. That is, $(e_t, \varepsilon_t, v_{\beta t}, v_{ct}, v_{ht})' \sim \mathcal{N}(0, \text{diag}(\Omega_t, \Sigma, V_\beta, V_c, V_h))$, where $\text{diag}(\cdot)$ creates a block diagonal matrix. Moreover, all of the covariance matrices except Σ are diagonal. Appendix A provides details on the priors and the posteriors of the parameters.

This threshold factor model has some advantages over continuous time-varying loading models and Markov switching (MS) loading models. In continuous time-varying loadings framework, the (time-varying) importance of a factor can be inferred through the magnitude of the loading over time. However, there is no scale which indicates how small λ_{jt} should be so that the factor is considered irrelevant/redundant. Hence, when a factor becomes important is very subjective. In our threshold model, on the other hand, the threshold is estimated. Therefore the data determine when a factor should be included in the analysis. In an MS setup, one can have two (or a finite number of) regimes for the loadings: significant and insignificant regimes. Both MS and the threshold model behave similarly when a loading is shut-down to 0. However, for the time periods when a factor is significant, the threshold model allows continuous loadings which ensures a better fit than MS loading models.

2.1 Bayesian Estimation

The estimation of the parameters and latent processes of the factor model relies mostly on the results of Nakajima and West (2013b). We employ the Markov chain Monte Carlo (MCMC) method to estimate the joint distribution of the unobserved variables. The full posterior density conditional on the data is $p(\Psi_{0:T}, \delta, \theta, \gamma, \Phi, \Sigma | X_{(1:N,1:T)}, Y_{(1:m,1:T)})$ where $\Psi_{0:T} = \{c_{0:T}, \beta_{0:T}, f_{1:T}, h_{0:T}\}$ are the latent time-varying processes, $\delta = \{\delta_1, \ldots, \delta_p\}$ are the latent thresholds for each non-zero element of the loading matrix, $\theta = \{\theta_c, \theta_h, \theta_\beta\}$ where $\theta_g = \{\mu_g, \alpha_g, \sigma_g^2\}$ for $g \in \{c, h, \beta\}$, γ is $N \times m$ matrix of measurement equation parameter, Φ and Σ are the VAR parameters, and $\{X_{(1:N,1:T)}, Y_{(1:m,1:T)}\}$ is the data X_{it} and Y_{jt} for $i = 1, \ldots, N$, $j = 1, \ldots, m$ and $t = 1, \ldots, T$.

The estimation of $c_{0:T}$ and $f_{1:T}$ can be performed by forward filtering backward sampling algorithm conditional on the hyperparameters, the time-varying volatility and the data. In this paper we use Carter and Kohn (1994) algorithm which draws the time series of the latent process in a state space representation. The volatility process $h_{0:T}$ is sampled by standard MCMC techniques developed for univariate stochastic volatility models conditional on the measurement equation parameters and the data. The parameters θ_c and θ_h are sampled easily after conditioning on $c_{0:T}$ and $h_{0:T}$, respectively, as in simple univariate AR(1) models.

We use Metropolis–Hasting algorithm to draw $\delta, \beta_{0:T}, \theta_\beta$. The estimation of these parameters is deeply analyzed in Nakajima and West (2013a). The candidate for β is drawn from a distribution as if there is no threshold. The draws for θ_β are required to be compatible with the threshold parameters because the prior and the posterior of δ depends on θ_β.

We perform 25000 iterations and discarded the first 20000 draws as burn-in period. Convergence of most of the parameters is achieved. Estimation details are given in the Appendix A.2, but for further details readers should refer Nakajima and West (2013a,b).

2.2 Identification Restrictions for Factors

As widely covered in the literature, the estimation of the true factors cannot be achieved. Instead only the space spanned by the factors can be estimated. Moreover, unless we apply some restrictions, we cannot identify the factors and loadings separately, see Bai (2003). In other words, for any given factor f and loadings Λ the following observational equivalence holds: $\Lambda f = \Lambda R R^{-1} f = \tilde{\Lambda}\tilde{f}$ for invertible $k \times k$ matrix R, i.e., same results can be achieved by two different sets of factors and factor loadings. Thus we need to fix the rotation of the factors, namely fixing the matrix R, by putting k^2 restrictions.

In Principal Component Analysis, a statistical method to extract factors from data sets, the most common restrictions are to assume ff'/T being identity matrix ($k(k+1)/2$ restrictions) and $\Lambda\Lambda'$ being diagonal ($k(k-1)/2$ restrictions). However different restrictions have been adopted by both dynamic factor and FAVAR models. For instance Bernanke et al. (2005) and numerous others following their work restrict the top $k \times k$ block of Λ to be identity. Some of the dynamic factor model papers such as Aguilar and West (2000) and Nakajima and West (2013b) restrict the top $k \times k$ block of Λ to be lower triangular with unit diagonals which leads $k(k+1)/2$ restrictions. Additionally they restrict the covariance matrix of the factors, Σ to be diagonal which brings along $k(k-1)/2$ more restrictions.

We believe that restricting the covariance matrix of the factors by forcing for unit diagonals and hence imposing zero correlation between factors is a very strong restriction. The impulse response functions are generated through the covariance matrix. Thus, such restrictions are indeed undesirable. Furthermore, we would like to keep the factor loadings as free as possible since the interpretation of the factors are based on the loadings.

In this paper, we impose diagonality on the lower $k \times k$ block of Λ and set the diagonals of the top $k \times k$ block of Σ to be one. Restricting the bottom part of the factor loadings has some intuitive grounds. The ordering of our data set allows us to assume that each of the last k variables is only explained by one factor.[2] Moreover, setting the variances of the unobserved

[2]The corresponding variables in the data set are the credit variables. They are labelled as variables 151 to 157 in Appendix D.

factors, the corresponding diagonal elements of Σ, as 1 is just a normalization. Leaving off–diagonal elements of the covariance matrix of the factors unrestricted indicates that correlation among factors is allowed, e.g. the correlation between so called 'inflation factor' and 'interest rate factor' is left unrestricted in our analysis. Restrictions on both covariance matrix, k, and the factor loadings, $k^2 - k$, provide us the number of restrictions, k^2, we need for identification.

3 The Data

Factor models entail large information sets. Our data consist of 158 US macroeconomic aggregates and are inspired by Stock and Watson (2005) (SW) data set. The original SW data set and its modified versions have been used by numerous papers, such as Belviso and Milani (2006) and Ludvigson and Ng (2009a,b). In the latter, the authors touch upon the interpretation of factors and 131 monthly series in their data cover the time span of January 1964 - December 2007. We update and extend the SW data set. Although the original SW data set is monthly, we prefer to work with a quarterly data set for computational ease. Hence the resulting data set is from 1964:Q1 to 2013:Q1.[3] The number of lags in the VAR(q) is taken to be 4 throughout the analysis. Yet, the model yields similar results under different choice of lags.

We do not require any ex ante categorization of the data. However, we can benefit from looking at it in detail and also reporting the results in accordance with the different classes of variables. The data subgroups and the corresponding number of variables are shown in Table 1 below. The data set for factor extraction includes 157 variables. The last variable, Federal Funds Rate is used as the policy variable thus it is not included in the data set from which we extract the factors.

The analysis requires all series to be stationary. This is ensured by taking differences or logarithms of the series and in some cases both. Adding more series into the data and the longer time span require different transformation codes than SW's. The resulting codes are presented in the data description.

4 Results

We employ a Bayesian framework to extract the factors and estimate the hyperparameters. To do so first requires the exact number of factors in the data to be determined. The next step is to analyze the factor loadings over time to assign an economic meaning to the factors.

[3]Appendix D presents the full data description including the data sources. Most of the series are taken from St. Louis Fed Economic Research database (henceforth FRED) unless otherwise indicated.

Table 1: Subgroups in the Data Set

Macroeconomic Subgroups	Number of Variables
Production	20
(Un)Employment	27
Housing	13
Interest Rate	15
Inflation	29
Finance	13
Money	22
Expectations	7
Credit	11
Federal Funds Rate (FFR)	1

Note: Appendix explains which series form these categories.

4.1 Number of Factors

All factor related models require an initial step of determining the number of factors. There are statistical ways to seek the optimal number. Among all, the most frequently used is the information criteria for static factors proposed by Bai and Ng (2002). The crucial point in determining the optimal number is to realise that different time spans might offer different number of factors. Table 2 shows the results of a naive inspection on this matter.

Table 2: Number of Factors for Different Time Spans

Time Range	Number of Factors
1964Q1 - 2000Q4	6
1964Q1 - 2001Q1	7
1964Q1 - 2007Q4	7
1964Q1 - 2008Q1	8
1964Q1 - 2013Q1	8

The table presents how many factors are suggested by the information criteria for the corresponding time span of the data set. The data until the end of 2000 suggest six factors. However adding just the first quarter of 2001 into the time span changes the suggested number of factors to seven. This change is not because of a sudden appearance of an actual meaningful factor. Instead, probably, there are nonlinearities caused by abrupt changes in the data set, such as the dot-com bubble in the beginning of 2001 for this particular case. The same can be observed again by adding the first quarter of 2008 into the data span, in this case due to the Great Recession. Hence, caution should be taken before treating these factors as latent variables although they survive the information criteria.

The Bai and Ng (2002) information criteria suggest that there are 8 factors in our data for the whole time span. The FAVAR model of Stock and Watson (2005) use 7 factors, only some of which are later shown to accurately construct the forecast error decomposition for individual series. Analogously, Ludvigson and Ng (2009a,b) used SW data set and extracted 8 factors as suggested by the information criteria. We, similar to Stock and Watson (2005), use 7 factors in this paper. The results of the subsequent sections show that only 5 to 6 factors are assigned economic meanings.[4] This also supports the fact that the immediate appearance of the additional factors is *artificial*. The remaining 'unmeaningful' factors are generally shut down.

4.2 Interpreting the Factors

Given that the factor loadings are shut down for so-called irrelevant time periods, we can observe the remaining (non-zero) loadings. This enables us to relate the factors and variables to particular data groups. If a factor's loadings are rarely induced to zero only for a specific group of macro variables, we link that factor to the corresponding data group. The interpretation of factors depends on the 'survival rate' of the process β_{jt}. The survival rate aims to show how frequently the factor loadings are above the estimated threshold, i.e., *not* shut down to zero, and therefore the corresponding factors are relevant. We take this ratio by averaging both over simulations and time periods. Mathematically, survival rate of the j^{th} loading is $1/(TS)\sum_{t,s}\mathbb{1}(\lambda_{jt}^{(s)} \neq 0)$ where S is the number of simulations after burn-in period and $\lambda_{jt}^{(s)}$ is the s^{th} iteration of MCMC estimate of λ_{jt}. This is one of the ways of interpreting factors, which we pursue in this paper. Another would be to obtain a time-varying survival rate by averaging only over the simulations and checking the time series of loadings but interpreting the factors would be comparably harder in this case.

We introduce the subgroups of the data in Section 3 even though we treat the data as a whole for the MCMC. We ultimately intend to attach the factors to these different subgroups. Table 3 demonstrates the survival rates of all seven factors for each of these subgroups.[5] [6]

[4] The same analysis was also repeated for 8 factors but there were no considerable changes in the results. Similarly, only 5 to 6 factors are found meaningful.

[5] The rows of the table indicate the average the survival rates of the top 60% of the factor loadings for the corresponding factors. Frankly, this is just an adaptation for the ease of interpretability. The selection of the top percentile does *not* change the results but makes the interpretation more straightforward.

[6] Survival rates are aggregated over simulations and time. Therefore they are subject to the estimation uncertainty. We check the changes in survival rates over time, after a large number of simulations. The variance of the change is almost negligible. Therefore, estimation uncertainty in determining the survival rates does not change the interpretation of the factors.

The bold numbers emphasize the highest survival rates of the corresponding factors. For the production variables, for instance, the first factor is *not* shut down 63% of the time. Over time and simulations, this signifies that the first factor is above the estimated threshold with 63% probability. The fourth factor has by far the highest survival rate, 78%, among others for production. One factor might be related to other categories of the data as well, e.g. the fourth factor is also influential on housing variables with 85% survival rate. Production and housing are two highly related economic indicators hence the fourth factor can be processed as the real activity factor and is now called as 'Real' as an abbreviation.

Table 3: Survival Rates of the Factor Loadings

	$\mathbf{f_1}$	$\mathbf{f_2}$	$\mathbf{f_3}$	$\mathbf{f_4}$	$\mathbf{f_5}$	$\mathbf{f_6}$	$\mathbf{f_7}$
	Emp	*InfFn*	—	*Real*	*Expc*	—	*IntR*
Production	0.63	0.32	0.40	**0.78**	0.36	0.56	0.58
(Un)employment	**0.85**	0.21	0.16	0.42	0.64	0.09	0.37
Housing	0.47	0.17	0.13	**0.85**	0.10	0.11	0.55
Interest Rate	0.12	0.04	0.09	0.44	0.18	0.06	**0.51**
Inflation	0.33	**0.67**	0.31	0.25	0.27	0.36	0.52
Finance	0.38	**0.57**	0.09	0.33	0.12	0.27	0.43
Money	0.22	0.22	0.21	0.29	0.18	**0.37**	0.36
Expectations	0.59	0.22	0.05	0.29	**0.75**	0.25	0.38

Following the above mentioned analogy, we mark the first factor as employment factor, 'Emp'. In our framework, we should be careful about interpreting what a factor is truly capturing. The (un)employment partition of the data includes variables for both unemployment and employment. Can we know for sure whether the employment factor is really an employment factor or rather an unemployment factor? Visual inspection helps us to determine the actual interpretation of this factor.[7] We can simply check the correlations of every single variable with the employment factor.

The positive correlations accumulated in Figure 1 correspond to the unemployment variables. Other variables in this same data category exhibit negative relationships with the first factor. Moreover, most of the variables (such as production, housing, expectations) are negatively correlated with this factor. Therefore, this factor can safely be identified as the unemployment factor.[8]

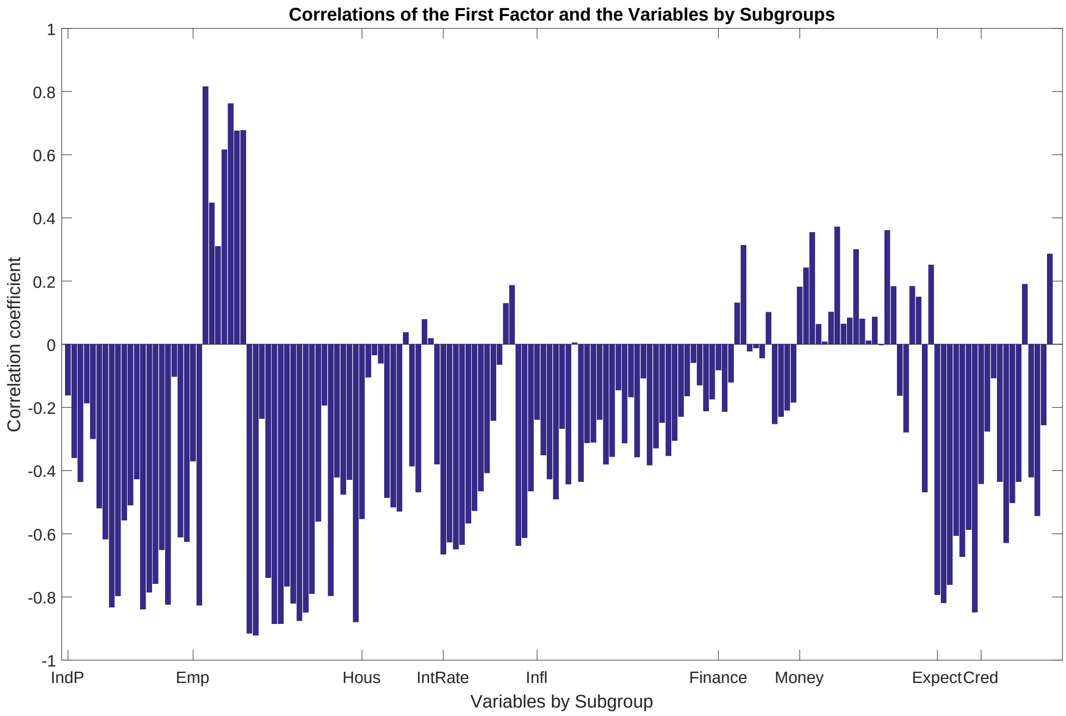
The second factor loads on inflation and financial variables. We cannot distinctly name this

[7] To identify the nature of this factor we can also put some sign restrictions on factor loadings at the beginning of the analysis. We do not pursue this here.

[8] When we observe the impulse response functions of the factors after an unemployment shock in the following sections, this notion also becomes more clear.

factor due to the difficulty of differentiating the effects of inflation and financial variables, hence it is indicated as 'InfFn'.[9] The third factor is the most insignificant factor among all. This also supports the idea that some factors might be generated artificially due to capturing the nonlinearity in the data. Hence, this factor does not carry any essential information and can be left without a specific interpretation.

Figure 1: The correlation between the variables and the first factor



Notes: Chart shows the correlation between each variable in the data set, grouped in subcategories, with the first factor.

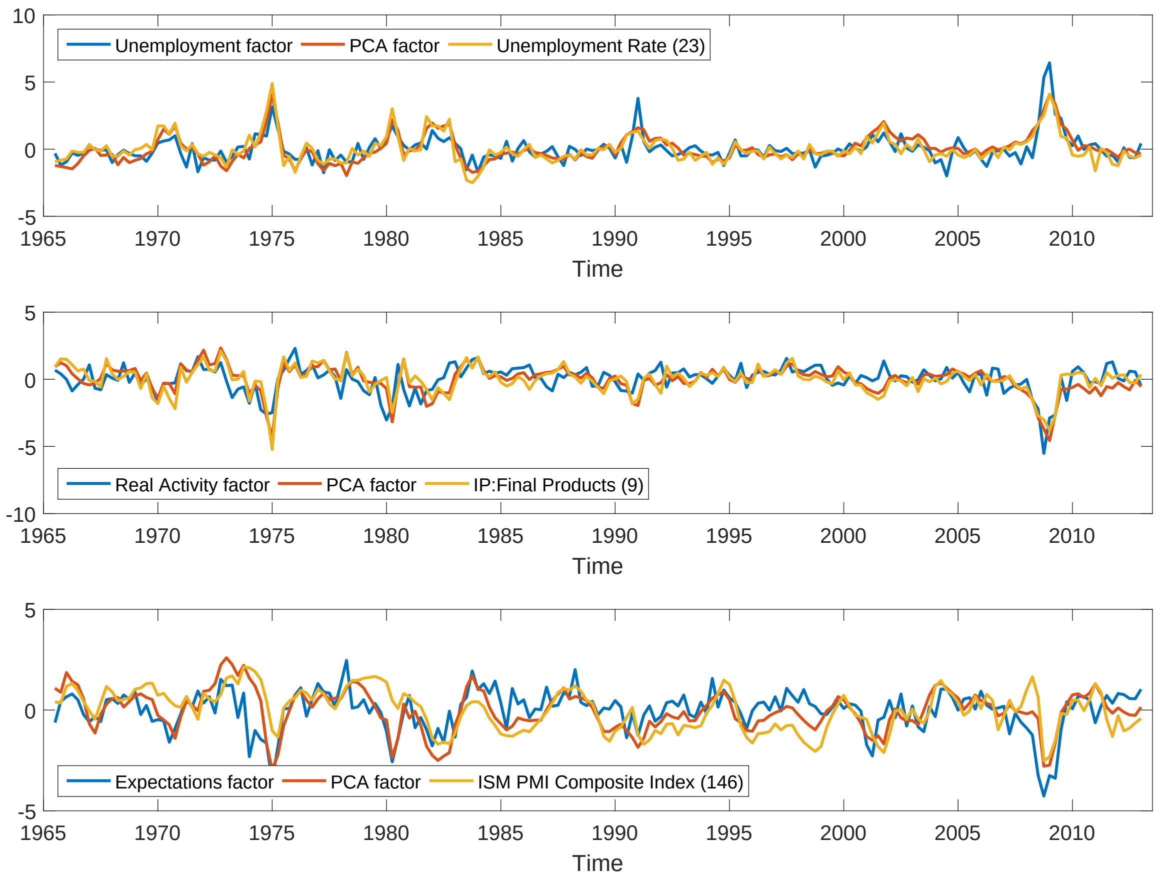
The fifth factor clearly explains the expectation variables hence is indicated as 'Expc'. Expectation measures are highly related to other subgroups in the data. Stock and Watson (2005) included these indexes into the corresponding subgroups. For instance the ISM Production Index in our expectation data group is included in the real activity variables in SW data set. Nevertheless, we are able to find a strongly distinctive factor associated with the expectation variables. The existence of this factor should not be ignored in our case.

Money related variables have not been assigned to a particular factor with confidence. Even though the most significant factor for these variables is factor 6, it might not be a conclusive result thereby it brings this factor into question. The last factor very distinctively loads on interest rate and real economy variables. It is not surprising that one factor affects more than one group as in the case of the second factor. Yet, we call the last factor as the interest rate factor.

[9] An anonymous referee addressed that the variables that belong to the inflation and financial subgroups in the data can be considered as 'price' series and therefore this factor can be called 'prices'. We leave the decision to the reader.

The restrictions imposed to the model fix the rotation of the factors, i.e. we choose basis functions for the space spanned by the factors. Papers which forcefully assign meaning to the factors (for instance, by extracting a factor from a subgroup) might end up having factors more than the dimension of the true factor space. Therefore, we believe that some of these extracted factors are either orthogonal to the true factor space or a linear combination of the true factors. According to our results here and those of similar papers', we infer that there are only five to six factors in this data set.[10]

Figure 2: Threshold FAVAR factors vs PCA factors



We can easily compare the relative perfomance of our approach with PCA approach. In Figure 2, we plot three of our factors with their PCA counterparties, which are extracted from the associated data subgroups. These subgroups rely on the interpretation in Table 3.[11] We also overlap the charts with the most representative series of each economic activity.[12]

[10] Appendix C provides details on the results when we impose different identification restrictions. Whichever different identification schemes we use for the estimation, we could not find any factor that explains credit variables even if credit variables are not imposed any restrictions in other specifications.

[11] Namely, given that our first factor is identified as unemployment factor, we extract a factor from the (un)employment series 21 to 47, detailed in Appendix D. For the real activity factor, we use variables from 1 to 20 and 48 to 60 to extract the first principal component. The principal component of the expectations series is extracted from the variables 140 to 146. Charts presenting the other factors are available upon request.

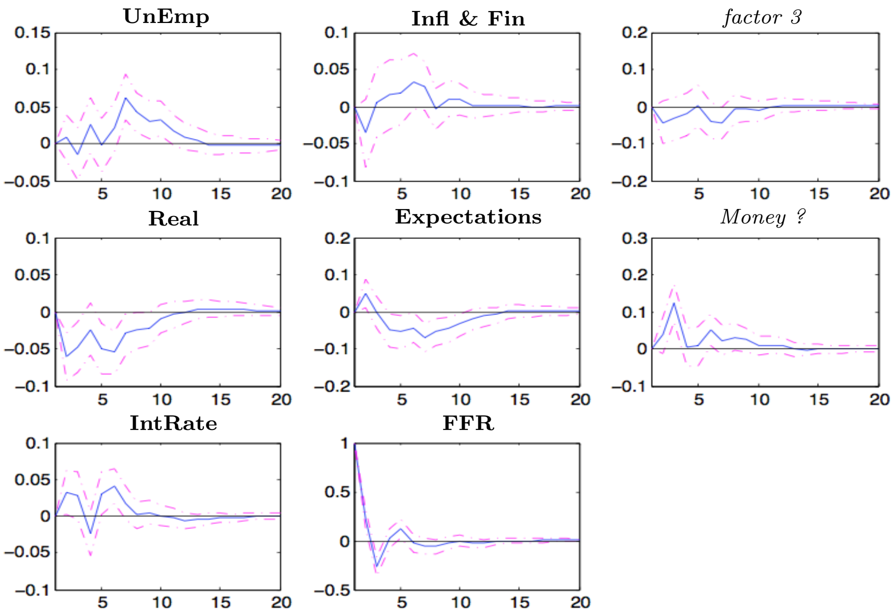
[12] All series are demeaned and standardized prior to the PCA.

The unemployment factor, in the top panel of Figure 2, closely tracks the PCA factor and the unemployment rate. Note that the unemployment factor is estimated from the whole data set whereas its PCA counterparty is extracted only from the relevant data category. Similarly, the relative performances of both real activity factor and the expectations factor show that the interpretation of the factors is successfully achieved.

5 Impulse Response Analysis

This section presents the impulse response functions of the factors and some selected variables to particular shocks. We adopt Cholesky decomposition for identification.[13] Figure 3 reports the responses of the factors to a 1 unit shock on FFR implying contractionary monetary shock. The last of the eight plots in each figure presents response of FFR itself. The confidence bands correspond to the 68% confidence bands.[14]

Figure 3: The responses of the factors and FFR to a 1 unit shock on *FFR*



Notes: The confidence bands correspond to the 68% confidence bands.

The contractionary monetary policy shock has a relatively positive impact on unemployment factor, consistent with what economic theory suggests. Immediate response of the financial variables causes inflation and financial market factor to respond with a small downward tendency although the overall effect is short-lived.

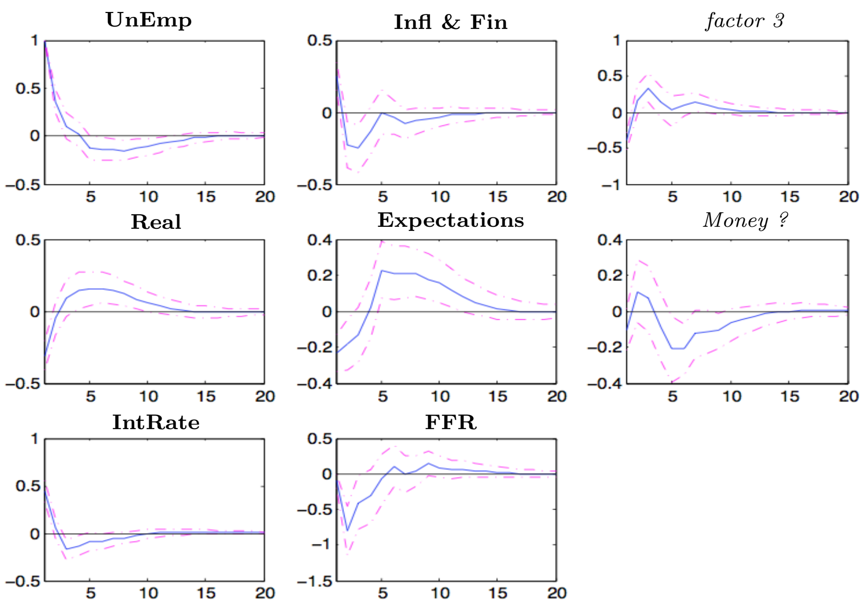
[13] Attached meanings on the factors might enable us to impose different and maybe more accurate VAR identification restrictions as in Appendix C. Cholesky decomposition is represented here just for computational advantages.

[14] The results which are not displayed in this section or in Appendix are available upon request.

The monetary shock has almost no effect on the third factor. This supports the fact that this factor cannot be interpreted though the survival rates in Section 4.2. An adverse monetary shock causes a drop in the real economy factor. Expectations factor has a small upward adjustment first but then its response becomes negative, consistent with the deteriorating expectations following monetary contraction.The money factor responds positively and stays significant until the effect slowly fades. The corresponding data series in the data include reserve aggregates. Therefore observing an increase in the money factor as a response to a contractionary monetary shock is intuitive. Lastly, interest rate factor has an upward tendency in general which is a natural response after a monetary contraction.

It is worthwhile to discuss the responses of the factors to the shocks on other factors. This is one of the crucial conveniences of FAVAR models. We illustrate this by concentrating on the impulse response functions of the factors and the FFR when there is an one unit adverse shock to unemployment factor. The resulting responses are displayed in Figure 4. A sudden jump in unemployment decreases inflation and finance factor over time. The responses of real activity and expectations factors support an expected fall in these activities as a response to an unemployment shock. Moreover, the money factor and FFR are also negatively affected by this shock whereas the response of interest rate has an upward move in the first quarters.

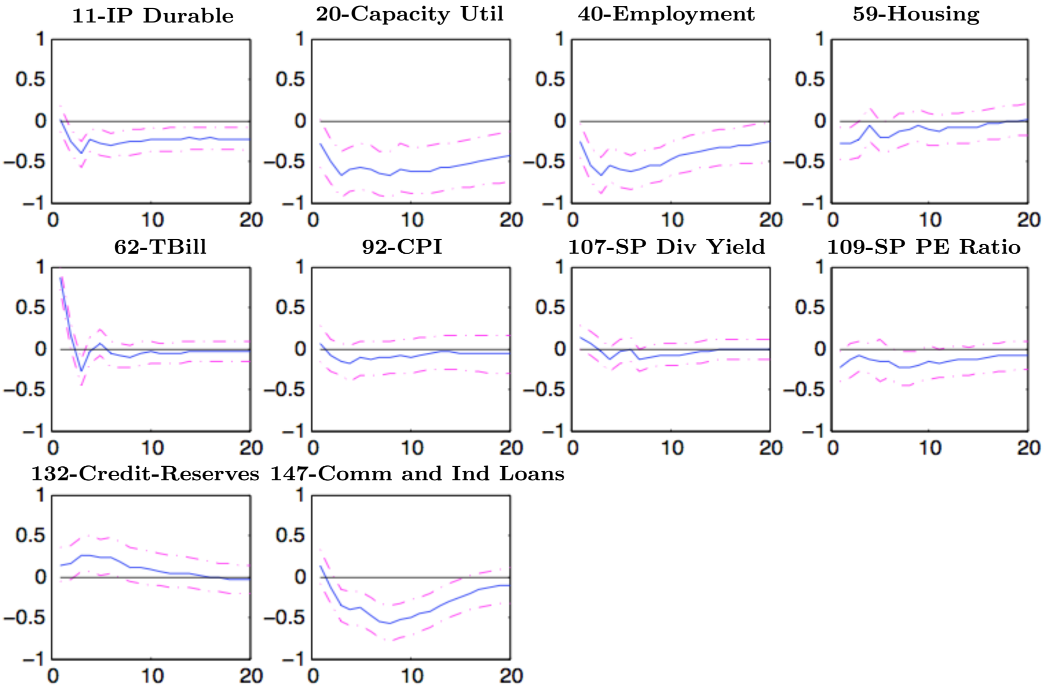
Figure 4: The responses of the factors and FFR to a 1 unit shock on *unemployment factor*



Notes: The confidence bands correspond to the 68% confidence bands.

Another advantage of FAVAR models is that we can observe the impulse response functions of individual variables. This provides a more intensive check on the model specification. Hence we analyze the responses of various macroeconomic measures against a one unit contractionary monetary shock.[15] We have a selection of different types of variables chosen from the subgroups of the data. The ordering of these variables on the data set are given next to the variable names on Figure 5.

Figure 5: The responses of the variables to a 1 unit shock on *FFR*



Notes: The confidence bands correspond to the 68% confidence bands.

There are a couple noteworthy findings. First, a contractionary monetary shock causes a fall in industrial production and capacity utilization. Second, both the employment and the housing measures have a downward adjustment. Third, 3-month Treasury Bill interest which closely tracks FFR increases, as similar to the findings of Bernanke et al. (2005). Lastly, dividend yields first exhibit an upward move however they drop over time along with the loans.

As first identified by Sims (1992), the VAR literature suffers from a phenomenon so called *price puzzle*. In theory, monetary tightening should decrease the prices. However, prices are commonly estimated to respond to monetary tightening with an increase in VARs. One of the novelties of FAVAR models is to eliminate price puzzle by making use of large data sets. In our model, CPI reacts slightly positively at the first quarter but the response becomes negative afterwards. Therefore we can infer that this model eliminates the price puzzle while this response might seem insignificant.

[15]Our methodology carries similar features to the time varying parameter models. Note that we estimate the model with the full sample. The resulting impulse response functions shown here are mapped into the individual variables at a given time, i.e. with the estimated factor loadings at the end of the estimation period.

6 Concluding Remarks

The recent literature has focused on the techniques to efficiently use large information sets. Combining Vector Autoregressions with factor models is a relatively recent but very fruitful method in this regard. However, factor augmented VAR models are not designed to interpret the extracted factors. In this paper, we attempt to designate an economic meaning to the factors through a latent threshold FAVAR model.

We apply a Bayesian approach to extract the factors, interpret them according to the survival rates of their factor loadings, and employ a VAR analysis to observe impulse response functions of the various measures. Empirical evidence suggests that we are able to relate most of the factors to certain subcategories of the data. Although Bai and Ng (2002) information criteria suggests the use of eight factors for our data set, we are able to find five to six meaningful factors, e.g. real activity factor, unemployment factor.

There are couple areas that might benefit from this approach. The potential implementation of the model, among many others, is twofold. First, it can be used on the stress testing front by performing structural analysis. Recently, central banks have heavily invested on their stress testing framework alongside stress test scenarios published every year. The Federal Reserve, for instance, published its 2015 severe adverse scenario where the unemployment increases by 4 percentage points, real GDP is 4.5% lower than its level in the third quarter of 2014 and CPI reaches 4.3%, see Board of Governers of the Federal Reserve System (2015). The Bank of England, see Bank of England (2014), published a tail risk scenario that starts with an initial shock to productivity which leads to a monetary policy response where Bank Rate rises by about 4 percentage point. Following these, the unemployment rate rises to 12%, a 35% fall in house prices is observed, and eventually real GDP growth troughs at about 3.5%. Calibrating these numbers is only the one side of the coin. The other is the need to investigate where shocks originate. From a macroeconomic perspective, the effects of two shocks that come from different sources should have different impacts on the scale of the economy. For instance, a real GDP fall originating from a financial sector shock should have different impacts on the economy, both qualitatively and quantitatively, and different transmission mechanism than a *same size* fall in real GDP driven by a shock arising from unemployment or the housing market. Calibrating the variations in macroeconomic indicators under stress should account for where shocks arise from even if they eventually lead to a same size change. Our approach can identify initial shocks by using interpretable factors which carry information on specific sectors of the economy and help gauge the ultimate numbers to be used in stress scenarios.

Second, this method can be easily extended to perform small open economy analysis. The first possible implication of this extension is to exploit the effects of a monetary contraction/expansion in a large open economy to a small open economy. Especially recently, this channel attracts more attention due to the uncertainty that might arise in small open economies, such as Canada, United Kingdom, as a response to a change in the US interest rate. With the proposed method, we have a tool to investigate the transmission of the monetary policy from one country to another by also capturing the features of different sectors in each country. Similarly, we can explore the interconnectedness of two countries' financial sectors and/or housing sectors etc. We can easily study the propagation mechanism of, for example, a financial shock to the US economy on other countries along with the magnitude, duration and persistence of this particular shock.

The paper is open to some extensions. We seek to obtain the results under different restrictions, such as different structural VAR restrictions. They might lead to better impulse responses. Looking for *the best* factor identification restrictions might yield *the most* meaningful factors. Forecasting of particular macroeconomic series can be performed by using the proposed model. A noteworthy extension is to repeat this exercise with different data sets. More micro-oriented series, such as consumption-saving measures and various indexes, or different geographical variables can be analyzed with the aid of this model.

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Appendix

A Priors and Posteriors

Prior and posterior specifications and MCMC mostly rely on Nakajima and West (2013a). This section is designed to analyze all in detail however readers can refer the original source if needed.

A.1 Priors

For $g \in \{\beta, c, h\}$ the priors of the parameters are as follows

$$\begin{aligned}
\mu_{i,g} &\sim \mathcal{N}(\mu_{i0}, \omega_{i0}^2) \\
(\alpha_{i,g}+1)/2 &\sim Beta(\alpha_{01}, \alpha_{02}) \\
\sigma_{i,g}^{-2} &\sim \mathcal{G}(v_{0i}/2, V_{0i}/2) \\
\beta_{i1}|\theta_\beta &\sim \mathcal{N}(\mu_{i,\beta}, \sigma_{i,\beta}^2/(1-\alpha_{i,\beta}^2)) \\
d_i|\theta_\beta &\sim \mathcal{U}\left(0, |\mu_{i,\beta}| + K\nu_i\right),
\end{aligned}$$

where $\nu_i^2 = \sigma_{i,\beta}^2/(1-\alpha_{i,\beta}^2)$ and $\sigma_{i,\beta}^2$ is the i^{th} diagonal element of V_β. Basically, the term ν_i^2 is the unconditional variance of β_{it}.

A.2 MCMC Estimation Steps

To perform MCMC, we use Gibbs sampling, and Metropolis-Hasting (MH) algorithm for variables related to the threshold δ. Here is the outline and some details of the MCMC estimation.

Sampling β:
The process $\beta_{0:T}$ is sampled by Metropolis-within-Gibbs sampling method. In particular, MH sampling is used for β_t conditional on β_{-t} and $\{\theta_\beta, \delta, h_{1:T}, f_{1:T}, Y_{1:T}, X_{1:T}\}$ for $t = 1, \ldots, T$. If there was no threshold, we could have easily sampled β_t's by using Kalman filter type algorithm. Hence, in the accept-reject algorithm, β_t^* which is sampled from a hypothetically no-threshold model is used as a proposal. Note that Ω_t has 0 in the off-diagonals, thus the variables in each row of the measurement equation is uncorrelated over i. That is, we can sample each row of Λ_t independently from other rows. The conditional posterior of $k \times 1$ vector β_t under this case is $\mathcal{N}(\beta_t|m_t, M_t)$ where $i = 1, \ldots, N$ and for $t = 2 : T-1$

$$\begin{aligned}
M_t^{-1} &= e^{-h_{it}} f_t f_t' + V_\beta^{-1}(I + \alpha_\beta' \alpha_\beta) \\
m_t &= M_t[e^{-h_{it}} f_t \tilde{X}_{it} + V_\beta^{-1}\{\alpha_\beta(\beta_{t-1} - \beta_{t+1}) + (I - 2\alpha_\beta + \alpha_\beta'\alpha_\beta)\mu_\beta\}]
\end{aligned}$$

for $t=1$ and $t=T$

$$\begin{aligned} M_1^{-1} &= e^{-h_{i1}} f_1 f_1' + V_{\beta,0}^{-1} + V_\beta^{-1}(I + \alpha_\beta' \alpha_\beta) \\ m_1 &= M_1[e^{-h_{i1}} f_1 \tilde{X}_{i1} + V_{\beta,0}^{-1}\mu_\beta + V_\beta^{-1}\alpha_\beta\{\beta_2 - (I-\alpha_\beta)\mu_\beta\}] \end{aligned}$$

$$\begin{aligned} M_T^{-1} &= e^{-h_{iT}} f_T f_T' + V_\beta^{-1} \\ m_T &= M_T[e^{-h_{iT}} f_T \tilde{X}_{iT} + V_\beta^{-1}\{\alpha_\beta\beta_{T-1} - (I-\alpha_\beta)\mu_\beta\}], \end{aligned}$$

where $V_{\beta,0}$ is the unconditional variance of β_t and $\tilde{X}_{it} = X_{it} - \gamma_i' Y_t$

The acceptance probability is

$$\alpha(\beta_t, \beta_t^*) = \min\left\{1, \frac{\mathcal{N}(\tilde{X}_{it}|f_t'\lambda_t^*, \exp(h_{it}))\mathcal{N}(\beta_t|m_t, M_t)}{\mathcal{N}(\tilde{X}_{it}|f_t'\lambda_t, \exp(h_{it}))\mathcal{N}(\beta_t^*|m_t, M_t)}\right\}.$$

Sampling δ:
The posterior distribution of δ_i is conditioned on $(k-1)\times 1$ vector δ_{-i} and $\{\theta_\beta, h_{1:T}, f_{1:T}, Y_{1:T}, X_{1:T}\}$. The threshold is also sampled by MH algorithm. The proposal is drawn from the conditional prior distribution $\delta_i^* \sim U\left(|\mu_i| + K\nu_i\right)$. The acceptance probability is

$$\alpha(\delta_i, \delta_i^*) = min\left\{1, \prod_{t=1}^{T} \frac{\mathcal{N}(\tilde{X}_{it}|f_t'\lambda_t^*, \exp(h_{it}))}{\mathcal{N}(\tilde{X}_{it}|f_t'\lambda_t, \exp(h_{it}))}\right\}.$$

The parameter K is a tuning parameter. It determines how large the threshold can be, thus in return, it determines the shut-down frequency of β. Nakajima and West (2013a) suggested $K=3$ based on simulation performances, that is the threshold is drawn from a 3-standard-deviation interval. Our estimation results were pretty robust to changes in K - we estimated the model with $K \in \{1.65, 2, 3\}$.

Sampling $\{\mu_\beta,\ \alpha_\beta,\ \sigma_{i,\beta}^{-2}\}$:
These are the parameters associated with the autoregressive process for β_t. The posteriors of these parameters are typical except that they are truncated on a set where the parameter draws are compatible with the upper bound of the threshold: $D_i = \{\delta_i < |\mu_{i\beta}| + K\nu_i\}$.

The posterior density of $\mu_{i\beta}$ is $p(\mu_{i\beta}|\alpha_{i\beta}, \sigma_{i\beta}^2, \beta_{i,1:T}, \delta_i) \propto \mathcal{TN}_{D_i}(\mu_{i\beta}|\hat{\mu_i}, \hat{\omega}_i^2)(|\mu_{i\beta}| + K\nu_i)^{-1}$ where $\mathcal{TN}_{D_i}$ denotes the density of truncated normal on the set D_i, and

$$\hat{\omega}_i^2 = \left\{\frac{1}{\omega_{i0}^2} + \frac{(1-\alpha_i^2) + (T-1)(1-\alpha_1)^2}{\sigma_{iV}^2}\right\}^{-1}$$

$$\hat{\mu}_i = \hat{\omega}_i^2\left\{\frac{\mu_{i0}}{\omega_{i0}^2} + \frac{(1-\alpha_i^2)\beta_{i1} + (1-\alpha_i)\sum_{t=1}^{T-1}(\beta_{i,t+1} - \alpha_i\beta_{it})}{\sigma_{iV}^2}\right\}.$$

Acceptance rate for the candidate which is drawn from the conditional posterior density is $\min\left\{1, \frac{|\mu_{i\beta}|+K\nu_i}{|\mu^*_{i\beta}|+K\nu_i}\right\}$.

The conditional posterior density of $\alpha_{i\beta}$ is

$$p(\alpha_{i\beta}|\mu_{i\beta}, \sigma^2_{i\beta}, \beta_{i,1:T}, \delta_i) \propto Beta(\alpha_{i\beta})(1-\alpha^2_{i\beta})^{1/2}\mathcal{TN}_{(-1,1)\times D_i}(\hat{\alpha}_i, \sigma^2_{\alpha_i})(|\mu_{i\beta}|+K\nu_i)^{-1},$$

where $\hat{\alpha}_i = \sum_{t=1}^{T-1}\bar{\beta}_{i,t+1}\bar{\beta}_{it}/\sum_{t=2}^{T-1}\bar{\beta}^2_{it}$ and $\sigma^2_{\alpha_i} = \sigma^2_{i,\beta}/\sum_{t=2}^{T-1}\bar{\beta}^2_{it}$ with $\bar{\beta}_{it} = \beta_{it} - \mu_i$.

The candidate drawn from the conditional posterior density is accepted with the probability

$$\min\left\{1, \frac{Beta(\alpha^*_i)(1-\alpha^{*2}_i)^{1/2}\{|\mu_{i\beta}|+K\nu^*_i\}}{Beta(\alpha_{i\beta})(1-\alpha^2_{i\beta})^{1/2}\{|\mu_{i\beta}|+K\nu_i\}}\right\}.$$

The conditional posterior density of $\sigma^{-2}_{i,\beta}$

$$p(\sigma^{-2}_{i,\beta}|\mu_{i\beta}, \alpha_{i\beta}, \beta_{i,1:T}, \delta_i) \propto \mathcal{TG}_{D_i}(\sigma^{-2}_{i,\beta}|\hat{v}_i/2, \hat{V}_i/2)(|\mu_{i\beta}|+K\nu_i)^{-1}$$

where the $\mathcal{TG}_{D_i}$ is the density of the implied gamma distribution truncated on D_i, $\hat{v}_i = v_{0i} + T$ and $\hat{V}_i = V_{0i} + (1-\alpha^2_{i\beta})\bar{\beta}^2_{i1} + \sum_{t=1}^{T-1}(\bar{\beta}_{i,t+1} - \alpha_{i\beta}\bar{\beta}_{it})^2$.

Accepting the candidate, drawn from the conditional posterior density, with probability

$$\min\left\{1, \frac{|\mu_{i\beta}|+K\nu_i}{|\mu_{i\beta}|+K\nu^*_i}\right\}.$$

Initial Values: We need to choose initial values for some processes to start the Markov chain. Moreover, the Monte Carlo estimation results should be robust to different initial values. In this regard, we have tested the analysis against different initial values. The results are not intensely different. However it is worthwhile to note that there are some 'bad' initial values. The chains produced by these construct non-positive-definite covariance matrix estimates. In this case, the chain cannot proceed. Yet, once we avoid these initial values, our estimation is robust to different initial values.

For the factors, we choose the principal component analysis estimates as initial values. For other processes $\beta_{0:T}, c_{0:T}, h_{0:T}$, the initial values are drawn from the corresponding unconditional distributions. For instance, $h_t \sim \mathcal{N}(\mu_h, \sigma^2_h/(1-\alpha^2_h))$.

Next, we outline briefly the steps of the MCMC estimation. Note that in each step, updated variables from the previous steps are used.

Step 1: Draw $\beta_{0:T}$

Conditional on $\{\theta_\beta, \delta, c_{1:T}, h_{1:T}, f_{1:T}, \gamma, Y_{1:T}, X_{1:T}\}$, we draw $\beta_{0:T}$ by MH algorithm as explained above, where the candidate is drawn from a no-threshold model distribution.

Step 2: Draw δ

Conditional on $\{\theta_\beta, \beta_{1:T}, c_{1:T}, h_{1:T}, f_{1:T}, \gamma, Y_{1:T}, X_{1:T}\}$, we draw the threshold δ. The candidate is drawn from the conditional prior.

Step 3: Draw $\theta_\beta = \{\mu_\beta, \alpha_\beta, V_\beta\}$

Conditional on $\{\beta_{1:T}, \delta\}$, estimation of θ_β is performed as in a typical AR(1) process. The only difference is that the estimated parameters need to be consistent with the threshold set D_i.

Step 4: Draw $c_{0:T}$

Conditional on $\{\theta_c, \delta, \beta_{1:T}, h_{1:T}, f_{1:T}, \gamma, Y_{1:T}, X_{1:T}\}$, the model can be written easily in a state representation.

$$X_t = c_t + \Lambda_t f_t + \gamma Y_t + e_t$$
$$c_t = \mu_c + \alpha_c(c_{t-1} - \mu_c) + v_{ct}$$

Then the process $c_{0:T}$ is drawn in a forward filtering backwards sampling algorithm (Carter and Kohn (1994)).

Step 5: Draw $\theta_c = \{\mu_c, \alpha_c, V_c\}$

Conditional on $c_{0:T}$, we draw θ_c in a simple AR(1) model.

Step 6: Draw $h_{0:T}$

Conditional on $\{\theta_h, \delta, \beta_{1:T}, c_{1:T}, f_{1:T}, \gamma, Y_{1:T}, X_{1:T}\}$, the stochastic volatility $h_{0:T}$ is drawn in a typical SV estimation method. We use MH algorithm step to accept/reject a candidate drawn from the conditional posterior.

Step 7: Draw $\theta_h = \{\mu_h, \alpha_h, V_h\}$

Conditional on $h_{0:T}$, we draw θ_h in a simple AR(1) model as in Step 5.

Step 8: Draw $f_{1:T}$

Conditional on $\{\delta, \beta_{1:T}, c_{1:T}, h_{1:T}, \gamma, Y_{1:T}, X_{1:T}\}$, the latent factors can be drawn in a similar way as $c_{0:T}$ is drawn in Step 4. To transform the model into state space representation, we need to first transform the factors and Y_t into companion form.

Let $F_t = (f_t', Y_t')'$ be $(K \times 1)$ where $K = k + m$, $\tilde{F}_t = (F_t', \ldots, F_{t-q+1}')'$ be $(Kq \times 1)$, $\tilde{\Lambda}_t = [\Lambda_t, \gamma, 0_{(N\times(Kq-K))}]$ be $(N \times Kq)$, $\tilde{\varepsilon}_t = (\varepsilon_t', 0_{(Kq-K)\times 1}')'$ be $(Kq \times 1)$, and $(Kq \times Kq)$ matrix $\mathbf{\Phi}$ is the companion form of the VAR(q) matrices $\Phi(L)$. Then the state space representation of the factors together with the policy variables is as follows.

$$X_t = c_t + \tilde{\Lambda}_t \tilde{F}_t + e_t$$
$$\tilde{F}_t = \mathbf{\Phi} \tilde{F}_{t-1} + \tilde{\varepsilon}_t$$

Note that the covariance matrix of $\tilde{\varepsilon}_t$ is degenerate, therefore we need to adjust the Kalman filter accordingly and take the corresponding the first $(K \times 1)$ part of the final draw.

Step 9: Draw $\mathbf{\Phi}, \Sigma$

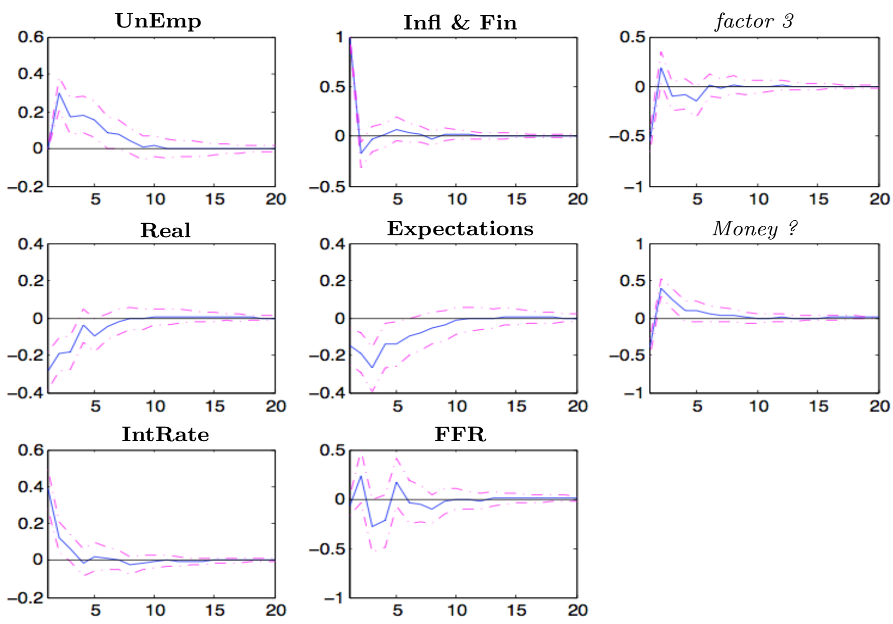
Conditional on $\{f_{1:T}, Y_{1:T}\}$, estimation of $\mathbf{\Phi}$ and Σ is done as in a typical VAR(1) setting $\tilde{F}_t = \mathbf{\Phi} \tilde{F}_{t-1} + \tilde{\varepsilon}_t$.

Step 10: Draw γ

Conditional on $\{\delta, \beta_{1:T}, c_{1:T}, h_{1:T}, f_{1:T}, Y_{1:T}, X_{1:T}\}$, drawing γ is like drawing a coefficient in a simple linear regression: $X_t - \Lambda_t f_t - c_t = \gamma Y_t + e_t$.

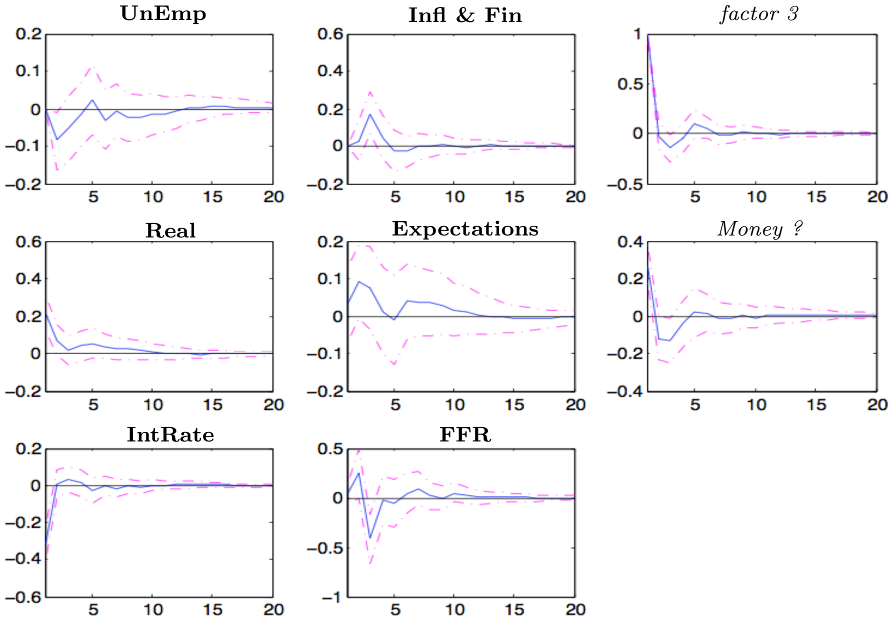
B Impulse response functions

Figure B.1: The responses of the factors and FFR to a 1 unit shock on *inflation and finance* factor



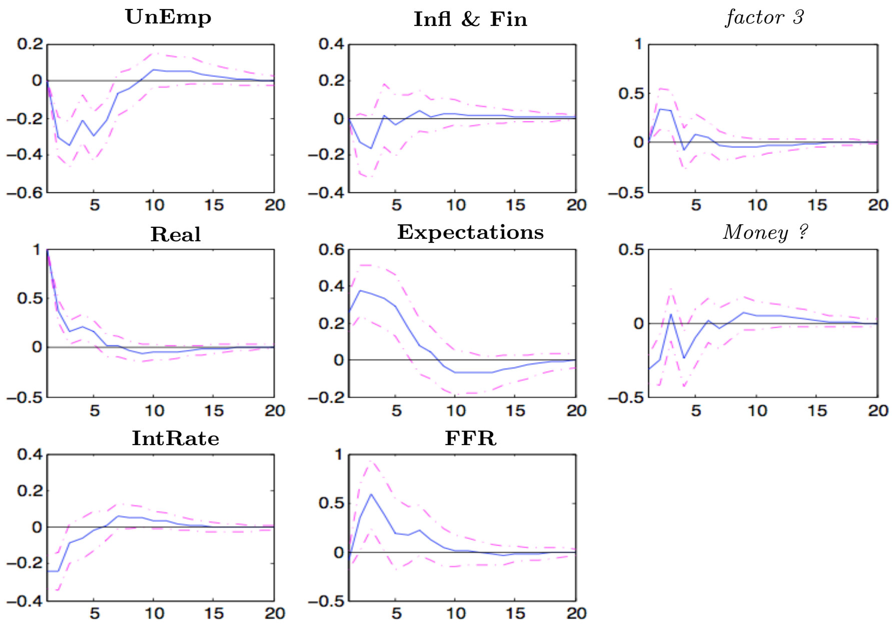
Notes: The confidence bands correspond to the 68% confidence bands.

Figure B.2: The responses of the factors and FFR to a 1 unit shock on *third* factor



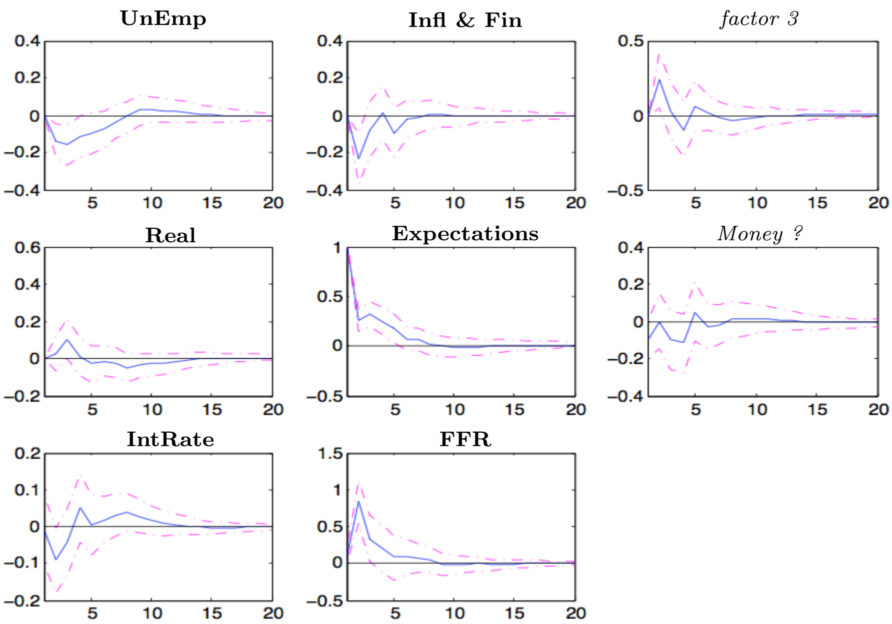
Notes: The confidence bands correspond to the 68% confidence bands.

Figure B.3: The responses of the factors and FFR to a 1 unit shock on *real activity* factor



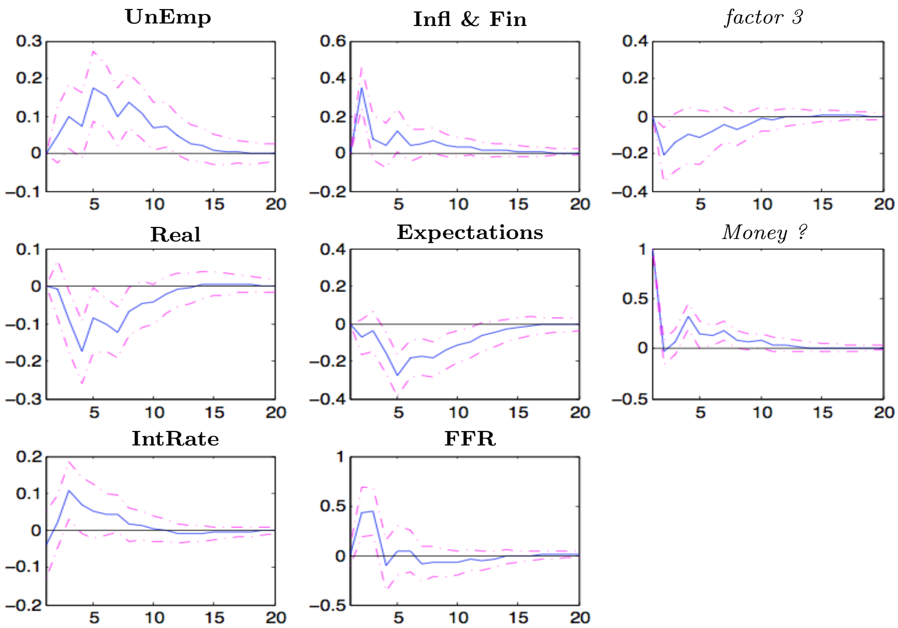
Notes: The confidence bands correspond to the 68% confidence bands.

Figure B.4: The responses of the factors and FFR to a 1 unit shock on *expectations* factor



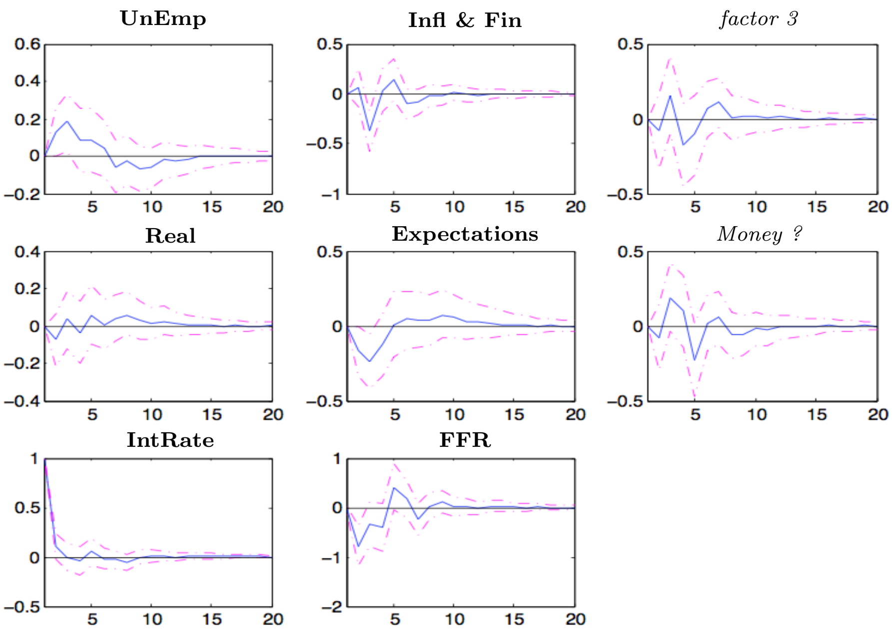
Notes: The confidence bands correspond to the 68% confidence bands.

Figure B.5: The responses of the factors and FFR to a 1 unit shock on *money* factor



Notes: The confidence bands correspond to the 68% confidence bands.

Figure B.6: The responses of the factors and FFR to a 1 unit shock on *interest rate* factor



Notes: The confidence bands correspond to the 68% confidence bands.

C Different Restrictions on Λ_t

The results presented in Table 3 are obtained when seven credit variables are placed at the end of the data set. Hence each of them are forced to be loaded only by one factor. Given these identification restrictions, our model leads us to the interpretation of the factors in Table 3. In regards to the identification and hence interpretation, can we improve the results by changing the restrictions in the loadings?

The answer is *'not necessarily'*. The zero restrictions in the loading matrix fix the rotation of the factors. Even though we assign new restrictions inspired by the results above (e.g. restricting an unemployment variable to be loaded only by the first factor, an expectation variable to be loaded by only the fifth factor etc.), imposing different restrictions changes the rotation of the factors, thereby changing the meanings of the factors.

Table A1 below presents the results when we impose new restrictions on Λ_t. These new restrictions are imposed according to the results in Table 3. As one can easily see, the interpretations and the importance of the factors change dramatically. Now, there is a very distinct 'Hous' factor. The fourth factor now loads on both production and employment variables. The meaning of the fifth factor does not change, it can still be called as expectation factor. Unlike the results of Table 3, here finance and inflation factors can be differentiated. Again, one factor, f_2, cannot

not explain any data group significantly; and one factor, f_7 is uninterpretable as it does not load a particular category.

Table A1: Survival Rates of the Factor Loadings under Different Restrictions

	$\mathbf{f_1}$	$\mathbf{f_2}$	$\mathbf{f_3}$	$\mathbf{f_4}$	$\mathbf{f_5}$	$\mathbf{f_6}$	$\mathbf{f_7}$
	Hous	—	*Fin*	*PrEm*	*Expc*	*Inf*	—
Production	0.53	0.15	0.42	**0.78**	0.41	0.43	0.38
(Un)Employment	0.49	0.16	0.24	**0.72**	0.50	0.20	0.46
Housing	**0.93**	0.34	0.26	0.16	0.27	0.27	0.34
Interest Rate	0.33	0.04	0.26	0.38	0.20	0.26	0.26
Inflation	0.23	0.33	0.36	0.20	0.36	**0.45**	0.30
Finance	0.24	0.12	**0.69**	0.15	0.27	0.45	0.24
Money	0.13	0.15	0.34	0.07	0.19	0.33	0.25
Credit	0.46	0.24	0.45	0.25	0.12	0.13	0.37
Expectations	0.53	0.34	0.26	**0.77**	**0.76**	0.01	0.16

D Data Description For SW Updated Data

Series are from generally from FRED. The series indicated whose source is indicated as FRED+SW are mainly gathered from FRED however the missing time periods are patched from Stock and Watson data set. There are two stock exchange variables taken from Shiller's data set, used in Stock Market Data Used in "Irrational Exuberance" Princeton University Press, 2000, 2005, updated. Moreover there are two stock exchange series taken from Stock and Watson data set but patched from www.multpl.com' for the missing values for the last months of the time period. Oil price is included in the data set however has not been used for the analysis in this paper. The analysis requires all series to be stationary. This is ensured by generally by taking differences or logarithms (and in some cases both). The rates are transformed either by keeping them as they are or taking the first or second differences. Similarly the levels are transformed by either taking logarithms or the first or second differences of logarithms. in this respect, 1: levels, 2: first difference, 3: second difference, 4: logarithm, 5: first difference of logarithm, 6: second difference of logarithm.

Table A2: Updated Stock and Watson Data

			Series ID	Tcode	Description	Units	Seasonal Adjustment	Source
1	PRODUCTION	INC	DDURRG3M086SBEA	6	Personal consumption expenditures: Durable goods (chain-type price index)	Index 09=100	SA	FRED
2		INC	DNDGRG3M086SBEA	5	Personal consumption expenditures: Nondurable goods (chain-type price index)	Index 09=100	SA	FRED
3		CONS	DPCERA3M086SBEA	5	Real personal consumption expenditures (chain-type quantity index)	Index 09=100	SA	FRED
4		CONS	DSERRG3M086SBEA	6	Personal consumption expenditures: Services (chain-type price index)	Index 09=100	SA	FRED
5		CONS	PCEPI	6	Personal Consumption Expenditures: Chain-type Price Index	Index 09=100	SA	FRED
6		INC	RPI	5	Real Personal Income	Bil. of Chained 09 $	SAAR	FRED
7		INC	W875RX1	5	Real personal income excluding current transfer receipts	Bil. of Chained 09 $	SAAR	FRED
8		IND	INDPRO	5	Industrial Production Index	Index 07=100	SA	FRED
9		IND	IPFINAL	5	Industrial Production: Final Products (Market Group)	Index 07=100	SA	FRED
10		IND	IPCONGD	5	Industrial Production: Consumer Goods	Index 07=100	SA	FRED
11		IND	IPDCONGD	5	Industrial Production: Durable Consumer Goods	Index 07=100	SA	FRED
12		IND	IPNCONGD	5	Industrial Production: Nondurable Consumer Goods	Index 07=100	SA	FRED
13		IND	IPBUSEQ	5	Industrial Production: Business Equipment	Index 07=100	SA	FRED
14		IND	IPMAT	5	Industrial Production: Materials	Index 07=100	SA	FRED
15		IND	IPDMAT	5	Industrial Production: Durable Materials	Index 07=100	SA	FRED
16		IND	IPNMAT	5	Industrial Production: nondurable Materials	Index 07=100	SA	FRED
17		IND	IPFPNSS	5	Industrial Production: Final Products and Nonindustrial Supplies	Index 07=100	SA	FRED
18		IND	IPFUELN	5	Industrial Production: Fuels	Index 07=100	NSA	FRED
19		UTIL	TCU	1	Capacity Utilization: Total Industry	% of Capacity	SA	FRED+SW
20		UTIL	MCUMFN	1	Capacity Utilization: Manufacturing (NAICS)	% of Capacity	SA	FRED+SW
21	EMPLOYMENT	EMP	CLF16OV	5	Civilian Labor Force	Thous. of Persons	SA	FRED
22		EMP	CE16OV	5	Civilian Employment	Thous. of Persons	SA	FRED
23		UNEMP	UNRATE	2	Civilian Unemployment Rate	%	SA	FRED
24		UNEMP	UEMPMEAN	2	Average (Mean) Duration of Unemployment	Weeks	SA	FRED
25		UNEMP	UEMPLT5	5	Civilians Unemployed - Less Than 5 Weeks	Thous. of Persons	SA	FRED
26		UNEMP	UEMP5TO14	5	Civilians Unemployed for 5-14 Weeks	Thous. of Persons	SA	FRED
27		UNEMP	UEMP15OV	5	Civilians Unemployed - 15 Weeks & Over	Thous. of Persons	SA	FRED
28		UNEMP	UEMP15T26	5	Civilians Unemployed for 15-26 Weeks	Thous. of Persons	SA	FRED
29		UNEMP	UEMP27OV	5	Civilians Unemployed for 27 Weeks and Over	Thous. of Persons	SA	FRED
30		EMP	PAYEMS	5	All Employees: Total nonfarm	Thous. of Persons	SA	FRED
31		EMP	USPRIV	5	All Employees: Total Private Industries	Thous. of Persons	SA	FRED
32		EMP	CES1021000001	5	All Employees: Mining and Logging: Mining	Thous. of Persons	SA	FRED
33		EMP	USCONS	5	All Employees: Construction	Thous. of Persons	SA	FRED
34		EMP	MANEMP	5	All Employees: Manufacturing	Thous. of Persons	SA	FRED
35		EMP	DMANEMP	5	All Employees: Durable goods	Thous. of Persons	SA	FRED
36		EMP	NDMANEMP	5	All Employees: Nondurable goods	Thous. of Persons	SA	FRED
37		EMP	SRVPRD	5	All Employees: Service-Providing Industries	Thous. of Persons	SA	FRED
38		EMP	USTPU	5	All Employees: Trade, Transportation & Utilities	Thous. of Persons	SA	FRED
39		EMP	USWTRADE	5	All Employees: Wholesale Trade	Thous. of Persons	SA	FRED
40		EMP	USTRADE	5	All Employees: Retail Trade	Thous. of Persons	SA	FRED

			Series ID	Tcode	Description	Units	Seasonal Adjustment	Source
41	EMPLOYMENT	EMP	USFIRE	5	All Employees: Financial Activities	Thous. of Persons	SA	FRED
42		EMP	USGOVT	5	All Employees: Government	Thous. of Persons	SA	FRED
43		EMP	CES0000000010	5	Women Employees: Total Nonfarm	Thous. of Persons	SA	FRED
44		EMP	CES0600000007	1	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	Hours	SA	FRED
45		EMP	AWOTMAN	2	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	Hours	SA	FRED
46		EMP	AWHMAN	1	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	Hours	SA	FRED
47		EMP	AWHI	5	Index of Aggregate Weekly Hours: Production and Nonsupervisory Employees: Total Private Industries	Index 02=100	SA	FRED
48	HOUSING	HOUS	HOUST	4	Housing Starts: Total: New Privately Owned Housing Units Started	Thous. of Units	SAAR	FRED
49		HOUS	HOUSTNE	5	Housing Starts in Northeast Census Region	Thous. of Units	SAAR	FRED
50		HOUS	HOUSTMW	5	Housing Starts in Midwest Census Region	Thous. of Units	SAAR	FRED
51		HOUS	HOUSTS	5	Housing Starts in South Census Region	Thous. of Units	SAAR	FRED
52		HOUS	HOUSTW	4	Housing Starts in West Census Region	Thous. of Units	SAAR	FRED
53		HOUS	PERMIT	4	New Private Housing Units Authorized by Building Permits	Thous. of Units	SAAR	FRED
54		HOUS	PERMITNE	4	New Private Housing Units Authorized by Building Permits in the Northeast Census Region	Thous. of Units	SAAR	FRED
55		HOUS	PERMITMW	5	New Private Housing Units Authorized by Building Permits in the Midwest Census Region	Thous. of Units	SAAR	FRED
56		HOUS	PERMITS	4	New Private Housing Units Authorized by Building Permits in the South Census Region	Thous. of Units	SAAR	FRED
57		HOUS	PERMITW	4	New Private Housing Units Authorized by Building Permits in the West Census Region	Thous. of Units	SAAR	FRED
58		HOUS	PERMIT1	5	New Private Housing Units Authorized by Building Permits - In Structures with 1 Unit	Thous. of Units	SAAR	FRED
59		HOUS	HOUST1F	5	Privately Owned Housing Starts: 1-Unit Structures	Thous. of Units	SAAR	FRED
60		HOUS	MSACSR	5	Monthly Supply of Homes in the United States	Months' Supply	SA	FRED
61	INTEREST RATE	BILL	CPF3M	2	3-Month AA Financial Commercial Paper Rate	%	NSA	FRED+SW
62		BILL	TB3MS	2	3-Month Treasury Bill: Secondary Market Rate	%	NSA	FRED
63		BILL	TB6MS	2	6-Month Treasury Bill: Secondary Market Rate	%	NSA	FRED
64		BOND	GS1	2	1-Year Treasury Constant Maturity Rate	%	NSA	FRED
65		BOND	DGS3	2	3-Year Treasury Constant Maturity Rate	Avrg.	NSA	FRED
66		BOND	GS5	2	5-Year Treasury Constant Maturity Rate	%	NSA	FRED
67		BOND	GS10	2	10-Year Treasury Constant Maturity Rate	%	NSA	FRED
68		BOND	AAA	2	Moody's Seasoned Aaa Corporate Bond Yield	%	NSA	FRED
69		BOND	BAA	2	Moody's Seasoned Baa Corporate Bond Yield	%	NSA	FRED
70		SPRD	T1YFF	1	1-Year Treasury Constant Maturity Minus Federal Funds Rate	%	NSA	FRED+SW
71		SPRD	T5YFF	1	5-Year Treasury Constant Maturity Minus Federal Funds Rate	%	NSA	FRED
72		SPRD	T10YFF	1	10-Year Treasury Constant Maturity Minus Federal Funds Rate	%	NSA	FRED+SW
73		INTR	INTDSRUSM193N	2	Interest Rates, Discount Rate for United States	% per Annum	NSA	FRED
74		INTR	MPRIME	2	Bank Prime Loan Rate	%	NSA	FRED
75		INTR	INTGSBUSM193N	2	Interest Rates, Government Securities, Government Bonds for United States	% per Annum	NSA	FRED
76	INFLATION	PPI	PPIFGS	6	Producer Price Index: Finished Goods	Index 82=100	SA	FRED
77		PPI	PPIFCG	5	Producer Price Index: Finished Consumer Goods	Index 82=100	SA	FRED
78		PPI	PPIITM	5	Producer Price Index: Intermediate Materials: Supplies & Components	Index 82=100	SA	FRED
79		PPI	PPICMM	5	Producer Price Index: Commodities: Metals and metal products: Primary nonferrous metals	Index 82=100	NSA	FRED
80		PPI	PFCGEF	5	Producer Price Index: Finished Consumer Goods Excluding Foods	Index 82=100	SA	FRED

			Series ID	Tcode	Description	Units	Seasonal Adjustment	Source
81	INFLATION	PPI	PPIACO	5	Producer Price Index: All Commodities	Index 82=100	NSA	FRED
82		PPI	PPICPE	5	Producer Price Index: Finished Goods: Capital Equipment	Index 82=100	SA	FRED
83		PPI	PPICRM	5	Producer Price Index: Crude Materials for Further Processing	Index 82=100	SA	FRED
84		PPI	PPIENG	5	Producer Price Index: Fuels & Related Products & Power	Index 82=100	NSA	FRED
85		PPI	PPIFCF	5	Producer Price Index: Finished Consumer Foods	Index 82=100	SA	FRED
86		PPI	PPIFGS	6	Producer Price Index: Finished Goods	Index 82=100	SA	FRED
87		PPI	PPIIDC	5	Producer Price Index: Industrial Commodities	Index 82=100	NSA	FRED
88		CPI	CPIAUCSL	6	Consumer Price Index for All Urban Consumers: All Items	Index 82-84=100	SA	FRED
89		CPI	CPIAPPSL	6	Consumer Price Index for All Urban Consumers: Apparel	Index 82-84=100	SA	FRED
90		CPI	CPITRNSL	5	Consumer Price Index for All Urban Consumers: Transportation	Index 82-84=100	SA	FRED
91		CPI	CPIMEDSL	6	Consumer Price Index for All Urban Consumers: Medical Care	Index 82-84=100	SA	FRED
92		CPI	CUSR0000SAC	5	Consumer Price Index for All Urban Consumers: Commodities	Index 82-84=100	SA	FRED
93		CPI	CUUR0000SAD	6	Consumer Price Index for All Urban Consumers: Durables	Index 82-84=100	NSA	FRED
94		CPI	CUSR0000SAS	6	Consumer Price Index for All Urban Consumers: Services	Index 82-84=100	SA	FRED
95		CPI	CPIULFSL	6	Consumer Price Index for All Urban Consumers: All Items Less Food	Index 82-84=100	SA	FRED
96		CPI	CUUR0000SA0L2	6	Consumer Price Index for All Urban Consumers: All items less shelter	Index 82-84=100	NSA	FRED
97		CPI	CUSR0000SA0L5	6	Consumer Price Index for All Urban Consumers: All items less medical care	Index 82-84=100	SA	FRED
98		CPI	CUSR0000SAF11	5	Consumer Price Index for All Urban Consumers: Food at home	Index 82-84=100	SA	FRED
99		CPI	CUUR0000SEFV	6	Consumer Price Index for All Urban Consumers: Food away from home	Index 82-84=100	NSA	FRED
100		EARN	CES0600000008	6	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing	$ per Hour	SA	FRED
101		EARN	CES2000000008	6	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction	$ per Hour	SA	FRED
102		EARN	CES3000000008	6	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing	$ per Hour	SA	FRED
103		EARN	AHETPI	6	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private	$ per Hour	SA	FRED
104		EARN	CES0500000030	6	Average Weekly Earnings of Production and Nonsupervisory Employees: Total Private	$ per Week	SA	FRED
105	FINANCIAL MARKET	S&P	SP500	5	S&P 500 Stock Price Index	Index	NSA	FRED
106		S&P	SP600DIV	2	S&P 500 Stock Price Index: Dividend	Percent		Shiller
107		S&P	SP500DIVY	2	S&P 500 Dividend Yield	% per Annum		SW+Multpl
108		S&P	SP500EARN	4	S&P 500 Stock Price Index: Earnings	%	NSA	Shiller
109		S&P	SP500PE	5	S&P 500 Price Earnings Ratio	Ratio		SW+Shiller
110		EXRT	EXSZUS	5	Switzerland / U.S. Foreign Exchange Rate	Swiss Francs per Dollar	NSA	FRED+SW
111		EXRT	EXJPUS	5	Japan / U.S. Foreign Exchange Rate	Japanese Yen per Dollar	NSA	FRED+SW
112		EXRT	EXUSUK	5	U.S. / U.K. Foreign Exchange Rate	Dollar per British Pound	NSA	FRED+SW
113		EXRT	EXCAUS	5	Canada / U.S. Foreign Exchange Rate	Canadian Dollar per One U.S. Dollar	NSA	FRED+SW
114		DOWJ	DJCA	2	Dow Jones Composite Average	Index	NSA	FRED
115		DOWJ	DJIA	2	Dow Jones Industrial Average	Index	NSA	FRED
116		DOWJ	DJTA	2	Dow Jones Transportation Average	Index	NSA	FRED
117		DOWJ	DJUA	2	Dow Jones Utility Average	Index	NSA	FRED
118	MONEY	MS	M1SL	6	M1 Money Stock	Bil. of $	SA	FRED
119		MS	M2SL	6	M2 Money Stock	Bil. of $	SA	FRED
120		MS	M2REAL	6	Real M2 Money Stock	Bil. of 82-83 $	SA	FRED

			Series ID	Tcode	Description	Units	Seasonal Adjustment	Source
121	MONEY	MS	AMBSL	6	St. Louis Adjusted Monetary Base	Bil. of $	SA	FRED
122		DEPO	TOTRESNS	6	Total Reserves of Depository Institutions	Bil. of $	NSA	FRED
123		DEPO	NONBORRES	3	Reserves Of Depository Institutions, Nonborrowed	Mil. of $	NSA	FRED
124		MS	BOGAMBSL	5	Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements (DISCONTINUED SERIES)	Bil. of $	SA	FRED
125		MS	CURRSL	6	Currency Component of M1	Bil. of $	SA	FRED
126		DEPO	DEMDEPSL	6	Demand Deposits at Commercial Banks	Bil. of $	SA	FRED
127		DEPO	EXCRESNS	5	Excess Reserves of Depository Institutions (DISCONTINUED SERIES)	Bil. of $	NSA	FRED
128		MS	MABMM301USM189S	5	M3 for the United States	Natinonal Currency	SA	FRED
129		MS	MBCURRCIR	6	Monetary Base; Currency In Circulation	Mil. of $	NSA	FRED
130		DEPO	NFORBRES	3	Net Free or Borrowed Reserves of Depository Institutions (DISCONTINUED SERIES)	Bil. of $	NSA	FRED
131		DEPO	REQRESNS	6	Required Reserves of Depository Institutions	Bil. of $	NSA	FRED
132		DEPO	RESBALNS	5	Total Reserve Balances Maintained with Federal Reserve Banks	Bil. of $	NSA	FRED
133		DEPO	SAVINGSL	5	Savings Deposits - Total	Bil. of $	SA	FRED
134		DEPO	STDCBSL	5	Small Time Deposits at Commercial Banks	Bil. of $	SA	FRED
135		DEPO	STDSL	5	Small Time Deposits - Total	Bil. of $	SA	FRED
136		DEPO	SVGCBSL	5	Savings Deposits at Commercial Banks	Bil. of $	SA	FRED
137		DEPO	TCDSL	6	Total Checkable Deposits	Bil. of $	SA	FRED
138		MS	M2MOWN	2	M2 Minus Own Rate	%	NSA	FRED
139		MS	M2MSL	5	M2 Less Small Time Deposits	Bil. of $	SA	FRED
140	EXPECTATIONS	PRIX	NAPMPI	1	ISM Manufacturing: Production Index	Index	SA	FRED
141		EMIX	NAPMEI	1	ISM Manufacturing: Employment Index	Index	SA	FRED
142		NEWO	NAPMNOI	1	ISM Manufacturing: New Orders Index	Index	SA	FRED
143		VEND	NAPMSDI	1	ISM Manufacturing: Supplier Deliveries Index	Index	SA	FRED
144		INVT	NAPMII	1	ISM Manufacturing: Inventories Index	Index	NSA	FRED
145		COMM	NAPMPRI	1	ISM Manufacturing: Prices Index	Index	NSA	FRED
146		PURC	NAPM	1	ISM Manufacturing: PMI Composite Index	Index	SA	FRED
147	CREDIT	CRED	BUSLOANS	5	Commercial and Industrial Loans, All Commercial Banks	Bil. of $	SA	FRED
148		CRED	CONSUMER	5	Consumer Loans at All Commercial Banks	Bil. of $	SA	FRED
149		CRED	OTHSEC	5	Other Securities at All Commercial Banks	Bil. of $	SA	FRED
150		CRED	REALLN	5	Real Estate Loans, All Commercial Banks	Bil. of $	SA	FRED
151		CRED	TOTALSL	5	Total Consumer Credit Owned and Securitized, Outstanding	Bil. of $	SA	FRED
152		CRED	NONREVSL	5	Total Nonrevolving Credit Owned and Securitized, Outstanding	Bil. of $	SA	FRED
153		CRED	INVESTNSA	5	Securities in Bank Credit, All Commercial Banks	Bil. of $	NSA	FRED
154		CRED	LOANINVNSA	5	Bank Credit, All Commercial Banks	Bil. of $	NSA	FRED
155		CRED	LOANS	5	Loans and Leases in Bank Credit, All Commercial Banks	Bil. of $	SA	FRED
156		CRED	OLLACBM027NBOG	5	Other Loans and Leases, All Commercial Banks	Bil. of $	NSA	FRED
157		CRED	USGSEC	5	Treasury and Agency Securities at All Commercial Banks	Bil. of $	SA	FRED
158		FFR	FEDFUNDS	2	Effective Federal Funds Rate	%	NSA	FRED