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Abstract

We examine the dynamic effects of credit shocks using a large data set of U.S. economic and financial indicators in a structural factor model. An identified credit shock resulting in an unanticipated increase in credit spreads causes a large and persistent downturn in indicators of real economic activity, labor market conditions, expectations of future economic conditions, a gradual decline in aggregate price indices, and a decrease in short- and longer-term riskless interest rates. Our identification procedure, which imposes restrictions on the response of a small number of economic indicators, yields interpretable estimated factors, and allows us to perform counterfactual experiments. Such an experiment suggests that credit spread shocks have largely contributed to the deterioration in economic conditions during the Great Recession.

Key words: credit shocks, FAVAR, structural factor analysis

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1 Introduction

The financial crisis of 2007-2009 caused the most important global economic downturn since the Great Depression. It renewed interest in properly understanding the connection between the real economy and the financial sector. Empirical studies, among others, by Stock and Watson (1989, 2003), Gertler and Lown (1999), Mueller (2007), and Del Negro and Schorfheide (2012), have found that credit spreads (the difference between corporate bond yields and yields on same-maturity Treasury securities) have significant forecasting power in predicting economic growth. In part, this is because asset prices and credit spreads reflect market participants' expectations about future economic conditions. However, Gilchrist, Yankov and Zakrajšek (2009), henceforth GYZ, have shown that shocks to corporate bond yields — based on a broad set of individual firms's bond prices instead of relying on common aggregate credit spread indices — *cause* significant fluctuations in economic activity. Indeed, the strong tightening in US credit conditions in 2007 and 2008 and the associated contraction in economic activity that followed suggests that credit conditions may have important effects on the economy.[1] Understanding the joint dynamics of the real economy and the financial sector could lead to more timely and hopefully more pre-emptive policy responses. This calls for a comprehensive analysis of the quantitative effects of credit shocks on US economic variables and requires an empirical framework that is sufficiently rich to capture the information necessary to account for these joint dynamics.

In this paper, we re-examine the evidence concerning the propagation mechanism of credit shocks on economic activity and a broad range of other macroeconomic and financial series. We assume that all economic and financial indicators considered may be decomposed into an aggregate component driven by a relatively small number of *common factors*, and a series-specific (idiosyncratic) component which is unrelated to aggregate conditions. Accordingly, we characterize the joint dynamics of all indicators using a structural factor model, or Factor-Augmented VAR (FAVAR), which we estimate using large panels of U.S. monthly and quarterly data. The dynamic effects of credit shocks are then obtained after imposing a small number of restrictions on the response of a few selected indicators.

Factor models are particularly suited for such an analysis. By imposing fewer restrictions on the data set than fully structural models, they are less prone to model misspecification. Moreover, they have several advantages over standard VAR models: i) by allowing us to consider the large amount of information potentially observed by agents, factor models min-

[1]Other studies such as Helbling et al. (2011), Gambetti and Musso (2012), Peersman (2012), Eickmeier and Ng (2015) have identified different credit and loan shocks using sign-restrictions, and have found a significant impact on real activity.

imize the risk of omitted variable bias discussed e.g. in Sims (1992) or Bernanke, Boivin and Eliasz (2005); ii) they are not sensitive to the choice of a specific (possibly arbitrary) data series to represent a general economic concept such as "economic activity" or "financial conditions"; and iii) they allow us to analyze the response of a large set of variables of interest to identified shocks.[2]

Earlier applications of FAVAR models have often imposed restrictions on the response of some of the common factors to shocks, which in turn imposes restrictions on the response of the whole set of economic variables. Here, instead, we impose the minimum amount of restrictions necessary to identify shocks to credit conditions, by constraining only the response of a few selected observable variables, as proposed by Stock and Watson (2005, 2016).

The empirical approach is related to that of GYZ, but differs from it in important ways. In order to determine their credit shocks, GYZ impose potentially strong identifying assumptions. In particular, they assume that no macroeconomic variable, including measures of economic activity, prices or interest rates can respond contemporaneously to credit shocks. This assumption may be restrictive, e.g., if changes in credit spreads affect contemporaneously overall financial conditions, including interest rates. It may potentially attribute an overly strong effect of credit spreads on economic variables by preventing a possible contemporaneous drop in the yield on riskless securities, which might mitigate the effect of a credit tightening. In addition, GYZ assume that the factors summarizing macroeconomic indicators are contemporaneously uncorrelated with the factors summarizing all credit spreads, regardless of the source of disturbances. To the extent that such assumptions are violated, their results might be contaminated. Our identification schemes relax these assumptions.

Our results show that an unexpected increase in credit spreads causes a significant contemporaneous drop in yields of Treasury securities at various maturities, and has a significant effect in the same month on other variables such as consumer expectations, commodity prices, capacity utilization, hours worked, housing starts, etc, in contrast to GYZ's assumption. This unexpected increase in the external finance premium also results in a significant and persistent economic slowdown, in the months following the shock. The responses generated by our identifying procedure yield a realistic picture of the effect of credit shocks on the economy, and provide valuable information about the transmission mechanism of these shocks. Moreover, we find that the extracted common factors capture an important dimension of business cycle fluctuations. Notably, credit shocks have quantitatively impor-

[2] In addition, on a more technical note, factor models are are less likely than VARs to be subject to non-fundamentalness issues raised by Forni et al. (2009).

tant effects on numerous indicators of real activity and prices, leading indicators, and credit spreads, as they explain a substantial fraction of the variability of these series.

An advantage of our identification procedure is that it allows us to recover underlying "structural" factors that have an interesting economic interpretation. This allows us to perform counterfactual experiments. Results from such a counterfactual experiment indicate that the credit shocks explain a large part of the decline in many activity and price series, as well as the Federal funds rate in 2008 and 2009.[3]

We consider a battery of specifications. Our first FAVAR model is estimated using a monthly balanced panel. We impose a recursive assumption on a small number of data series to identify structural shocks. In our second specification, we consider a mixed-frequencies monthly panel augmented with quarterly data. We impose a recursive identification scheme that explicitly distinguishes between the monetary policy shocks and credit shocks, and that allows the Federal funds rate (the instrument of policy) to respond on impact to credit shocks, in contrast to GYZ. Furthermore, to make sure that our credit shocks do not reflect exogenous changes in desired investment, we attempt to separately identify shocks to credit conditions and shocks to investment. In contrast to the previous model, we find that interest rates fall significantly on impact in response to credit shocks. As a result, indicators of economic activity register a (slightly) smaller decline. This suggests that monetary policy may mitigate the effects of a credit shock on economic activity. While shocks to credit conditions and to investment may be difficult to disentangle, we take comfort in the fact that the impulse responses to the credit shocks from our FAVAR are consistent with those from a standard fully-structural DSGE model that includes both credit spread and marginal efficiency of investment shocks.

As part of the robustness analysis, we consider FAVAR specifications with observable factors. Overall, the results are robust: in each specification, an adverse shock to credit conditions causes a significant and persistent economic downturn. This reinforces our empirical evidence about the real effects of financial disturbances on economic activity.

Finally, we study the relevance of the large data sets by comparing results from FAVAR models and small-scale VAR models. While the responses of key macroeconomic series to credit shocks are found to be qualitatively similar to those from a small-scale VAR model, credit shocks generate a substantially larger share of economic fluctuations in the FAVAR models than in the small-scale VAR. Given that the VAR likely omits relevant information, it is likely misspecified and thus does not properly capture the source or propagation of key structural shocks, making it less reliable than the FAVAR models. In addition, the factor

[3]This is in line with recent findings of Stock and Watson (2012).

models provide a more complete and comprehensive picture of the effects of credit shocks since the impulse responses and the variance decomposition of all variables can be obtained.

In the next section, we briefly review some mechanisms linking credit shocks and economic variables. Section 3 presents the structural factor model and discusses various estimation and identification issues. The main results are presented in Section 4, followed by the robustness analysis. In Section 6, we compare the results to those obtained from smaller-scale structural VAR models. Section 7 concludes. The Appendix provides more details on the identification of structural shocks in a FAVAR model, the impulse responses to credit spread and investment shocks in a DSGE model, impulse responses following a monetary policy shock, and describes the data sets used.

2 Some Theory

In this section we briefly review various mechanisms that connect financial and economic variables, and the channels through which shocks on the credit market could affect economic activity.

Financial frictions are crucial when linking the credit market conditions to economic activity. In their presence, the composition of the borrowers' net worth becomes important due to the incentive problems faced by the lenders [Bernanke and Gertler (1995), and Bernanke, Gertler and Gilchrist (1999)]: a borrower with a low net worth relative to the amount borrowed has a higher incentive to default. Given this agency problem, the lender demands a higher premium to provide external funds, which raises the external finance premium. Therefore, economic downturns and associated declines in asset values tend to produce an increase in the external finance premium for borrowers holding these assets in their portfolio. The higher external finance premium, in turn, leads to cuts in investments, and hence in production, employment, and thus in the overall economic activity, which induces asset prices to fall further, and so on. This is essentially the so-called financial accelerator mechanism.

Several other transmission channels, focusing on the credit supply, have also been introduced in the literature. The narrow credit channel focuses on the health of the financial intermediaries and their agency problems in raising funds. The capital channel can transmit credit conditions to the economic activity, if banks' capital is affected. In that case, banks must reduce the supply of loans, resulting in a higher external finance premium. In summary, Bernanke and Gertler (1995) identify two channels through which a shock to the external finance premium can affect the real activity. First, according to the *balance sheet channel*, a deterioration in a firm's net worth results in an increase of its external finance premium, and thus causes a reduction in investment, employment, production, and prices; this channel can be broadly seen as affecting the demand of credit. Second, according to the *bank lending channel*, a deterioration of the financial intermediaries' external finance premium constrains the supply of loans and hence causes a reduction in economic activity.

Credit risks and their effect on economic conditions have also been modeled in a general equilibrium framework. For instance, Christiano, Motto and Rostagno (2003, 2009, 2014), in a series of papers, augment a medium-size DSGE model similar to Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007) with a financial accelerator mechanism linking conditions on the credit market to the real economy through the external finance premium following Bernanke, Gertler and Gilchrist (1999). They furthermore introduce a so-called "risk shock," which captures the exogenously time-varying cross-sectional standard deviation of idiosyncratic productivity shocks, and which directly moves credit spreads by changing agency costs. Christiano, Motto and Rostagno (2014), find that such "risk shocks" account for a large share of US GDP fluctuations. In addition, Gilchrist, Ortiz and Zakrajšek (2009) estimate a similar model in which they introduce two financial shocks: a financial disturbance shock that directly affects the external finance premium (corresponding to the "risk shock" just discussed), and a net worth shock affecting the balance sheet of a firm. The second shock can be viewed as a credit demand shock, whose effect depends on the degree of financial market frictions. After estimating the structural model using US data covering the 1973-2008 period, Gilchrist, Ortiz and Zakrajšek (2009) find that both financial shocks cause an increase in the external finance premium, which, through the financial accelerator, implies a persistent slowdown in economic activity and in investment.

3 Econometric Framework in Data-Rich Environment

It is common to estimate the effects of identified macroeconomic shocks using small-scale vector autoregressions (VARs). Such models may however present several issues. Due to the small amount of information in the model, relative to the information set potentially observed by agents, the VAR can easily suffer from an omitted variable problem that can affect the estimated impulse responses or the variance decomposition. Related to that, Forni et al. (2009) argue that while non-fundamentalness is generic of small scale models, it is highly unlikely to arise in large dimensional dynamic factor models.[4] In addition, a potential

[4]If the shocks in the VAR model are fundamental, then the dynamic effects implied by the moving average representation can have a meaningful interpretation, i.e., the structural shocks can be recovered from current and past values of observable series.

problem pertains to the choice of a specific data series to represent a general economic concept, which may be arbitrary. Finally, VARs allow us to produce impulse responses only for the relatively small set of variables included in the estimation.

One way to address all these issues is to take advantage of information contained in large panel data sets using dynamic factor analysis, and in particular the factor-augmented VAR (FAVAR) model.[5] The importance of large data sets and factor analysis is now well documented in both forecasting and structural analysis literature [see Bai and Ng (2008) for an overview]. In particular, Bernanke, Boivin and Eliasz (2005) and Boivin, Giannoni and Stevanović (2009), have shown that incorporating information through a small number of factors corrects for various empirical puzzles when estimating the effects of monetary policy shocks.

We consider the static factor model[6]

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

$$F_t = \Phi(L) F_{t-1} + e_t, \tag{2}$$

where X_t contains N economic and financial indicators, F_t represents K unobserved factors ($N >> K$), Λ is a $N \times K$ matrix of factor loadings, u_t are idiosyncratic components of X_t that are uncorrelated at all leads and lags with F_t and with the factor innovations e_t. This model is an approximate factor model, as we allow for some limited cross-section correlation among the idiosyncratic components in (1).[7]

3.1 Estimation

The estimation of the model (1)–(2) is based on a two-step principal components procedure, where factors are approximated in the first step, and the dynamic process of factors is estimated in the second step. We rely on the result that factors can be obtained by a Principal Components Analysis (PCA) estimator. Stock and Watson (2002a) prove the consistency of such an estimator in the approximate factor model when both cross-section

[5] An alternative is to consider a large Bayesian VAR. See, among others, Banbura, Giannone, and Reichlin (2010), Koop (2013), Carriero, Clark, and Marcellino (2015) and Giannone, Lenza, and Primiceri (2015).

[6] It is worth noting that the static factor model considered here is not very restrictive since an underlying dynamic factor model can be written in static form [see Stock and Watson(2005)].

[7] We assume that only a small number of largest eigenvalues of the covariance matrix of common components may diverge when the number of series tends to infinity, while the remaining eigenvalues as well as the eigenvalues of the covariance matrix of specific components are bounded. See Bai and Ng (2008) and Stock and Watson (2016) for an overview of the modern factor analysis literature, and the distinction between exact and approximate factor models.

and time sizes, N and T, go to infinity, and without restrictions on N/T. Moreover, they justify using $\hat{F}_t$ as regressor without adjustment. Bai and Ng (2006) furthermore show that PCA estimators are $\sqrt{T}$ consistent and asymptotically normal if $\sqrt{T}/N \to 0$. Inference should take into account the effect of generated regressors, except when T/N goes to zero.

The principal components approach is easy to implement and does not require very strong distributional assumptions. Simulation exercises have shown that likelihood-based and two-step procedures perform quite similarly in approximating the space spanned by latent factors.[8] However, since the unobserved factors are first estimated and then included as regressors in the VAR equation (2), and given that the number of series in our application is small, relative to the number of time periods, the two-step approach may suffer from the "generated regressors" problem. To get an accurate statistical inference on the impulse response functions that accounts for uncertainty associated to factors estimation, we use the bootstrap procedure as in Bernanke, Boivin and Eliasz (2005).

3.2 Identification of structural shocks

To identify the structural shocks, we apply the contemporaneous timing restrictions procedure proposed in Stock and Watson (2005, 2016). This procedure identifies credit shocks by restricting only the impact response of a small number of economic indicators.

The approach adopted here contrasts with GYZ, who assume that credit shocks do not have a contemporaneous effect on *any* of the economic factors and indicators, including interest rates. Furthermore, unlike GYZ who estimate two orthogonal sets of factors — those explaining a panel of economic activity indicators, and factors related to credit spreads[9] — we do not need to make such a distinction, and thus do not need to assume that financial factors are orthogonal to other economic factors. Finally, contrary to other identification strategies that have been adopted in analyses using FAVAR models, we do not need to impose that any factor be observed, nor do we rely on the interpretation of a particular latent factor to characterize the responses of economic indicators to structural shocks.[10]

As in Stock and Watson (2005, 2016), we start by inverting the VAR process of factors

[8] See, Doz, Giannone and Reichlin (2006). Moreover, Bernanke, Boivin and Eliasz (2005) estimated their model using both two-step principal components and single-step Bayesian likelihood methods, and obtained essentially the same results.

[9] In GYZ, the credit shock is identified as an innovation to the first "financial factor" obtained as a principal component to a large panel of credit spread data.

[10] In Bernanke, Boivin and Eliasz (2005) and Boivin, Giannoni and Stevanović (2009), the authors impose a short-term interest rate as an observed factor, and the monetary policy shock is identified by assuming that all latent factors driving other economic variables do not respond contemporaneously to innovations in the short-term interest-rate.

(2), assuming stationarity, and substitute the resulting expression into (1), to obtain the moving-average representation of X_t:

$$X_t = B(L)e_t + u_t, \tag{3}$$

where $B\,(L) \equiv \Lambda[I - \Phi(L)L]^{-1}$. We assume that the number of static factors, K, is equal to the number of structural shocks and that the factor innovations e_t are linear combinations of structural shocks ε_t:

$$\varepsilon_t = He_t, \tag{4}$$

where H is a nonsingular square matrix and $\mathrm{E}[\varepsilon_t \varepsilon_t'] = I$. Using (4) to replace e_t in (3) gives the structural moving-average representation of X_t:

$$X_t = B^\star(L)\varepsilon_t + u_t, \tag{5}$$

where $B^\star(L) \equiv B(L)H^{-1} = \Lambda[I - \Phi(L)L]^{-1}H^{-1}$. Equation (5) allows us in turn to compute impulse response functions to structural shocks in ε_t.

To identify the structural shocks ε_t, we assume that $K-1$ indicators do not respond on impact to certain shocks. Specifically, we organize the data in X_t so that these indicators appear first, and impose contemporaneous timing restrictions on the $N \times K$ impact matrix $B^\star(0)$ in (5), so that it takes the form

$$B_0^\star \equiv B^\star\,(0) = \begin{bmatrix} x & 0 & \cdots & 0 \\ x & x & \ddots & 0 \\ x & x & \ddots & 0 \\ x & x & \cdots & x \\ \vdots & \vdots & \ddots & \vdots \\ x & x & \cdots & x \end{bmatrix}, \tag{6}$$

where x stands for unrestricted elements.

To estimate the matrix H, we proceed as in Stock and Watson (2005, 2016), noting that $B^\star_{0:K}\varepsilon_t = B_{0:K}e_t$ implies $B^*_{0:K}B^{*\prime}_{0:K} = B_{0:K}\Sigma_e B'_{0:K}$, where $B_{0:K}$ contains the first K rows of $B_0 \equiv B\,(0) = \Lambda$, $B^\star_{0:K} = B_{0:K}H^{-1}$, and Σ_e is the covariance matrix of e_t. Since $B^\star_{0:K}$ is a $K \times K$ lower triangular matrix, then it must be the case that $B^*_{0:K}$ can be obtained by performing a Choleski decomposition of $(B_{0:K}\Sigma_e B'_{0:K})$, i.e.: $B^*_{0:K} = \mathrm{Chol}(B_{0:K}\Sigma_e B'_{0:K})$. It follows that $H = \left(B^{*}_{0:K}\right)^{-1} B_{0:K}$, or

$$H = [\mathrm{Chol}(B_{0:K}\Sigma_e B'_{0:K})]^{-1} B_{0:K}. \tag{7}$$

The estimate of H is then obtained by replacing $B_{0:K}$ and Σ_e with their estimates in (7). Note that the identifying assumptions are imposed on $K(K-1)/2$ contemporaneous responses of particular indicators in our data set to structural shocks. This allows us to just-identify the matrix H and hence the structural shocks of interest through equation (4).

This identification procedure bears some similarities with the standard recursive identification in VAR models, but also some key differences. In contrast to the standard recursive identification, our procedure does not prevent a priori the latent *factors* from responding contemporaneously to certain structural shocks. However, as noted in Stevanović (2015), when the series-specific term u_t is present, as is the case in FAVARs, the identifying assumptions on $B_0^{\star}$ do constrain the dynamics of the factors in a way that depends on the loadings Λ which connect the economic indicators to the factors.

To better understand these constraints, consider the following stylized example. Suppose that there are only two factors, economic activity (y_t) and credit (s_t), whose dynamics are given by a structural VAR(1) process

$$H \begin{bmatrix} y_t \\ s_t \end{bmatrix} = A \begin{bmatrix} y_{t-1} \\ s_{t-1} \end{bmatrix} + \varepsilon_t \tag{8}$$

where

$$H = \begin{bmatrix} 1 & h_{12} \\ h_{21} & 1 \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad E\left(\varepsilon_t \varepsilon_t'\right) = I_2,$$

and $h_{12}h_{21} \neq 1$ so that H is invertible. $\varepsilon_{1,t}$ represents a shock to economic activity, while $\varepsilon_{2,t}$ denotes the shock to credit conditions that we are interested in identifying. Suppose furthermore that our set of observables X_t comprises two measures of activity, $y_{1,t}$ and $y_{2,t}$ — corresponding for instance to the unemployment rate and growth in industrial production —, and a measure of credit conditions, say a credit spread, sp_t, that load both on the activity and credit factors:

$$X_t = \begin{bmatrix} y_{1t} \\ sp_t \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \\ \lambda_{31} & \lambda_{32} \end{bmatrix} \begin{bmatrix} y_t \\ s_t \end{bmatrix} + u_t \tag{9}$$

where $u_t = [u_{1,t}\ u_{2,t}\ u_{3,t}]'$ is uncorrelated with ε_t at all leads and lags, and $E(u_t u_t')$ is diagonal.

Pre-multiplying the structural VAR (8) by H^{-1} yields the reduced form VAR

$$\begin{bmatrix} y_t \\ s_t \end{bmatrix} = \Phi \begin{bmatrix} y_{t-1} \\ s_{t-1} \end{bmatrix} + e_t$$

where $\Phi = H^{-1}A$, and $e_t = H^{-1}\varepsilon_t$. The observables relate in turn to the structural shocks as in (5):

$$X_t = \begin{bmatrix} y_{1t} \\ sp_t \\ y_{2t} \end{bmatrix} = \Lambda H^{-1} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} + \Lambda\Phi H^{-1} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \Lambda\Phi^2 H^{-1} \begin{bmatrix} \varepsilon_{1,t-2} \\ \varepsilon_{2,t-2} \end{bmatrix} + ... + u_t,$$

and the impact response of the observables to structural shocks is

$$B_0^* \;=\; \Lambda H^{-1} = (1 - h_{12}h_{21})^{-1} \begin{bmatrix} \lambda_{11} - \lambda_{12}h_{21} & \lambda_{12} - \lambda_{11}h_{12} \\ \lambda_{21} - \lambda_{22}h_{21} & \lambda_{22} - \lambda_{21}h_{12} \\ \lambda_{31} - \lambda_{32}h_{21} & \lambda_{32} - \lambda_{31}h_{12} \end{bmatrix}. \tag{10}$$

We identify the credit shock $\varepsilon_{2,t}$ by assuming, as in Stock and Watson (2005), that a sub-matrix of B_0^* is lower triangular. We suppose for instance that the indicator of activity $y_{1,t}$ does not respond on impact to a credit shock, $\varepsilon_{2,t}$, while the other indicators such as $y_{2,t}$ and sp_t may still respond contemporaneously to that shock. This amounts to assuming that the impact response of $y_{1,t}$ to $\varepsilon_{2,t}$ is equal to 0:

$$(1 - h_{12}h_{21})^{-1} (\lambda_{12} - \lambda_{11}h_{12}) = 0.$$

Looking at (8) and (9), we see that credit conditions s_t, affect the indicator of activity y_{1t} both directly through the loading λ_{12}, and indirectly, by affecting the activity factor y_t with weight h_{12}, and in turn the activity indicator y_{1t} with weight $\lambda_{11}h_{12}$. So, intuitively, the above restriction states that the sum of direct and indirect effects of the shock $\varepsilon_{2,t}$ on the activity indicator y_{1t} is zero.

Now, what are the implications of this identification restriction on the other observable series? Under the restrictions just discussed, the rotation matrix H must be such that $h_{12} = \lambda_{12}/\lambda_{11}$. In particular, if the indicator of activity $y_{1,t}$ does not load on the credit factor (so that $\lambda_{12} = 0$), then our identifying assumption implicitly requires that $h_{12} = 0$, i.e., that economic activity does not depend contemporaneously on credit conditions. More generally, if $y_{1,t}$ loads on the credit factor, then the identifying restriction implies that the direct and indirect effects of credit shocks on $y_{1,t}$ cancel out. Regarding the second activity measure, $y_{2,t}$, if it loads on s_t in the same fashion as $y_{1,t}$, i.e., $\lambda_{32} \simeq \lambda_{12} = 0$, then its impulse response to the credit shock will also be zero or at least not significant. In that case, imposing the valid restriction $\lambda_{32} = 0$ could improve the precision of the estimation.[11] On the other hand, if the indicator of activity $y_{2,t}$ does respond on impact to credit conditions — say because that indicator focuses on a sector highly dependent on financial conditions — then we would not want to assume that y_{1t} and y_{2t} respond in the same fashion to credit. Even if $y_{1,t}$ and $y_{2,t}$ are unconditionally correlated, these indicators need not load similarly on s_t. Imposing only the minimal set of restrictions to just-identify structural shocks is then more robust.

Appendix A further discusses the identification of structural shocks by performing a Monte Carlo experiment in a FAVAR specification discussed below. It shows that the identification strategy adopted is able to recover the true impulse response functions, i.e., both the contemporaneous effects and the propagation mechanism.

3.3 Data and main specifications

We use two main specifications of the FAVAR involving different identifying restrictions and also an increasingly large number of economic and financial indicators. The time span for all panels starts in 1959M01 and ends in 2009M06. All series are initially transformed to induce stationarity. The description of the series and their transformation is presented in Appendix E.

Common proxies of the external finance premium of borrowing firms are the credit spreads for non-financial institutions. Our benchmark measure will be the 10-year B-spread (i.e. the difference between BAA corporate bond yields and 10-year Treasury bond yields), although we considered as alternatives the 10-year A-spread and the 1-year B-spread. Table 1 and Figure 1 summarize these measures. Figure 1 reveals clearly that credit spreads, especially the 1-year B-spread, are positively correlated with the unemployment rate. This correlation confounds however both the effects of current economic conditions on credit spreads and the effects of the latter credit spreads on economic conditions. The exercises that follow attempt to disentangle these channels and in particular to insulate the quantitative effects on the economy of a disruption in credit conditions.

In our first specification, we consider a balanced panel containing 124 monthly U.S. economic and financial series. This is an updated version of the data set in Bernanke, Boivin and Eliasz (2005). We impose a recursive structure on the following four economic indicators:

[11]When imposing both $\lambda_{12} = 0$ and $\lambda_{32} = 0$, reduced-rank techniques must be used to estimate the rotation matrix H since B_0^* is not full rank matrix [see Stock and Watson (2005) for details].

[π_{CPI}, UR, FFR, $10yBS$], where π_{CPI} is the inflation rate calculated as the first difference in the log of the consumer price index (CPI), UR is the unemployment rate, FFR is the Federal funds rate, and $10yBS$ is the 10-year B-spread. Specifically, we list these indicators first in our data set X_t and assume that the matrix B_0^* is of the form (6) in the structural moving-average representation (5). This assumption implies that the inflation rate based on the consumer price index, the unemployment rate and the Federal Funds rate are the only indicators that do not respond immediately to a surprise increase in the 10-year B-spread, which is interpreted as the credit shock. The idea is that following credit shocks, it takes at least one month for the CPI and the unemployment rate to respond. We also assume here that the FOMC does not respond in the same month to unexpected credit shocks. (The next specification relaxes this restriction.) This identification scheme is related to the identification strategy in GYZ in the sense that the shock is seen as an unexpected increase in the external finance premium. However, it is important to remark that we do *not* impose that all the measures of economic activity, prices and interest rates respond with a lag to the credit shock. In particular, all indicators other than π_{CPI}, UR and FFR may respond contemporaneously to the credit shock.[12] Furthermore, the shock in our approach is a disturbance to the last element of the vector ε_t. It captures the surprise innovation in the B-spread, after accounting for fluctuations in past common factors as well as in the current factors that explain the behavior of π_{CPI}, UR, and FFR. The impact response of the B-spread is equal to the standard deviation of the credit shock, which is function of the relevant factor loadings in Λ and the corresponding elements in the rotation matrix H.

The second specification augments the monthly panel above with 58 important quarterly U.S. macroeconomic series, to yield a mixed-frequencies monthly panel of 182 indicators, over the same period.[13] The goal is to use the informational content from quarterly indicators so as to better approximate the space spanned by structural shocks, and thus to achieve a more reliable identification of these shocks.[14]

[12]Another possibility is to impose a block-recursive structure on each group (e.g. production, inflation, interest rates, etc.). However, we believe that our just-identified scheme is well suited since it is not obvious *ex ante* that all sectoral series load identically on the credit factor. We prefer to impose zero impact restrictions on aggregate measures of inflation and real activity, and leave the impulse responses of disaggregated series free to depend on their own exposure to credit market conditions, as given by the corresponding factor loadings. In addition, our approach is more robust than the over-identified restrictions structure. See Appendix A for more details.

[13]The mixed-frequencies panel is obtained using an EM algorithm as in Stock and Watson (2002b), and Boivin, Giannoni and Stevanović (2009).

[14]Adding more series is not obvious. While the two-step estimators are consistent even in presence of weak cross-correlation between the idiosyncratic errors, adding many data of the same type in the finite sample context could increase the amount of cross-correlation in the error term and alter the performance of the PCA estimator. However, the pre-screening proposed by Boivin and Ng (2006) is largely ad hoc, and the

Compared to the previous specification, we also use different identifying restrictions to estimate the credit shocks. Specifically, we assume a recursive structure in the following indicators [π_{PCE}, UR, ΔI, $10yBS$, FFR], where the credit shock and the monetary policy shock are ordered respectively fourth and fifth in ε_t. This particular identification scheme implies that the inflation rate based on the Personal Consumption Expenditure Price Index (π_{PCE}), the Unemployment Rate (UR) and real investment growth (ΔI) do not respond in the same month to both unexpected credit shocks and monetary policy shocks.

Regarding the latter restriction, recent research has suggested that shocks to physical investment constitute a key source of business cycle fluctuations (see, e.g., Greenwood et al., (1988), Greenwood et al. (1997), Fisher (2006), Justiniano et al. (2010, 2011)). Justiniano et al. (2011) argue that the investment shocks which are most relevant for business cycles take the form of so-called marginal efficiency of investment shocks, which perturb transformation of investment goods into productive capital. They suggest that such shocks may ultimately reflect at least in part more fundamental disturbances to financial intermediation. Indeed, they find that their estimated marginal efficiency of investment shocks are highly correlated with credit spreads. To avoid that our estimated shocks to credit conditions capture exogenous disturbances to investment, we include real investment among the series on which we impose restrictions, and assume that real investment does not respond in the same month to credit spread shocks. By imposing restrictions on the contemporaneous response of investment, we hope to better identify the credit spread shock.[15]

Finally, we let the Federal Funds Rate (FFR) respond immediately to all other shocks, including the credit shock. This contrasts with our first specification, in which assume that the FOMC does not let the FFR respond to contemporaneous credit spread shocks. While the assumption in FAVAR 1 may be plausible for most months, it is more questionable in periods in which credit spreads register large changes, such as in the fall 2008, when the FOMC sharply lowered the FFR as the financial conditions quickly deteriorated. As a

cost from using all series, if any, seems to be marginal in practice.

[15] While credit spreads may be correlated with marginal efficiency of investment shocks, the two should be distinguishable from one another. To illustrate this, consider for instance the estimated medium-scale DSGE model presented in Del Negro et al. (2015), which includes financial frictions, credit spread shocks and shocks to the marginal efficiency of investment. As shown in Figure 14 of Appendix B, an unanticipated increase in the spread causes a reduction in economic activity, hours worked, and investment, in this model. As the economy slows down the short-term interest rate (FFR) declines to mitigate the effects of the downturn. In comparison, Figure 15 shows the effect of an unanticipated (negative) shock to the marginal efficiency of investment in this model. Such a shock causes similarly a reduction in desired investment, economic activity, hours worked, and in the FFR. However, the credit spread also declines in this case. So while the spread and investment are negatively correlated on impact following spread shocks, these two variables are positively correlated on impact following a marginal efficiency of investment shock.

robustness check we thus consider an alternative assumption where the FOMC is allowed to respond contemporaneously to all shocks.

4 Results

In this section, we first present empirical results from our two main FAVAR specifications. We provide robustness results from additional specifications in the next section.[16] The lag order in VAR dynamics in (2) is set to 3 according to BIC. Finally, the 90% confidence intervals are computed using 5,000 bootstrap replications.

4.1 FAVAR 1 and monthly balanced panel

We estimate the first specification of the FAVAR using the monthly balanced panel. The recursive identification scheme, $[\pi_{CPI}, UR, FFR, 10yBS]$, implies extracting four static factors from the data, X_t.[17]

4.1.1 Impulse responses to credit shocks

Figure 2 plots the impulse responses of the level of key variables to the credit shock. On impact, the B-spread (lower right panel) rises by 19.2 basis points relative to its initial value. This unexpected increase in the external finance premium generates a significant and very persistent economic downturn, in line with the transmission channels discussed above. For example, industrial production (IP) falls little on impact but then by as much as 2% within the first 12 months, before returning to its initial level after 4 years. Average weekly hours worked and capacity utilization fall significantly on impact. Real personal consumption falls significantly and persistently along with consumer credit, though the consumption decline is more muted (about 0.3% after a year) than that of production and consumer credit, in line with theories emphasizing the intertemporal smoothing of consumption. The labor market indicators such as the unemployment rate and average unemployment duration rise significantly for about 3 years, while employment and wages (average hourly earnings) decline.

[16] While we can plot the impulse responses of all variables contained in the informational panel X_t, we will focus here on a subset of economic and financial indicators included in our data set.

[17] We have estimated the number of static and dynamic shocks using procedures in Amengual and Watson (2007), Bai and Ng (2002, 2007), Hallin and Liska (2007) and Onatski (2009, 2010). In case of balanced monthly panel (FAVAR 1), these information criteria and tests suggested between 2 and 7 static and dynamic shocks. In FAVAR 2 specification, it ranged between 3 and 8. Hence, we are confident in our choice of the number of common shocks.

The price indices based on the CPI, core CPI, and PPI, show almost no change on impact and present a very persistent decline thereafter, settling four years later at a permanently lower level than would have obtained without the credit shock. Note that while our identification restriction prevents the CPI-based inflation to change contemporaneously with the credit shock, other measures of inflation such as those based on the core CPI or the PPI are allowed to respond contemporaneously. The fact that they show no response on impact provides some comfort to our identifying assumption.

The leading indicators, such as consumer expectations, new orders, housing starts and commodity prices, all react negatively on impact, and remain below their initial level for at least a year. Similarly, 3-month and 10-year yields on Treasury securities fall markedly on impact and in years following the shock. While the Federal funds rate is prevented from declining on impact, by assumption, it does fall in the subsequent months, reaching a drop of about 40 basis points one year after the shock. The assumption of no contemporaneous change in the Federal funds rate could be justified by the fact that such changes occur mostly at pre-scheduled FOMC dates, and thus may not respond immediately to credit spread shocks. We will assess below how empirically realistic such an assumption is by considering alternative identifying restrictions. Note that as interest rates decrease the demand for monetary aggregate M1 increases, while M2 remains roughly unchanged.

Some of these responses, in particular those involving leading indicators and interest rates, contrast sharply with those of GYZ, who assumed that no macroeconomic variable could respond on impact to credit shocks. Yet, even though long-term rates fall and thereby partially offset the adverse effects of the credit shock by stimulating consumption and investment, economic activity remains depressed following the negative credit shock. Indeed our estimate of the effect of the credit shock on industrial production is not too different from that of GYZ.[18] Our arguably more realistic identifying assumptions yield quantitatively reasonable responses of a large set of variables. This reinforces GYZ's conclusion that disturbances to US credit markets can have an important impacts on economic activity.

4.1.2 Importance of credit shocks

Table 2 shows the importance of credit shocks in explaining economic fluctuations during our 1959-2009 sample. The middle column reports for key macroeconomic series, $x_{i,t}$, the contribution of the credit shock to the variance of the forecast error of the respective series at a 48-month horizon. Interestingly, the credit shock has important effects on many crucial

[18] GYZ find that industrial production falls by about one percent over a 24-month period following a shock corresponding to a 10-50 basis points increase in the credit spreads.

variables: it explains more than 50% of the forecast error variance of industrial production, consumer credit, capacity utilization rate, labor market series, some leading indicators and credit spreads. Table 2 also presents that common disturbances explain overall a large fraction of fluctuations in key economic time series. Indeed, the third column of Table 2 shows that the common component explains a sizeable fraction of the variability in most of the indicators listed, especially for industrial production, prices, financial indicators, average unemployment duration, capacity utilization and consumer expectations, though variables such the exchange rate seem to be driven mostly by other factors.

4.1.3 Interpretation of factors

An interesting feature of the identification approach is the rotation matrix H which can be used to interpret the estimated factors. Recall from Section 3.2, that structural shocks are a linear combination of residuals, $\varepsilon_t = He_t$. This allows us to rewrite the system (1)-(2) in its structural form

$$X_t = \Lambda^\star F_t^\star + u_t \tag{11}$$

$$F_t^\star = \Phi^\star(L) F_{t-1}^\star + \varepsilon_t \tag{12}$$

where $F_t^\star = HF_t$, $\Lambda^\star = \Lambda H^{-1}$, and $\Phi^\star(L) = H\Phi(L)H^{-1}$. Hence, given the estimates of F_t and H, we can obtain an estimate of the structural factors, $\hat{F}_t^\star = \hat{H}\hat{F}_t$, associated with the structural shocks ε_t.[19] Table 3 presents the correlation coefficients between the estimated rotated factors, $F_t^\star$, and the variables used in the recursive identification scheme. The factors and associated variables are plotted in Figure 3. The results reveal that the rotation by $\hat{H}$ yields estimated structural factors very close to the observed indicators used in the recursive identification scheme: the first rotated factor is highly correlated with π_{CPI}, the second is related to the unemployment rate, the third to the Federal funds rate and the last to our credit spread measure.

4.1.4 How important were credit spreads in the Great Recession?

Having estimated "structural" factors, it is now possible to use our model to evaluate the extent to which credit spreads have contributed to the economic downturn in the Great Recession. To do so, we simulate our estimated model in structural form, excluding the credit shock. Figure 4 plots the resulting simulated series (dashed black lines) as well as

[19]This gives "structural" factors as opposed to the statistically identified factors in Bai and Ng (2013).

actual data (solid blue lines) from 2007M1 to 2009M6, the date at which the recession officially ended.[20] The simulated series are obtained by using the system (11)-(12) where the last element of ε_t is set to zero in the FAVAR 1 from 2007M1 to 2009M6, and the initial conditions for the factors are given by the estimated value of F_t^* in 2006M12.

Figure 4 reveals that credit shocks were important during the Great Recession for many real activity and price series. The simulation shows that a mild downturn in many activity and price indicators would have taken place even in the absence of credit spread shocks. In response to this downturn, short-term interest rates would have been reduced, and a recovery would have been underway starting in late 2008, allowing short-term rates to begin to normalize by early 2009.

The jump in credit spreads, in particular in the Fall of 2008, was responsible for causing a much deeper recession and a collapse in many indicators. The simulation shows for example that credit spread shocks reduced industrial production and employment in mid-2009 by more than 20% and 7%, respectively, compared to the levels that would have been obtained without credit disturbances. Similarly, credit spread shocks are estimated to have increased the unemployment rate by more than 3 percentage points, and reduced the consumer price index by about 3%, by mid-2009. As a result, the Federal funds rate was lowered to near zero. These findings appear in line with Stock and Watson (2012) who point to exceptionally large shocks associated with financial disruptions and uncertainty in explaining the economic collapse during the Great Recession.

4.2 FAVAR 2 and mixed-frequencies panel

To assess the robustness of the results discussed above, we consider an alternative identification scheme and incorporate additional data. As mentioned in Section 3.3, our second specification uses the mixed-frequencies monthly panel and impose the recursive identification based on the following ordering $[\pi_{PCE}, UR, \Delta I, 10yBS, FFR]$. The credit shock and the monetary policy shock are ordered respectively fourth and fifth in ε_t. An advantage of this specification compared to the FAVAR 1 is that it allows the Federal funds rate to respond contemporaneously to credit shocks.

4.2.1 Responses to credit shocks

The impulse responses to an unexpected disturbance to credit conditions are presented in Figure 5. The impact response of the B-spread is a little more than 20 basis points, i.e., a

[20]According to the NBER, the Great Recession lasted from December 2007 to June 2009.

response similar to the one considered in FAVAR 1. In contrast to the previous specification, the Federal funds rate declines significantly on impact, now that its contemporaneous response is left unrestricted. This results in a large impact response of the 3-month Treasury bill yield, of the 10-year Treasury bond yield, and of the S&P composite common stock dividend yield. The sharp drop in the Federal funds rate and longer-term Treasury yields is associated with an overall slightly smaller response of economic activity measures to the credit shock, but the drop in the policy rate and in Treasury yields is not large enough to completely offset the effect of the credit shock. Indeed, the unexpected increase in the external finance premium still generates a significant and persistent economic slowdown and an associated large and persistent decline in price indexes. Industrial production, capacity utilization and employment present a significant downturn for about 18 months after the shock. The unemployment rate and the average unemployment duration both increase persistently, while employment and salary indicators decline. The leading indicators of economic activity — housing starts, new orders, and consumer expectations — also react negatively and significantly on impact.

Figure 6 displays the impulse responses of some monthly indicators constructed from the quarterly observed variables, such as various GDP components and two associated price indexes, to the same credit shock. While the investment series, and especially nonresidential investment fall significantly, and the GDP and PCE deflators decline in a persistent and significant fashion, the responses of the other variables are less precise.

These results are overall intuitive. They are also consistent with the predictions of the DSGE model discussed above and reported in Figure 14 of Appendix B, following a credit spread shock. This provides some comfort that our identification strategy has separated the exogenous disturbances to investment (such as shocks to the marginal efficiency of investment) from innovations affecting the credit.

Figure 7 plots the time series of credit shocks obtained from specifications FAVAR 1 and 2. Both series tend to co-move with the business cycle (as measured by the NBER recession dates), rise in recessions, and peak during the Great Recession. The two series are highly correlated, with a correlation coefficient around 0.8. We take comfort in the fact that both specifications of the FAVAR identify a very similar credit shock, despite their differences, and in particular despite the presence of investment shocks in the FAVAR 2.

Table 4 reports the contribution of the credit shock to the variance of the forecast error in key indicators, as well as the R^2 statistics measuring the importance of common factors in explaining fluctuations in these indicators. As for the FAVAR 1, the R^2 statistics are fairly high for many indicators, suggesting that aggregate disturbances explain overall a large fraction of fluctuations in these economic time series. While the credit shock still explains a relatively large fraction of the variance of the forecast error of prices, financial indicators including Federal funds rate, the capacity utilization rate and consumer credit, it explains a somewhat smaller fraction for real economic activity measures than was the case in the FAVAR 1 specification. For instance, the credit shock accounts now for 29% and 40% of the forecast error variance of industrial production and employment respectively. Furthermore, credit shocks in FAVAR 2 explain a small fraction of the forecast error variance of consumption and GDP. This is essentially due to the presence of investment shocks in this specification. Indeed, the orthogonalized shock to investment equation explains the majority of the variance in real GDP and real consumption.[21]

4.2.2 Interpretation of factors

As for the previous specification, the rotation matrix H can be used to interpret the factors. Table 5 contains the correlation coefficients between the estimated factors and the economic indicators used in the recursive identification scheme, and Figure 8 plots the rotated factors and the corresponding series. We find that the first structural factor is important for the inflation series and the second for unemployment rate. The third factor is positively related to the investment growth series and negatively correlated with the unemployment rate. The fourth factor captures the B-spread, while the fifth factor is related to the Federal funds rate.

4.2.3 Effects of credit spreads in the Great Recession

Again, we can assess how important the estimated credit spreads were in deepening the downturn in the 2007-2009 period. Figures 9 and 10 compare actual data (solid blue lines) with the simulated series of interest (dashed black lines) for the period 2007M1 to 2009M6, using the system (11)-(12) and setting the shock to the credit conditions (i.e., the fourth element of ε_t) to zero. The dashed-dotted red line show the same series simulated with the FAVAR 1 specification.

As for the previous specification, Figures 9 and 10 show that credit shocks were important in deepening the Great Recession for most real activity and price series. For instance, they reduced industrial production and employment in mid-2009 by more than 10% and 4%, respectively. In comparison to the FAVAR 1 specification, however, the tightening in credit conditions did not contribute as much to the decline in economic activity, according to

[21] These "investment shocks" need not correspond to true structural shocks to investment; they may correspond to shocks to the marginal efficiency of investment, productivity shocks, or even real demand shocks. For the purpose of this paper, it suffices that they be orthogonal to shocks to credit conditions.

FAVAR 2. The reason is that in the absence of credit shocks, the short-term interest rates would have risen more in FAVAR 2 than in FAVAR 1, and remained sensibly higher until the end of the sample. This would have in turn caused a slowdown in economic activity and a deterioration in labor market conditions.[22]

5 Further robustness analysis

To further appreciate the robustness of the results, we briefly discuss FAVAR models that include some observable factors in the transition equation along with the latent factors, as in Boivin, Bernanke and Eliasz (2005) and in Boivin, Giannoni and Stevanović (2009). The model is

$$X_t = \Lambda^F F_t + \Lambda^Y Y_t + u_t \tag{13}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t, \tag{14}$$

where F_t contains K latent factors and Y_t includes M observable series. In case of the two-step estimation procedure, the issue is to separate the space spanned by observable and unobservable factors. We considered two alternative approaches.[23] In either case, the identification of structural shocks is achieved by imposing a recursive structure on the VAR residuals in (14). In our context, Y_t contains a proxy of the external finance premium and may contain other observable series. For each estimation procedure, we tried several specifications:

[22] In addition, the Figures 16 and 17 in Appendix C plot the impulse responses to a credit spread shock estimated recursively from 2007M07 to 2009M06. The maximal effect and the persistence become more important from the end of 2008, which is explained partially by the change in the persistence of the credit shock itself. These changes appear much less important in the case of FAVAR 2.

[23] In the first approach, following Bernanke, Boivin and Eliasz (2005), Y_t contains the Federal Funds Rate (FFR). As these authors, we split the sample into a block of 'slow moving' series that do not respond immediately to a shock on FFR, and another consisting of 'fast moving' variables that are not restricted. The latent factors are obtained from the following steps: (i) Let $\hat{C}(F_t, Y_t)$ be the K principal components of X_t; (ii) Let X_t^S be the subset of 'slow moving' variables. Let $C^*(F_t)$ be the K principal components of X_t^S; (iii) Define $\hat{F}_t = \hat{C}(F_t, Y_t) - \hat{\beta}_Y Y_t$ where $\hat{\beta}_Y$ is obtained by least squares estimation of the regression $\hat{C}(F_t, Y_t) = \beta_C C^*(F_t) + \beta_Y Y_t + a_t$; (iv) Get the loadings by regressing X_t on $\hat{F}_t$ and Y_t.

In the second approach, following Boivin, Giannoni and Stevanović (2009), we estimate the latent factors through an iterative application of the principal components estimator. Starting from an initial estimate of F_t, F_t^0 which is the K first principal components of X_t: (i) Regress X_t on $\hat{F}_t^0$ and Y_t to obtain $\hat{\Lambda}^{F,j}$ and $\hat{\Lambda}^{Y,j}$; (ii) Compute $\tilde{X}_t^j = X_t - \hat{\Lambda}^{Y,j} Y_t$; (iii) Update $\hat{F}_t$ as the first K principal components of $\tilde{X}_t$. The main advantage of this procedure is that it does not rely on any temporal assumption between the observed factors and the informational panel.

- Y_t contains only one of the credit spreads;
- Y_t contains a credit spread and the Federal funds rate; we consider different orderings in Y_t;
- we vary the number of latent factors in F_t.

Overall, the results are very similar to those presented here. Each specification reveals a significant and persistent economic downturn following the credit shock, and depending on the identification procedure, the interest rates and leading indicators respond immediately to the shock. This reinforces our empirical evidence about the real effects of financial disturbances on economic activity.

6 Relevance of Large Data Sets

Our analysis has so far considered the effects of credit shocks in FAVAR models that exploit information from large panels of data series. Besides the fact that FAVAR models yield a more complete picture of the effects of particular shocks on the economy, a key justification for using such models is that they have been shown to address a number of empirical puzzles obtained in analyses of empirical models (VARs) involving a small number of data series, especially in response to unanticipated monetary policy shocks. A natural question is thus whether information from large data sets is also relevant to properly characterize the response of credit shocks. To address this question, we compare our findings to those obtained from standard structural VAR models. Our benchmark VAR model, similarly to Mueller (2007), has the following recursive ordering [π_{CPI}, UR, FFR, $10yBS$]. Hence, inflation, unemployment and the Federal funds rate cannot respond in the same month to an unexpected increase in the credit spread. This identifying assumption is the same as the one adopted in the FAVAR 1, although the key difference with respect to FAVAR 1, of course, is that we now consider only a small set of data series.

Figure 11 shows the effects of an unexpected increase in the 10-year B-spread of 19.2 basis points, i.e., the same magnitude as the one considered in FAVAR 1. The shock causes again a significant and persistent increase in the unemployment rate, a fall in the price level, and a persistent reduction of the Federal funds rate. The responses are however smaller than the ones obtained in the context of the FAVAR, which exploits information from a large data set. Since the small-scale VAR is a restricted version of the FAVAR 1, we view the VAR-based impulse responses as potentially more distorted than the ones obtained from the FAVAR.

As the benchmark VAR specification may be restrictive, we check the validity of our results by studying several alternative orderings and using as alternative credit spread measures the 1-year B-spread ($1yBS$) and the 10-year A-spread ($10yAS$). Table 6 lists all the structural VAR models considered, and Figure 12 compares their results. This figure shows that the impulse responses are fairly robust to different empirical measures of the external finance premium and to the ordering between monetary policy and credit shocks, with the exception of the SVAR containing the 1-year B-spread, which shows smaller responses to a same-sized shock.

Table 7 reports the contribution of credit shocks to the total variance of these series. Based on small-scale structural VARs, the credit shocks appear to contribute less to fluctuations in the CPI (less than 6%), and to the unemployment rate (no more than 20%) than is the case with both FAVAR models. The difference is particularly pronounced with the FAVAR 1 model, which is closest to the baseline VAR, and it remains even for the FAVAR 2 model, which includes even more sources of fluctuations (such as investment shocks).

One interesting finding is that the FAVAR impulse responses to credit shocks are qualitatively in line with the ones from the VARs, for the indicators included in the VAR. This suggests that after controlling for past inflation, unemployment and Federal funds rates, shocks to the credit market can be reasonably well captured by innovations in the credit spread. This contrasts with responses to monetary policy shocks, which, as discussed e.g. in Bernanke, Boivin and Eliasz (2005) and Boivin, Giannoni, Stevanovic (2009), show important qualitative differences between VAR and FAVAR responses of many variables. However, to obtain a correct gauge of the quantitative effect of credit shocks in explaining aggregate fluctuations also requires that the transmission mechanism of all shocks, including monetary shocks, be well specified. Given that relevant information may be omitted in small-scale VARs, calculations based on the FAVAR models are likely to be more reliable. These results indicate that credit shocks are indeed much more important in explaining economic fluctuations than the small-scale VAR models suggest.

7 Conclusion

In this paper, we have re-examined the evidence on the propagation mechanism of credit shocks to economic activity, in a data-rich environment, using several specifications of a structural factor model. We identified structural shocks by imposing a minimal number of restrictions on the impact responses of a few economic indicators, while letting the common factors respond.

The common factors are shown to explain an important fraction of the variability in observable variables and thus capture a sizeable dimension of the business cycle movements. Moreover, our identification approach allows us to recover underlying structural factors which have an interesting economic interpretation. A variance decomposition analysis suggests that credit shocks have important effects on several real activity measures, price indicators, leading indicators, and credit spreads.

Our identifying assumptions that leave unconstrained the contemporaneous responses of most indicators yield a more realistic picture of the effect of credit shocks on the economy than has been found to date, and provide valuable information about the transmission of these shocks. The results show that an unexpected increase of a measure of the external finance premium generates a statistically and economically significant economic downturn. This downturn is persistent and broad based, and results in a significant increase in the unemployment rate and a gradual decrease in price indexes. It takes place despite a rapid and significant decline in interest rates. Leading indicators, measures of confidence, and interest rates respond strongly and significantly on impact.

A simulation of the Great Recession period reveals that the jump in credit spreads, in particular in the Fall 2008, was responsible for causing a dramatic deepening of the recession. Finally, our results are largely robust to different FAVAR specifications and identification schemes.

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Table 1: Proxies for the external finance premium

Series description		Time span
FYAAAC	BOND YIELD: MOODY'S AAA CORPORATE	1959M01-2009M06
FYBAAC	BOND YIELD: MOODY'S BAA CORPORATE	1959M01-2009M06
FYGT1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.	1959M01-2009M06
FYGT10	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.	1959M01-2009M06
FYFF	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE)	1959M01-2009M06
Credit spreads		
10Y B-spread	FYBAAC-FYGT10	1959M01-2009M06
10Y A-spread	FYAAAC-FYGT10	1959M01-2009M06
1Y B-spread	FYBAAC-FYGT1	1959M01-2009M06

Table 2: Variance decomposition and R^2 in FAVAR 1

Variables	Credit shock contribution	R^2
IP	0.5780	0.7109
CPI	0.0487	0.8603
CORE CPI	0.1228	0.6136
3m TREASURY BILLS	0.1593	0.9180
10y TREASURY BONDS	0.0752	0.9259
UNEMPLOYMENT	0.4732	0.7368
M1	0.3822	0.0776
M2	0.0169	0.0552
CONSUMER CREDIT	0.6921	0.1775
EXCHANGE RATE average	0.0180	0.0754
COMMODITY PRICE INDEX	0.3143	0.5366
PPI: FINISHED GOODS	0.0292	0.7026
CAPACITY UTIL RATE	0.7606	0.7874
REAL PERSONAL CONSUMPTION	0.2493	0.1401
REAL PERS CONS: SERVICES	0.2855	0.1075
AVG UNEMP DURATION	0.3956	0.7315
EMPLOYMENT	0.6370	0.2867
AVG WEEKLY HOURS	0.7011	0.2994
AVG HOURLY EARNINGS	0.3578	0.1990
HOUSING STARTS	0.6369	0.4610
NEW ORDERS	0.5244	0.2482
S&PS: DIVIDEND YIELD	0.1162	0.6496
CONSUMER EXPECTATIONS	0.3176	0.5432
FFR	0.1563	0.9323
Bspread10y	0.7877	0.6413

Notes: The second column reports for key macroeconomic series, $x_{i,t}$, the contribution of the credit shock to the variance of the forecast error of the respective series at a 48-month horizon. The third column contains the fraction of the variability of this series explained by all common factors, i.e., the R^2 obtained from the regression of $x_{i,t}$ on $\lambda_i^{'} F_t$ for each indicator i, where $\lambda_i^{'}$ denotes the i-th row of matrix Λ in equation (1).

Table 3: Correlation between rotated factors and recursive identification series in FAVAR 1

	$F^*_{1.t}$	$F^*_{2.t}$	$F^*_{3.t}$	$F^*_{4.t}$
CPI inflation	0.9269	0.1389	0.5775	0.1811
UR	0.0644	0.8562	0.2236	0.7938
FFR	0.6392	0.3977	0.9575	0.4958
BSPREAD10y	-0.1353	0.6052	-0.1277	0.6525

Table 4: Variance decomposition and R^2 in FAVAR 2

Variables	Credit shock contribution	R^2
IP	0.4173	0.7319
CPI	0.4690	0.6446
CORE CPI	0.4974	0.6217
3m TREASURY BILLS	0.6057	0.8631
10y TREASURY BONDS	0.5453	0.9074
UNEMPLOYMENT	0.2565	0.7322
M1	0.1372	0.1185
M2	0.1280	0.0394
CONSUMER CREDIT	0.6217	0.1885
EXCHANGE RATE average	0.0348	0.0283
COMMODITY PRICE INDEX	0.8383	0.4944
PPI: FINISHED GOODS	0.4719	0.3297
CAPACITY UTIL RATE	0.8310	0.7398
REAL PERSONAL CONSUMPTION	0.0686	0.3840
REAL PERS CONS: SERVICES	0.2993	0.1076
AVG UNEMP DURATION	0.3701	0.5762
EMPLOYMENT	0.5280	0.3029
AVG WEEKLY HOURS	0.4098	0.3117
AVG HOURLY EARNINGS	0.3742	0.3334
HOUSING STARTS	0.6472	0.4361
NEW ORDERS	0.3474	0.2546
S&PS: DIVIDEND YIELD	0.5000	0.6039
CONSUMER EXPECTATIONS	0.2555	0.5032
FFR	0.5264	0.8807
Bspread10y	0.8529	0.6206
Real GDP	0.0234	0.9316
Real GDP: gds	0.0258	0.8862
Real GDP: svc	0.0378	0.8799
Employees Compensation	0.0583	0.8765
Gov Consumption	0.0363	0.6045
Investment	0.0364	0.8611
Invst: nonresidential	0.0423	0.8993
GDP deflator	0.1799	0.6535
PCE deflator	0.1168	0.7958

Notes: The second column reports for key macroeconomic series, $x_{i,t}$, the contribution of the credit shock to the variance of the forecast error of the respective series at a 48-month horizon. The third column contains the fraction of the variability of this series explained by all common factors, i.e., the R^2 obtained from the regression of $x_{i,t}$ on $\lambda_i^{'}F_t$ for each indicator i, where $\lambda_i^{'}$ denotes the i-th row of matrix Λ in equation (1).

Table 5: Correlation between rotated factors and recursive identification series in FAVAR 2

	$F^*_{1.t}$	$F^*_{2.t}$	$F^*_{3.t}$	$F^*_{4.t}$	$F^*_{5.t}$
PCE inflation	0.8908	0.1248	-0.1973	-0.1599	0.3710
UR	0.0702	0.8540	-0.6648	0.5509	0.7007
Investment growth	0.3428	0.0260	0.4658	-0.0539	-0.0234
B-spread: 10y	-0.1182	0.5956	-0.4703	0.7719	0.4086
FFR	0.5817	0.4118	-0.5319	-0.1400	0.7825

Table 6: VAR models specifications

VAR models	Wald causality ordering
Benchmark	$[\pi_t,\, UR_t,\, FFR_t,\, 10yBS_t]$
Model 2	$[\pi_t,\, UR_t,\, 10yBS_t,\, FFR_t]$
Model 3	$[\pi_t,\, UR_t,\, FFR_t,\, 1yBS_t]$
Model 4	$[\pi_t,\, UR_t,\, FFR_t,\, 10yAS_t]$

Table 7: Variance decomposition: contribution of the credit shock in four VAR models

Variables	Benchmark	Model 2	Model 3	Model 4
CPI inflation	0.0467	0.0569	0.0227	0.0322
Unemployment rate	0.1945	0.1694	0.0477	0.0933
FFR	0.1055	0.1572	0.0882	0.0778
B-spread: 10y	0.9156	0.8968		
B-spread: 1y			0.6069	
A-spread: 10y				0.9437

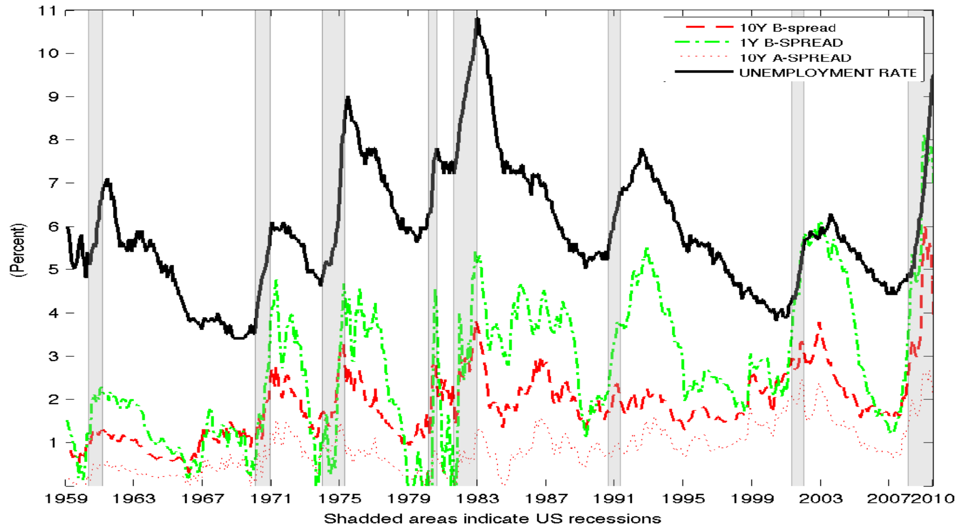

Figure 1: Measures of the external finance premium and unemployment

Notes: The figure shows several measures of credit spreads (defined in Table 1) and the unemployment rate.

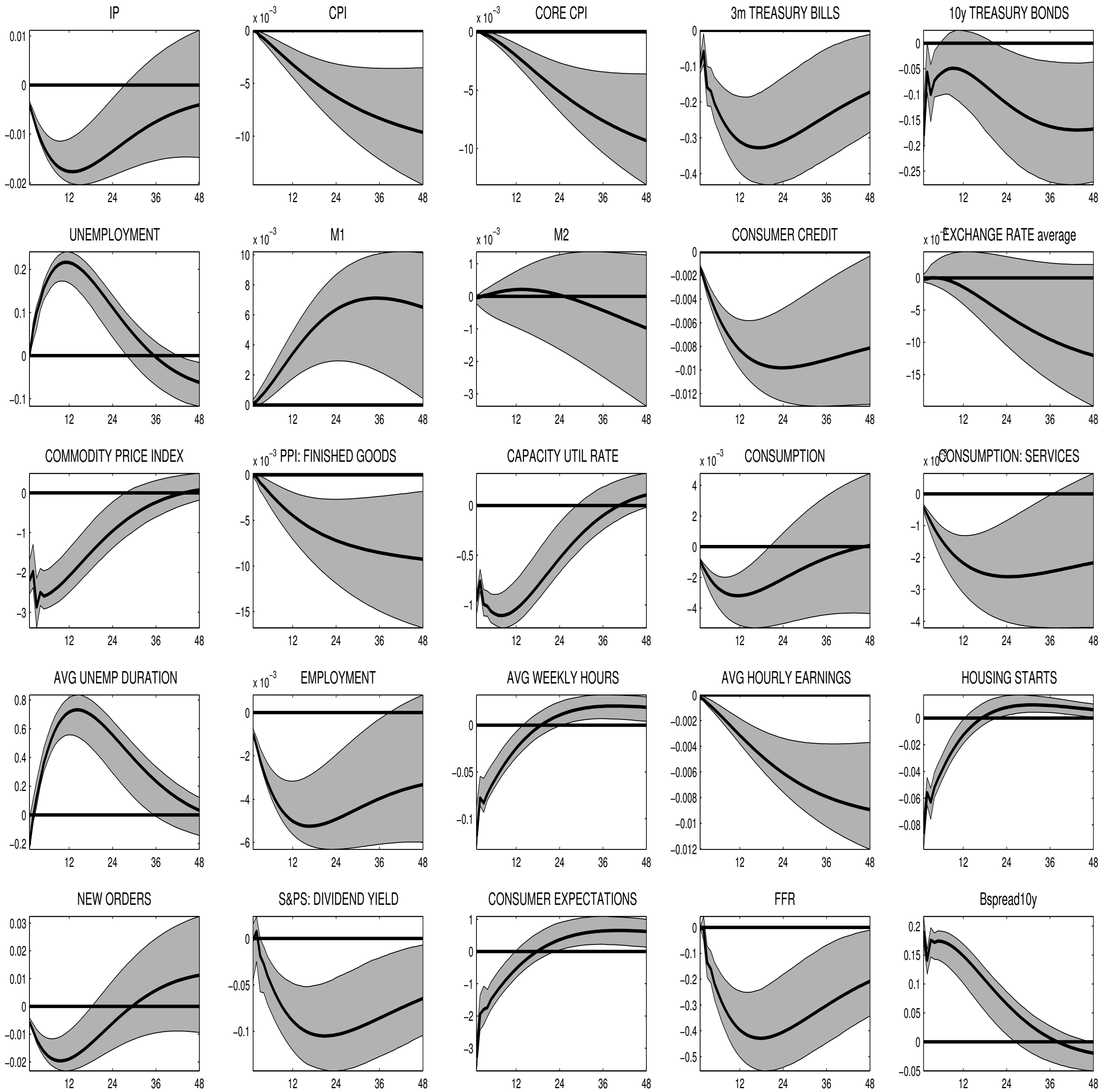

Figure 2: Dynamic responses of monthly variables to credit shock in FAVAR 1

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified through the recursive identification scheme, [π_{CPI}, UR, FFR, $10yBS$], where the credit shock is ordered last. The grey areas indicate the 90% confidence intervals computed using 5,000 bootstrap replications.

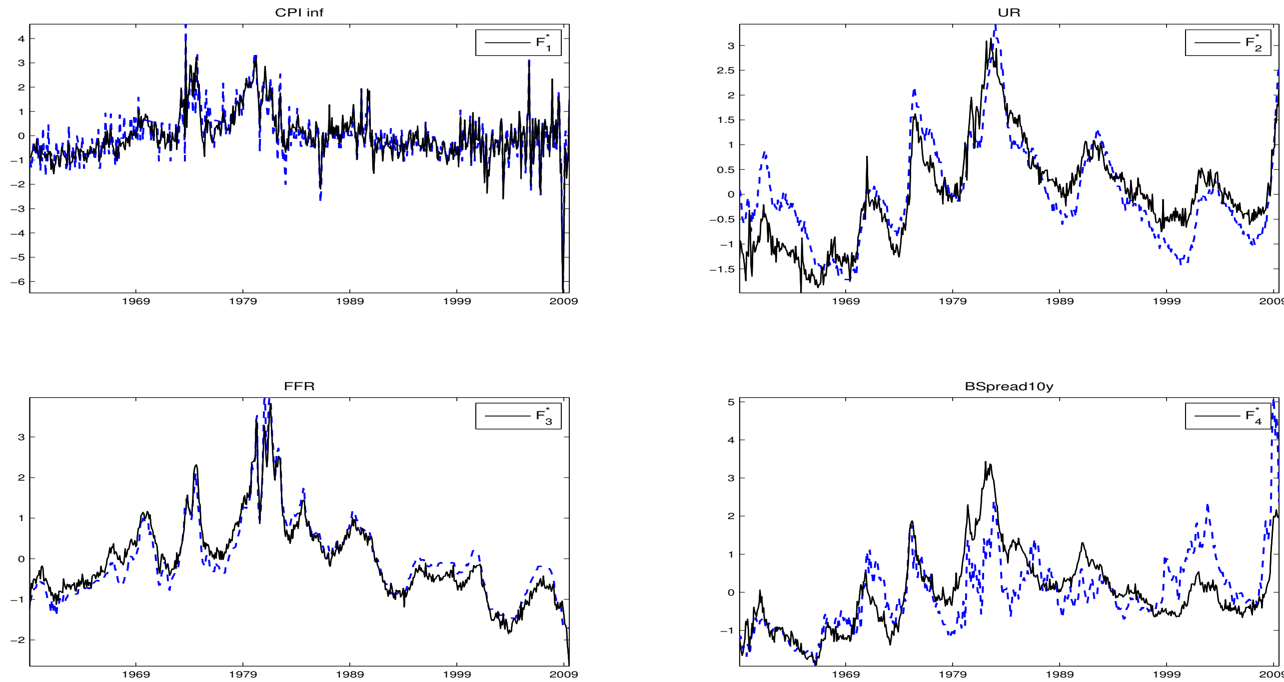

Figure 3: Rotated factors and variables used in recursive identification in FAVAR 1

Notes: The figure plots the estimated structural factors and the variables in the recursive identification scheme, [π_{CPI}, UR, FFR, $10yBS$].

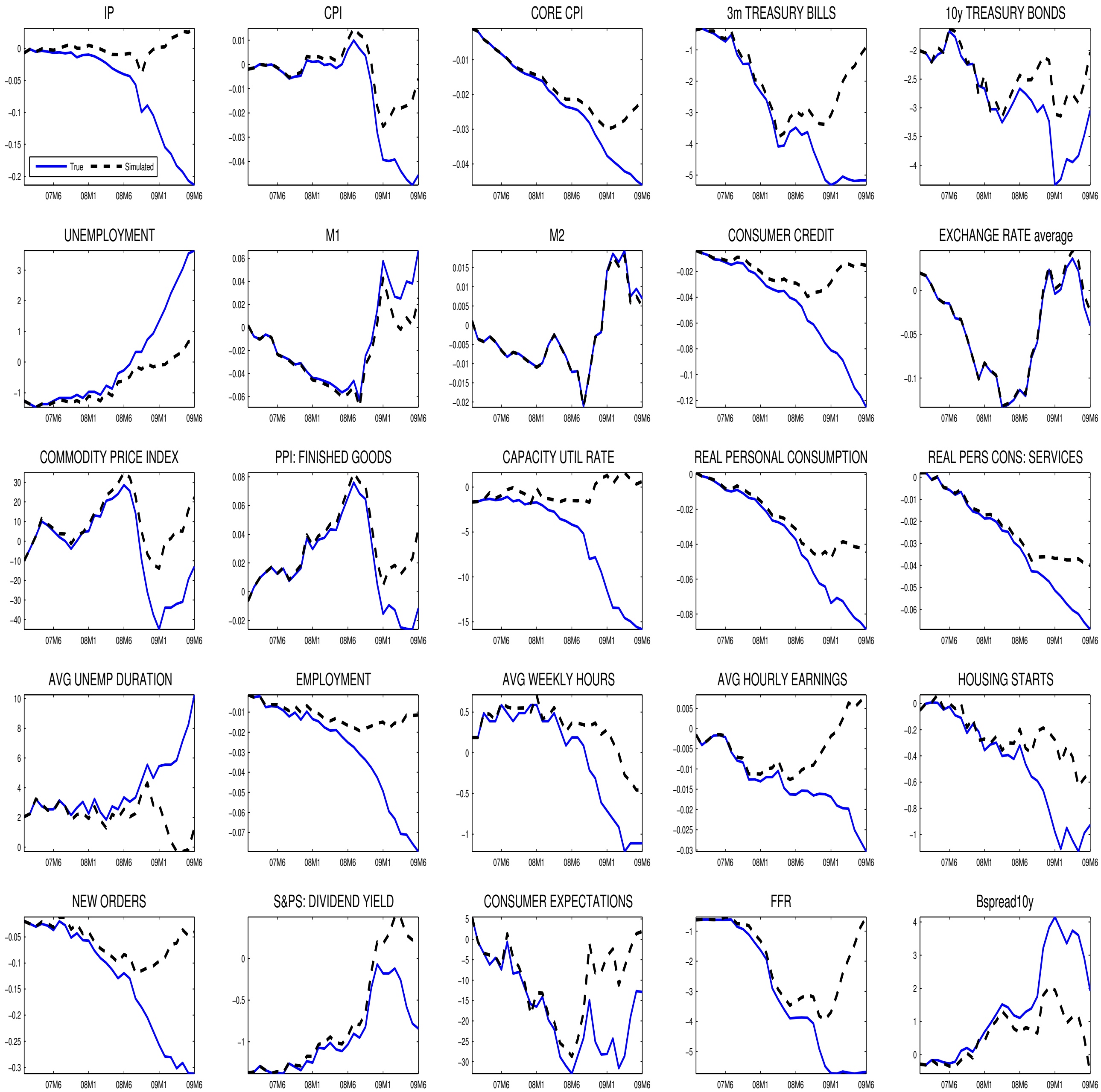

Figure 4: Data and simulated series without credit shocks from FAVAR 1

Notes: The figure plots the actual and simulated series of interest from 2007M1 to 2009M6, the date at which the recession officially ended. The blue lines represent actual data. The dashed black lines represent the simulated paths using the FAVAR 1 specification, excluding the credit shock.

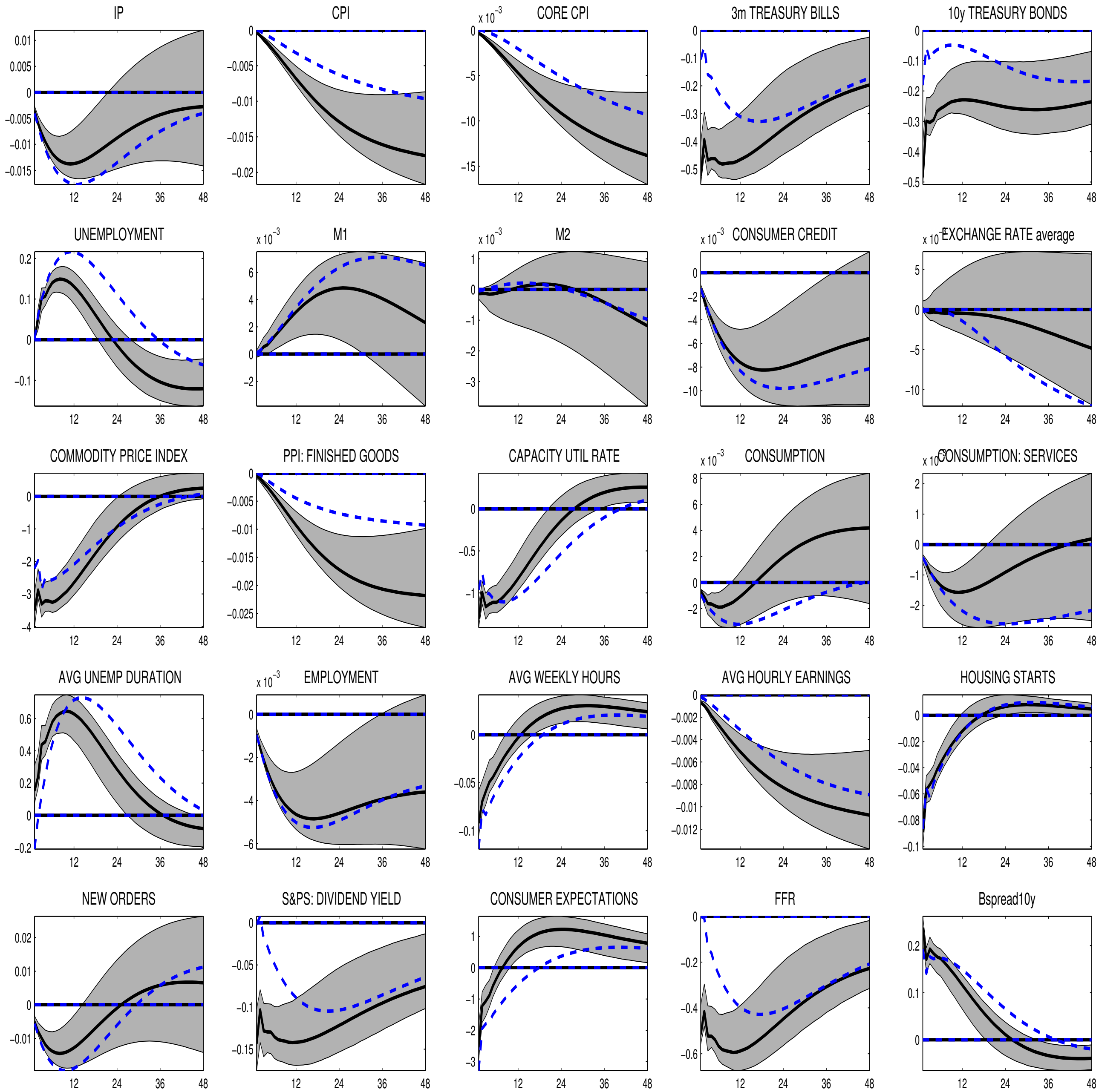

Figure 5: Dynamic responses of monthly variables to credit shock in FAVAR 2

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified through the recursive identification scheme, [π_{PCE}*,* UR*,* ΔI*,* $10yBS$*,* FFR*], where the credit shock is ordered fourth. The grey areas indicate the 90% confidence intervals computed using 5000 bootstrap replications. The dotted blue line indicates the impulse responses from FAVAR 1 specifications.*

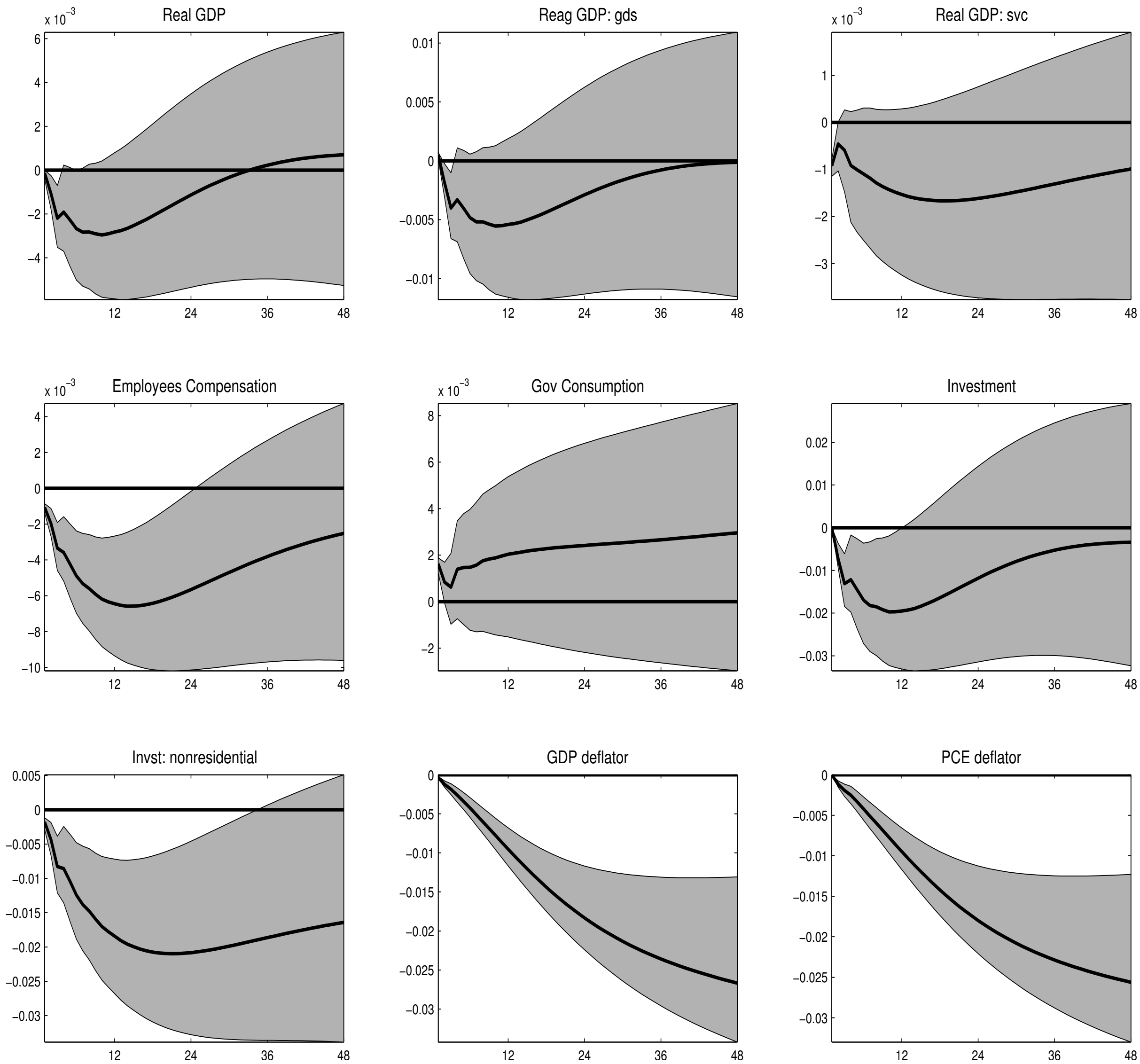

Figure 6: Dynamic responses of constructed monthly indicators to credit shock in FAVAR 2

Notes: The figure plots the monthly impulse responses of the level of key quarterly variables to the credit shock identified through the recursive identification scheme, [π_{PCE}, UR, ΔI, $10yBS$, FFR], where the credit shock is ordered fourth. The grey areas indicate the 90% confidence intervals computed using 5000 bootstrap replications.

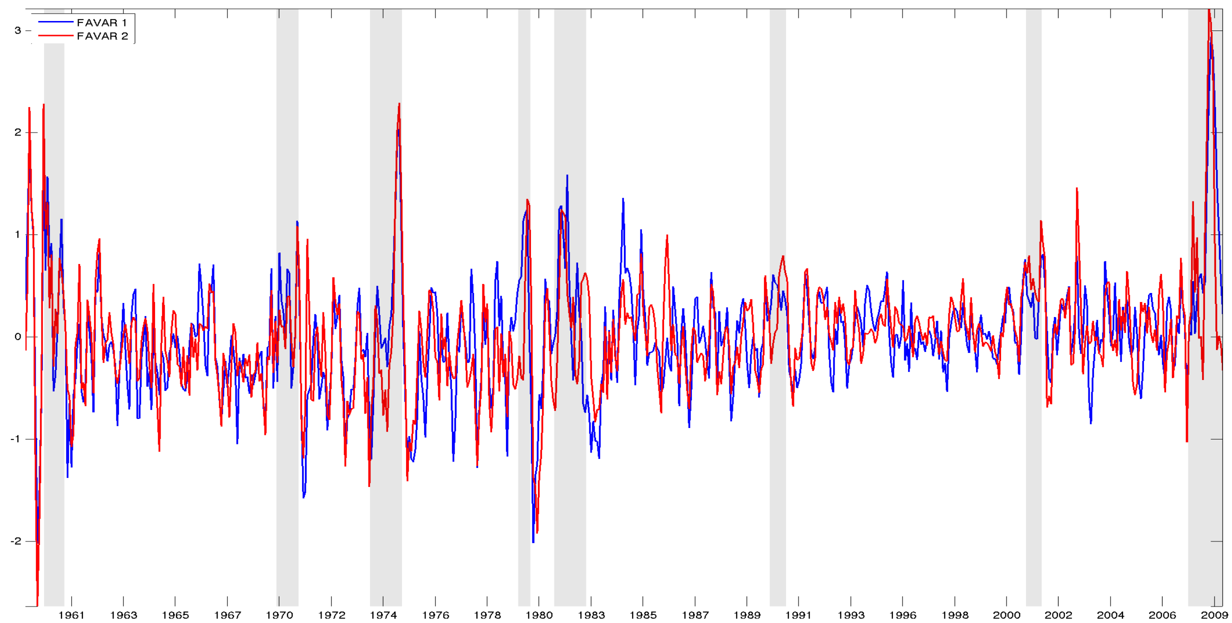

Figure 7: Time series of structural credit shocks

Notes: The figure plots the three months moving average of the time series of structural credit shocks from FAVAR 1 and FAVAR 2 specifications. The grey areas indicate the NBER recessions.

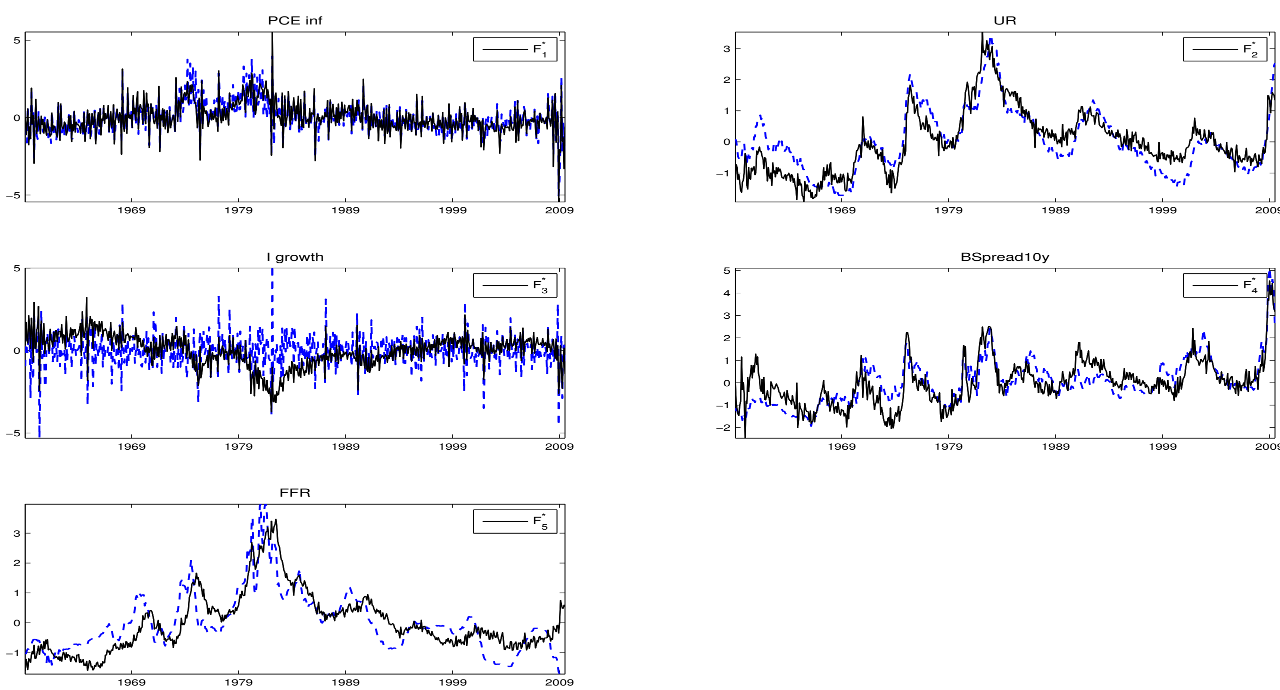

Figure 8: Rotated factors and variables used in recursive identification in FAVAR 2

Notes: The figure plots structural factors and variables in the recursive identification scheme,[π_{PCE}, UR, ΔI, $10yBS$, FFR].

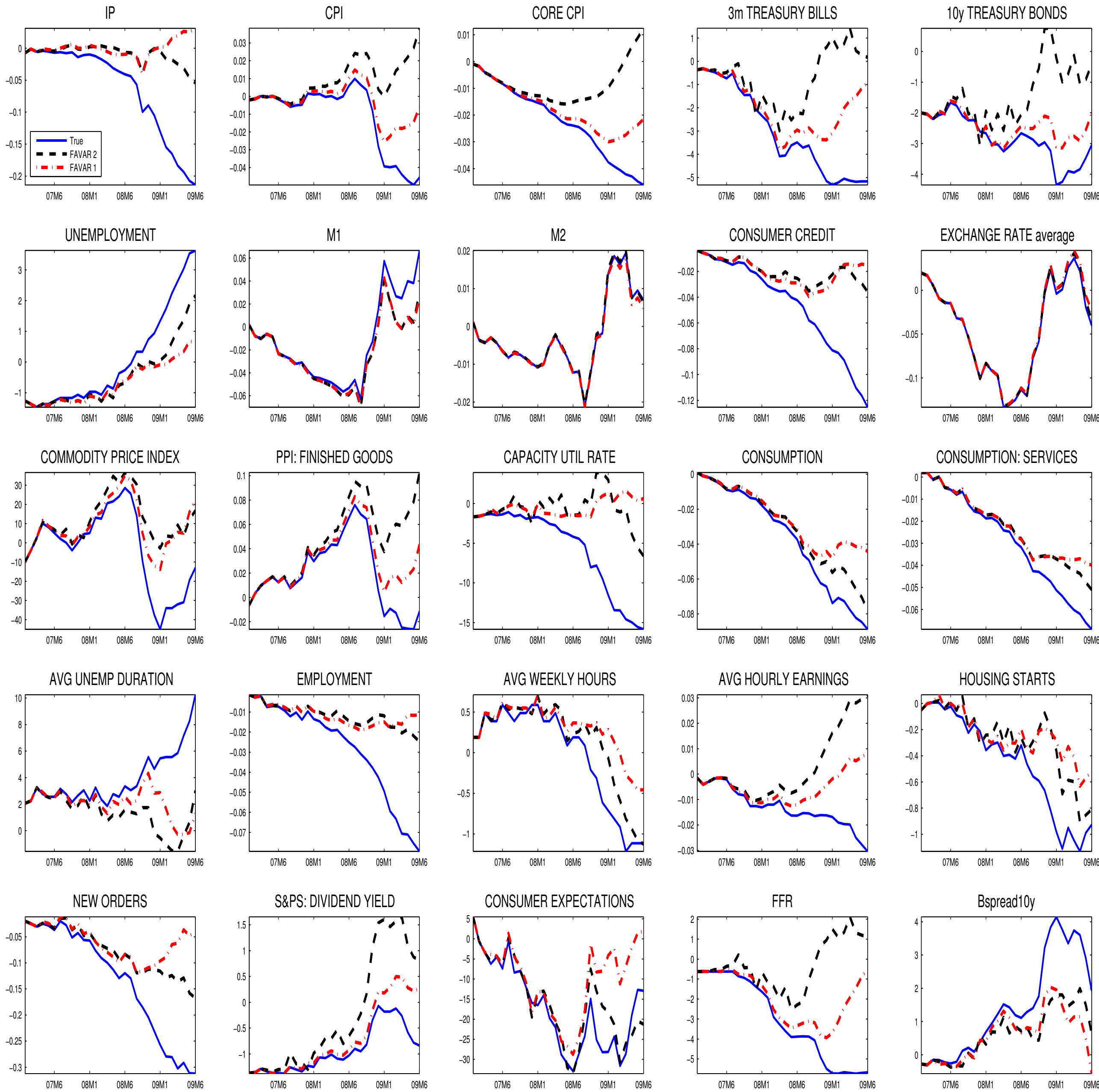

Figure 9: Data and simulated series without credit shocks from FAVAR 2

Notes: The figure plots the actual and simulated series of interest from 2007M1 to 2009M6, the date at which the recession officially ended. The blue lines represent actual data. The dashed black lines represent the simulated paths using the FAVAR 2 specification, excluding the credit shock. The dashed-dotted red lines show the simulated paths using the FAVAR 1 specification, excluding the credit shock.

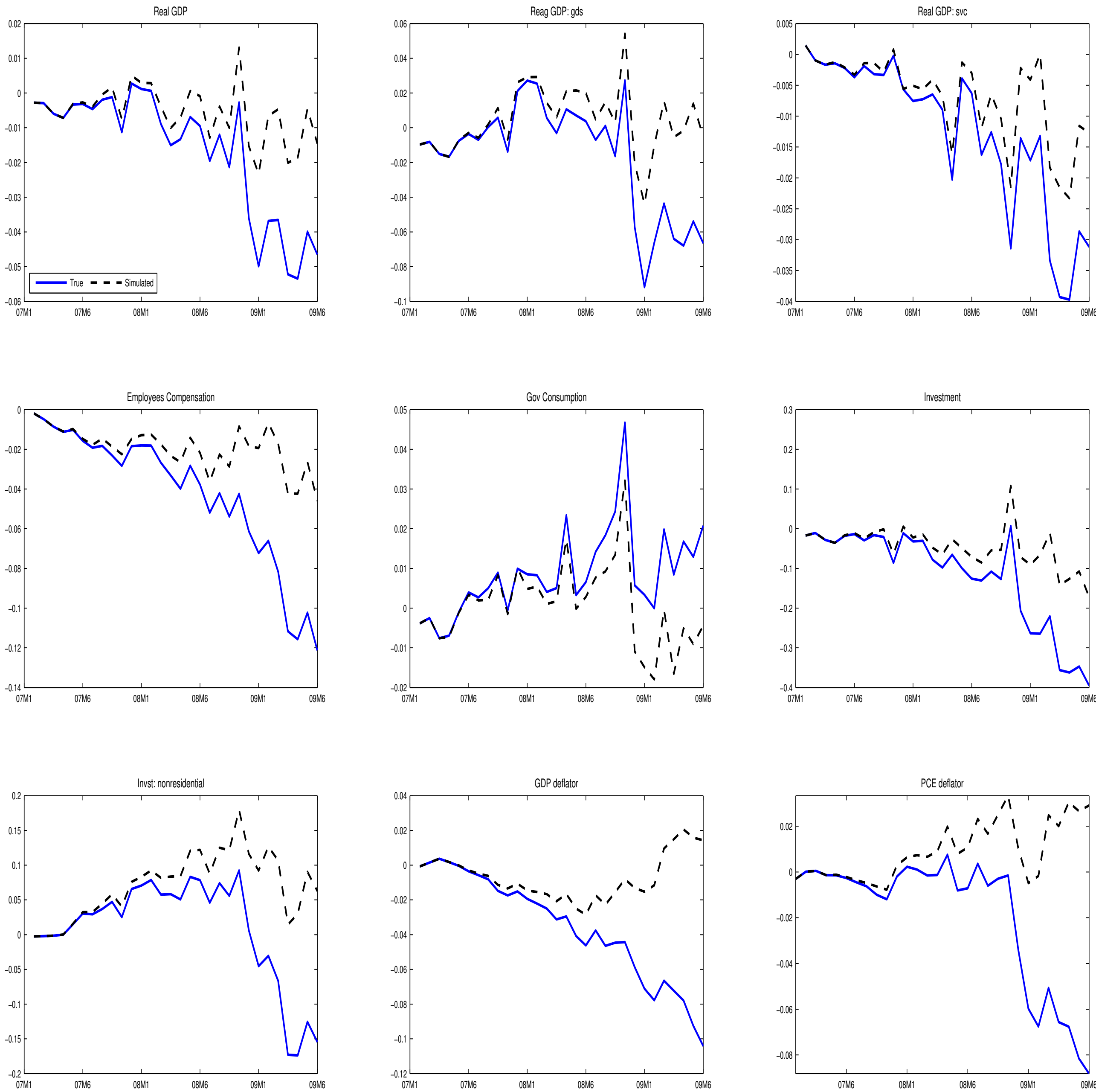

Figure 10: Simulated monthly indicators without credit shocks from FAVAR 2

Notes: The figure plots the the actual and simulated monthly measures of the quarterly series of interest from 2007M1 to 2009M6, the date at which the recession officially ended. The blue lines represent actual data. The dashed black lines represent the simulated paths using the FAVAR 2 specification, excluding the credit shock.

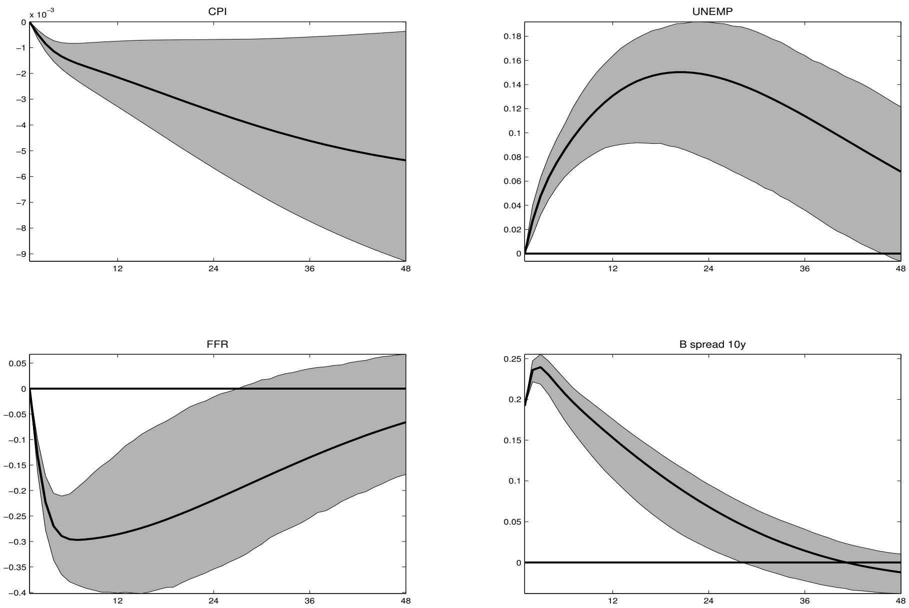

Figure 11: Impulse responses to a 19.2 bps credit spread shock in benchmark SVAR

Notes: The figure plots the impulse responses of the level of the variables to a 19.2 basis point credit shock identified through the recursive identification scheme, [π_{CPI}, UR, FFR, $10yBS$], where the credit shock is ordered last. The grey areas indicate the 90% confidence intervals computed using 5000 bootstrap replications.

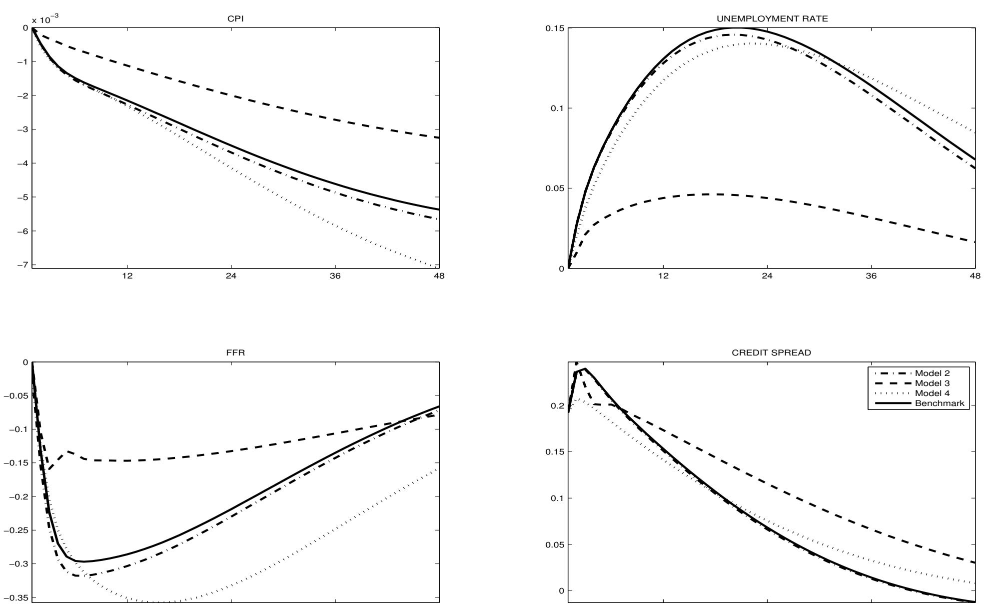

Figure 12: Impulse responses to a 19.2 bps credit spread shock in several SVAR models

Notes: The figure plots the impulse responses of the level of the variables to a 19.2 basis point credit shock in the SVAR models listed in Table 6.

A Appendix

Appendix A. Identification of Structural Shocks in FAVAR Models: A Monte Carlo Experiment

To validate the identification and construction of impulse responses we perform a Monte Carlo experiment calibrated on the specification FAVAR 1. The data generating process is the structural DFM:

$$\begin{aligned} X_t &= \Lambda^\star F_t^\star + u_t && \text{(A.1)} \\ F_t^\star &= \Phi^\star(L) F_{t-1}^\star + \varepsilon_t && \text{(A.2)} \end{aligned}$$

where $F_t^\star = HF_t$, $\Lambda^\star = \Lambda H^{-1}$, and $\Phi^\star(L) = H\Phi(L)H^{-1}$. The errors u_t and ε_t are iid N(0,1).

The coefficients in Λ, Φ and the rotation matrix H, as well as the lag order in VAR dynamics are exactly the ones from the FAVAR 1 specification. The time and cross-section sizes are 600 and 124 respectively. The initial conditions on factors VAR are the first three periods of rotated factors from FAVAR 1.

Figure 13 plots impulse responses from the simulation experiment. The black line represents the true impulse response functions obtained from (A.1)-(A.2). The blue line is the median simulated impulse response function out of 10,000 replications. The grey area represent 99% of simulated impulse responses. We can see that our identification strategy is able to recover the true impulse responses quite well, i.e., both the contemporaneous effects as well as the propagation mechanism. We also did a simulation experiment calibrated on the FAVAR 2 specification and the results are very similar.

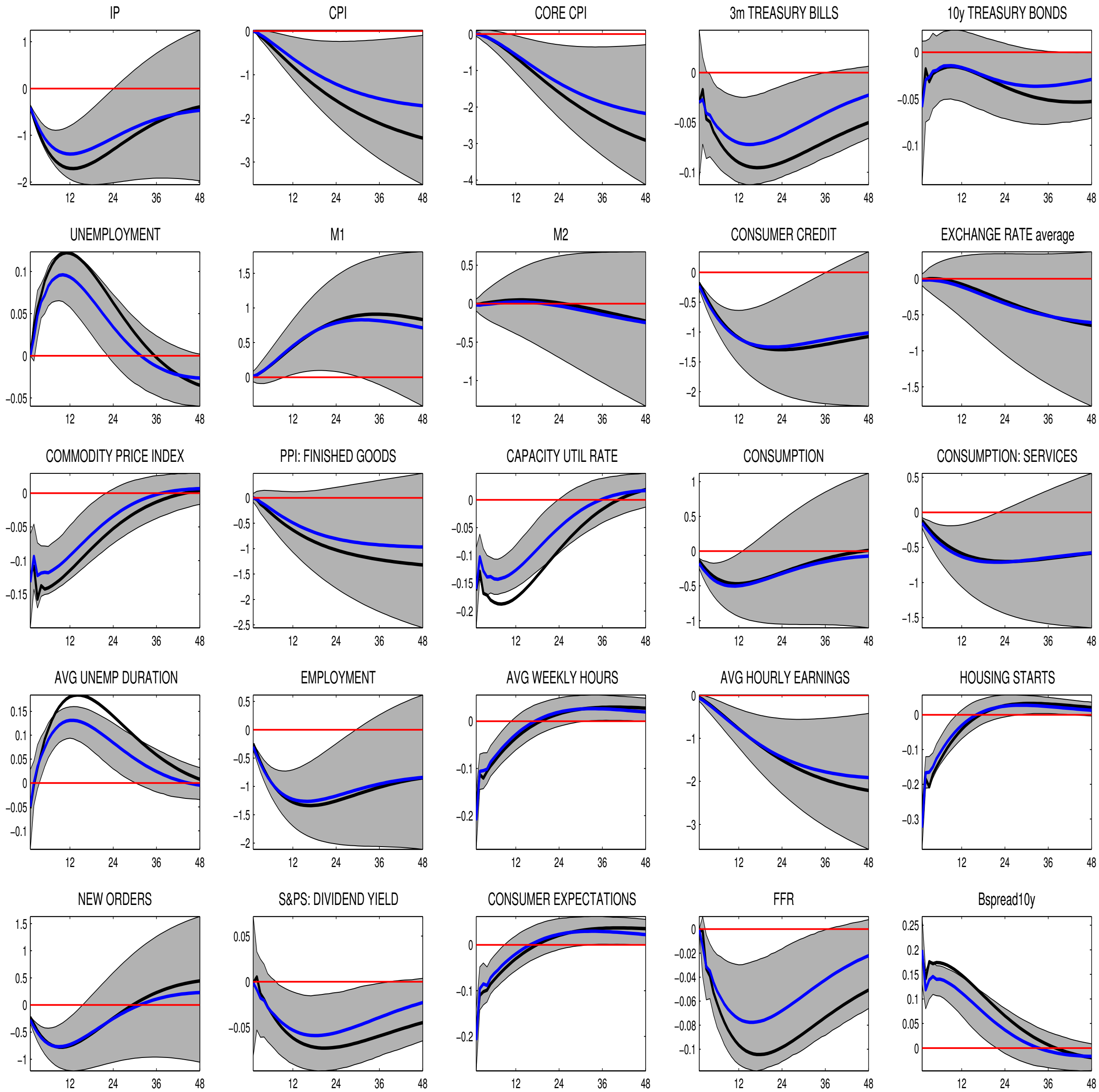

Figure 13: Dynamic responses based on simulations of FAVAR 1

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified through the recursive identification scheme, [π_{CPI}, UR, FFR, B-spread], where the credit shock is ordered last. The black line shows the true impulse response, the blue line is for the median simulated IRF, while the grey areas indicate the 99% of 10,000 simulated IRFs.

Appendix B. Impulse Responses to Credit Spread and Investment Shocks in a DSGE Model

The following figures show the impulse response functions of various variables to a credit spread shock and to an adverse shock to the marginal efficiency of investment based on the estimated medium scale model presented in Del Negro et al. (2015). The impulse response functions reported refer to the quarterly annualized growth rates of output, investment, consumption, as well as hours worked, the federal funds rate and the Baa-10y spread.

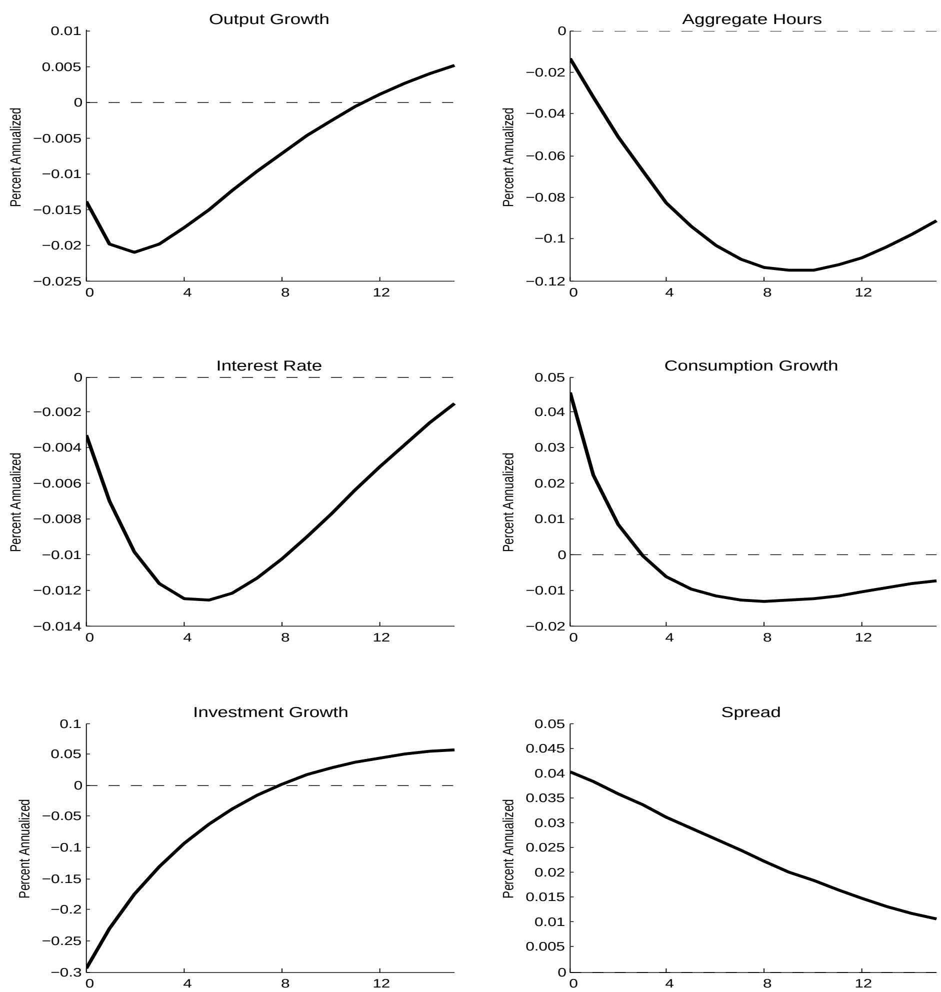

Figure 14: Dynamic responses to a spread shock in an estimated DSGE model

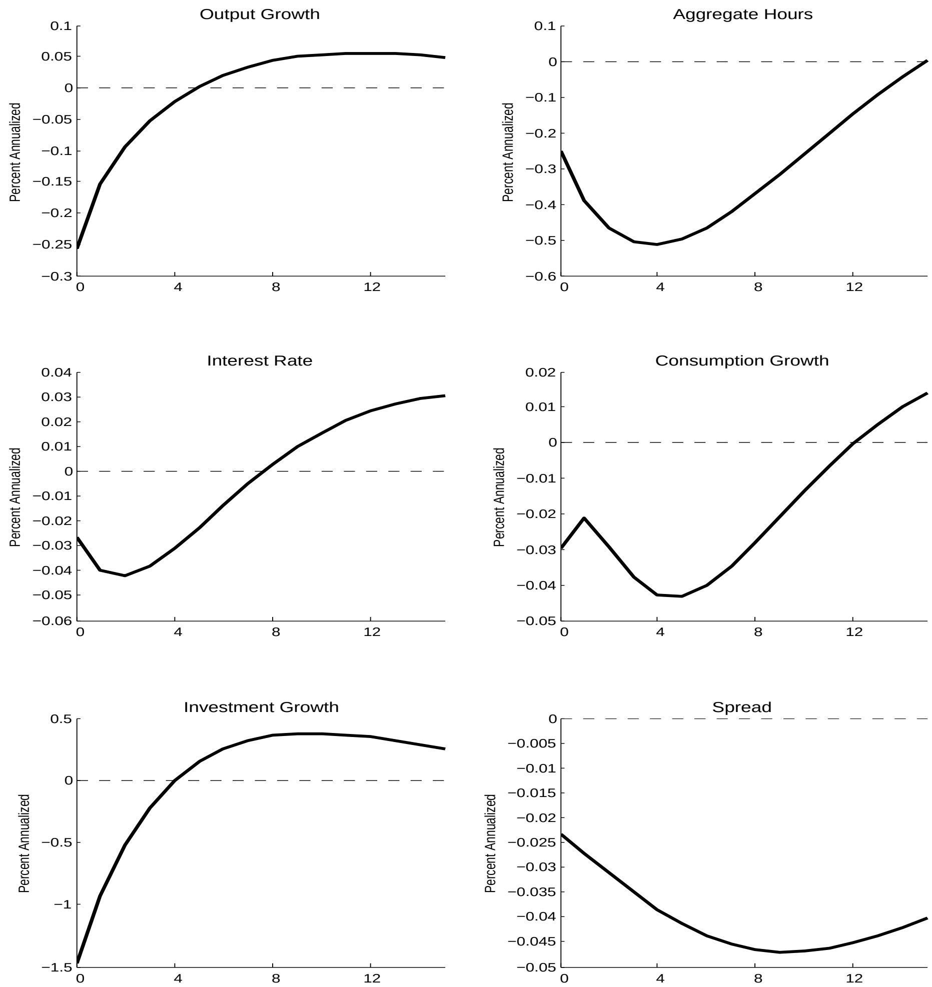

Figure 15: Dynamic responses to a shock to the marginal efficiency of investment in an estimated DSGE model

Appendix C. Recursive estimation of impulse responses to credit spread shock The Figures (16) and (17) plot the impulse responses to credit shocks estimated recursively from 2007M07 until the end of the sample, under FAVAR 1 and FAVAR 2 specifications respectively. We show only a subset of series in order to make the differences easy to read. The grey zone represent the 90% confidence bands from the full sample model.

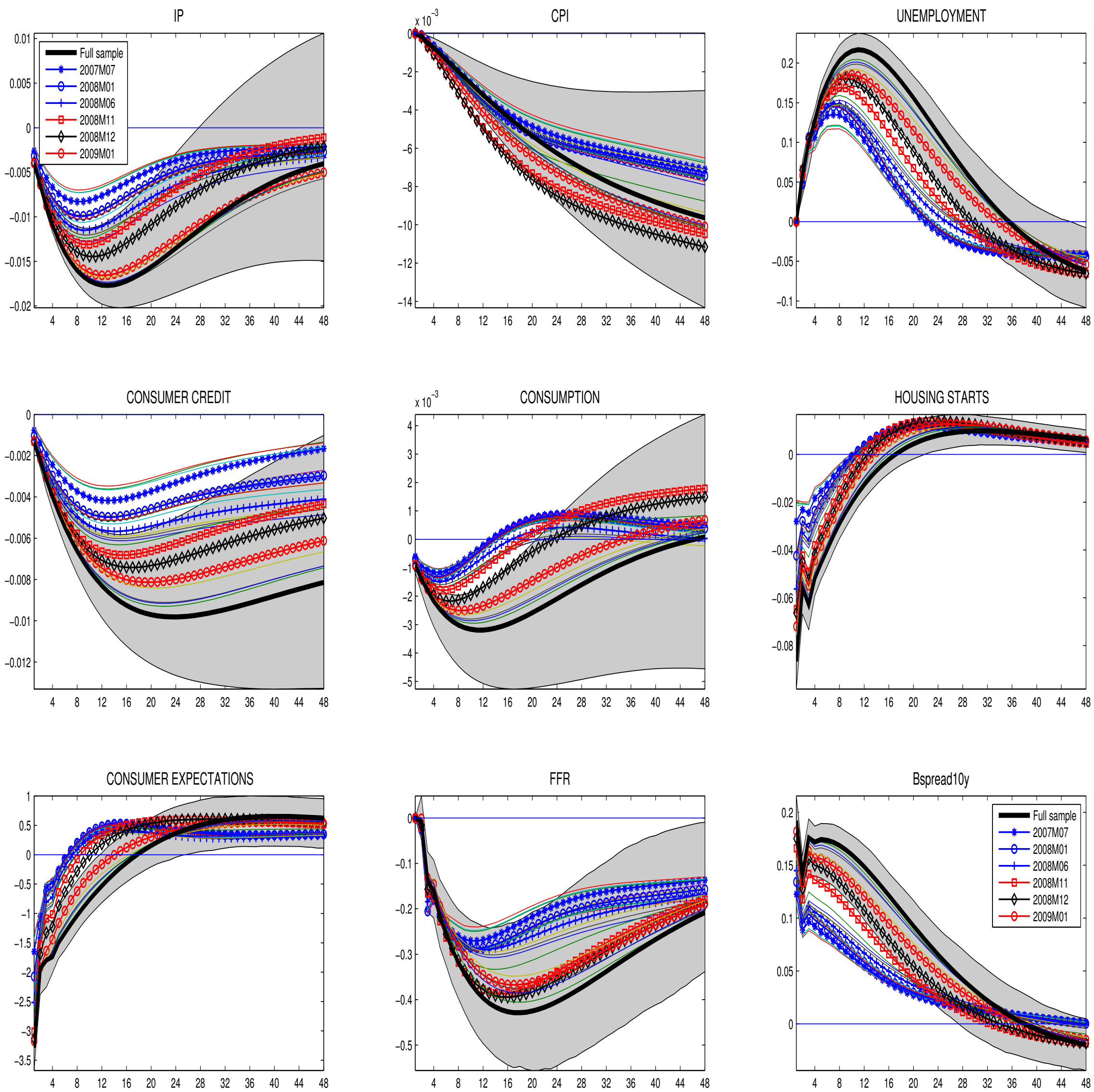

Figure 16: Dynamic responses to a spread shock in recursive FAVAR 1

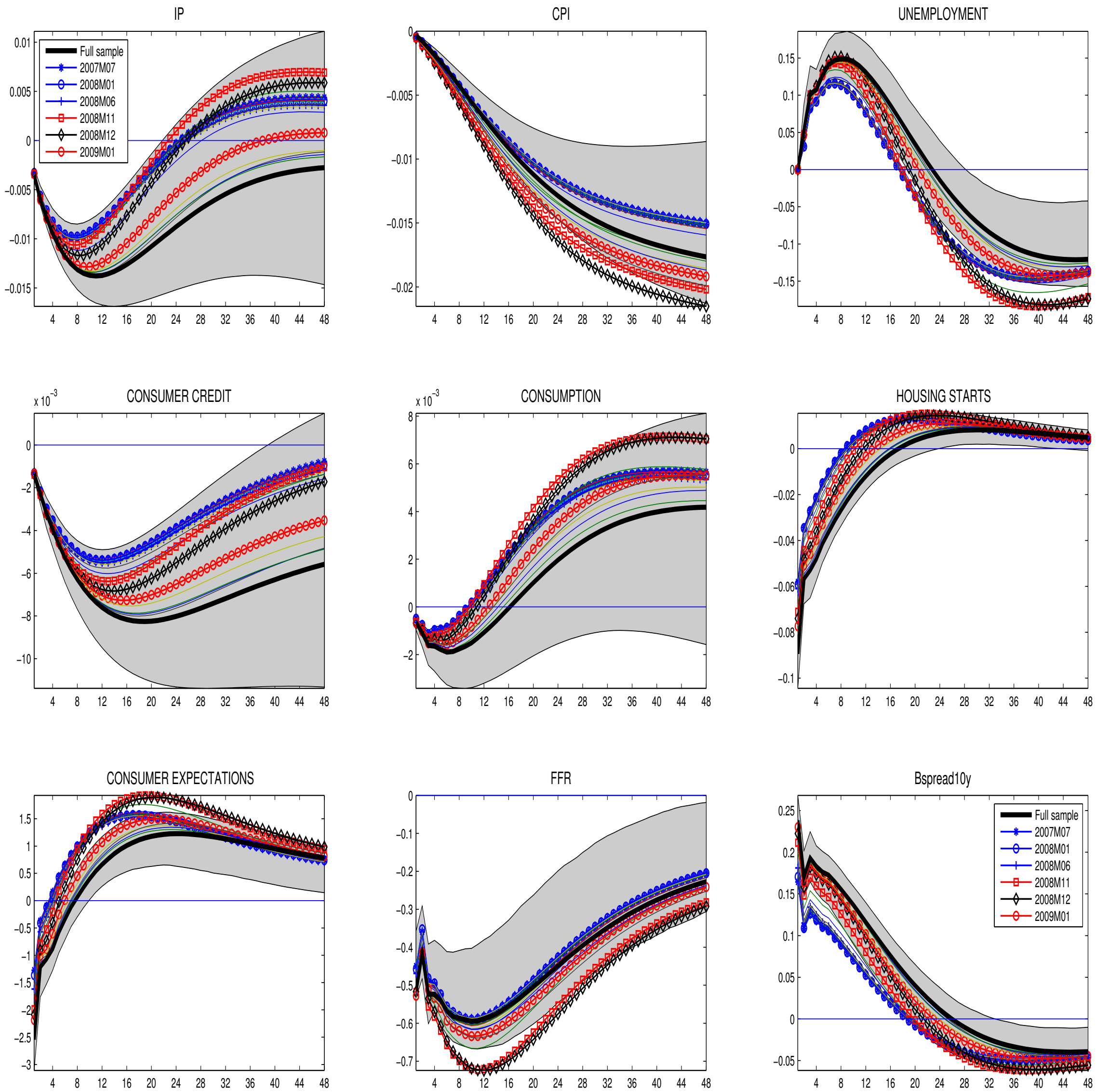

Figure 17: Dynamic responses to a spread shock in recursive FAVAR 2

Appendix D: Dynamic effects of the monetary policy shock

Here, we present the effects of the monetary policy using the same identification scheme as above, and using the monthly balanced panel and the mixed-frequencies monthly panel. In the first specification, FAVAR 1, the monetary policy shock is ordered third, and in FAVAR 2 it is the last element of the vector of identified structural shocks.

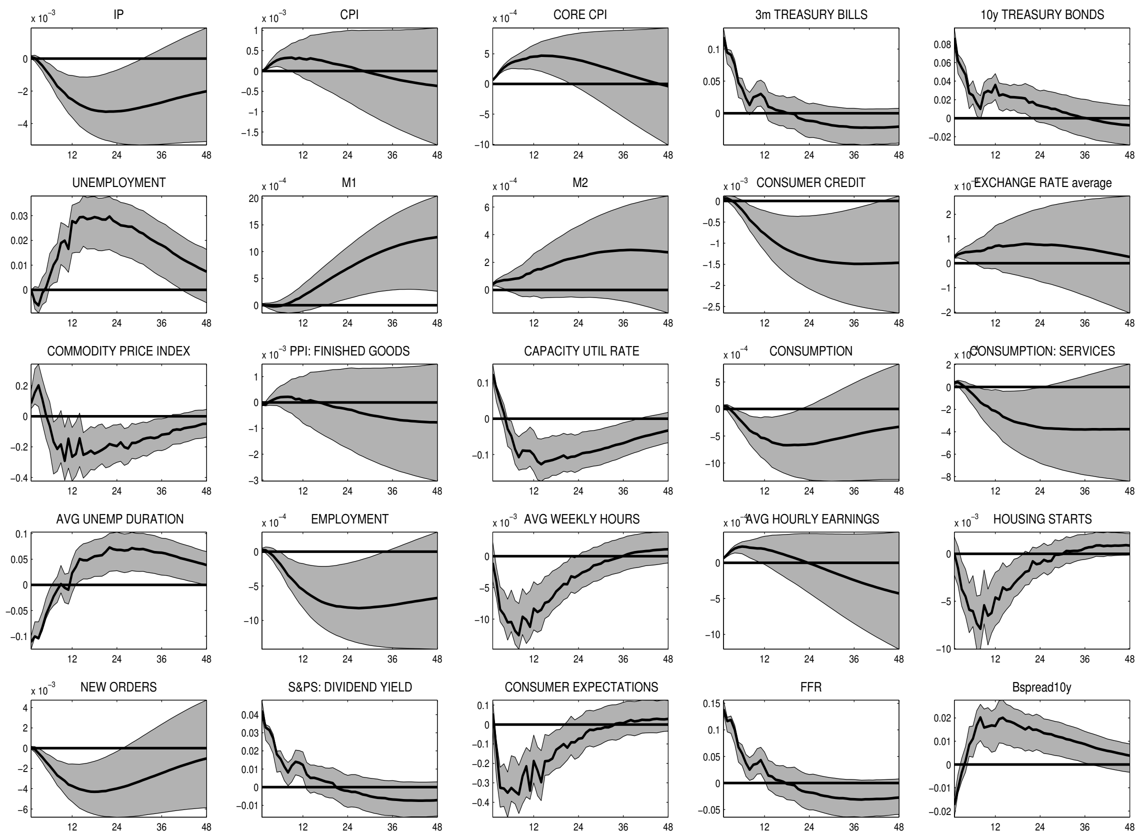

Figure 18: Dynamic responses of monthly variables to a monetary policy shock

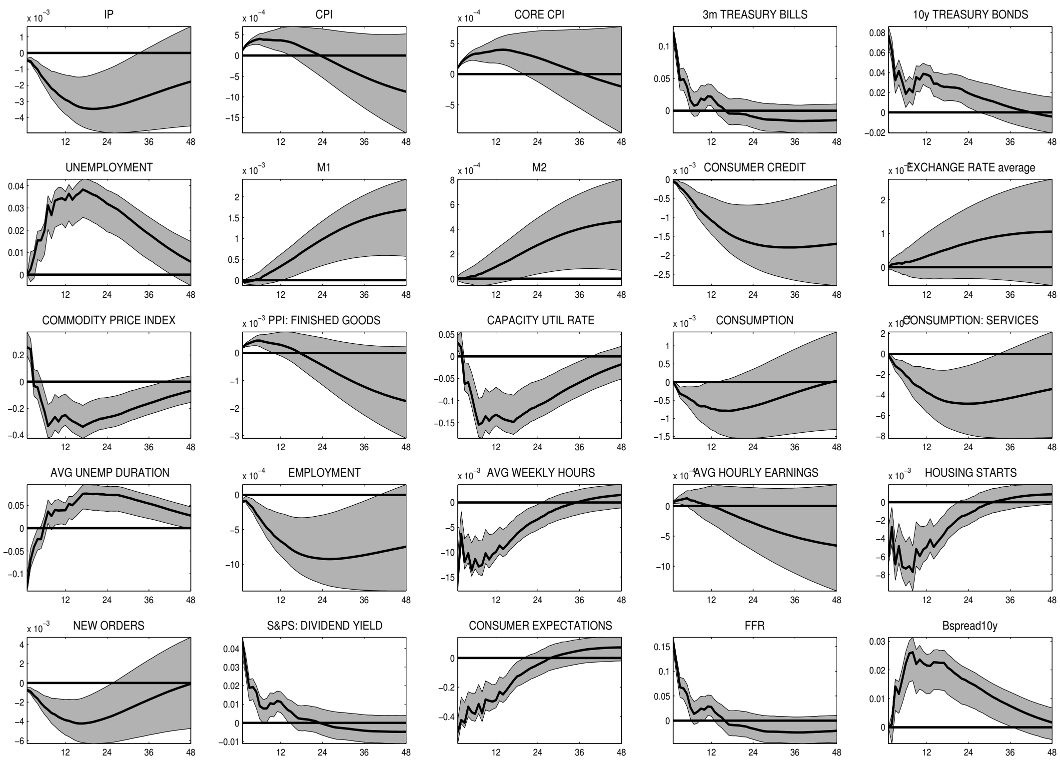

Figure 19: Dynamic responses of monthly variables to monetary policy shock using mixed-frequencies data

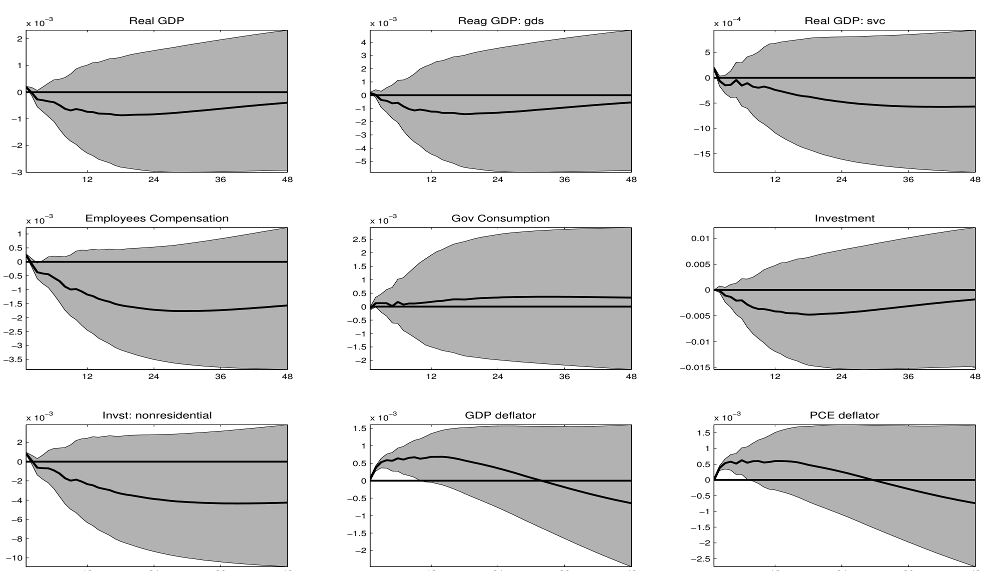

Figure 20: Dynamic responses of constructed monthly indicators to monetary policy shock using mixed-frequencies data

Appendix E: Data Sets

The transformation codes are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm; 0 - variable not used in the estimation (only used for transforming other variables). A * indicate a series that is deflated by the Gross Private Domestic Investment Price Deflator (series # 183). A ** indicate a series that is deflated with the GDP deflator (series # 181).

No.	Series Code	T-Code	Series Description
			Real output and income
1	IPS10	5	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX
2	IPS11	5	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL
3	IPS12	5	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS
4	IPS13	5	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS
5	IPS14	5	INDUSTRIAL PRODUCTION INDEX - AUTOMOTIVE PRODUCTS
6	IPS18	5	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS
7	IPS25	5	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT
8	IPS29	5	INDUSTRIAL PRODUCTION INDEX - DEFENSE AND SPACE EQUIPMENT
9	IPS299	5	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS
10	IPS306	5	INDUSTRIAL PRODUCTION INDEX - FUELS
11	IPS32	5	INDUSTRIAL PRODUCTION INDEX - MATERIALS
12	IPS34	5	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS
13	IPS38	5	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS
14	IPS43	5	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)
15	PMP	1	NAPM PRODUCTION INDEX (PERCENT)
16	PMI	1	PURCHASING MANAGERS' INDEX (SA)
17	UTL11	1	CAPACITY UTILIZATION - MANUFACTURING (SIC)
18	YPR	5	PERS INCOME CH 2000 $,SA-US
19	YPDR	5	DISP PERS INCOME,BILLIONS OF CH (2000) $,SAAR-US
20	YP@V00C	5	PERS INCOME LESS TRSF PMT CH 2000 $,SA-US
21	SAVPER	2	PERS SAVING,BILLIONS OF $,SAAR-US
22	SAVPRATE	1	PERS SAVING AS PERCENTAGE OF DISP PERS INCOME,PERCENT,SAAR-US
			Employment and hours
23	LHEL	5	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)
24	LHELX	4	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF
25	LHEM	5	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)
26	LHNAG	5	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)
27	LHTUR	1	UNEMPLOYMENT RATE: (
28	LHU14	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)
29	LHU15	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)
30	LHU26	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)
31	LHU27	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)
32	LHU5	1	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)
33	LHU680	1	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)
34	LHUEM	5	CIVILIAN LABOR FORCE: UNEMPLOYED, TOTAL (THOUS.,SA)
35	AHPCON	5	AVG HR EARNINGS OF PROD WKRS: CONSTRUCTION ($,SA)
36	AHPMF	5	AVG HR EARNINGS OF PROD WKRS: MANUFACTURING ($,SA)
37	PMEMP	1	NAPM EMPLOYMENT INDEX (PERCENT)
38	CES002	5	EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE
39	CES003	5	EMPLOYEES ON NONFARM PAYROLLS - GOODS-PRODUCING
40	CES004	5	EMPLOYEES ON NONFARM PAYROLLS - NATURAL RESOURCES AND MINING
41	CES011	5	EMPLOYEES ON NONFARM PAYROLLS - CONSTRUCTION
42	CES015	5	EMPLOYEES ON NONFARM PAYROLLS - MANUFACTURING
43	CES017	5	EMPLOYEES ON NONFARM PAYROLLS - DURABLE GOODS
44	CES033	5	EMPLOYEES ON NONFARM PAYROLLS - NONDURABLE GOODS
45	CES046	5	EMPLOYEES ON NONFARM PAYROLLS - SERVICE-PROVIDING
46	CES048	5	EMPLOYEES ON NONFARM PAYROLLS - TRADE, TRANSPORTATION, AND UTILITIES
47	CES049	5	EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE
48	CES053	5	EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE
49	CES088	5	EMPLOYEES ON NONFARM PAYROLLS - FINANCIAL ACTIVITIES
50	CES140	5	EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT
51	CES151	1	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - GOODS-PRODUCING
52	CES153	1	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - CONSTRUCTION
53	CES154	1	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - MANUFACTURING
54	CES155	1	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - MANUFACTURING OVERTIME HOURS
55	CES156	1	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - DURABLE GOODS
56	CES275	5	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - GOODS-PRODUCING
57	CES277	5	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - CONSTRUCTION
58	CES278	5	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFARM PAYROLLS - MANUFACTURING
			Real Consumption
59	JQCR	5	REAL PERSONAL CONS EXP QUANTITY INDEX (200=100), SAAR
60	JQCNR	5	REAL PERSONAL CONS EXP-NONDURABLE GOODS QUANTITY INDEX (200=100), SAAR
61	JQCDR	5	REAL PERSONAL CONS EXP-DURABLE GOODS QUANTITY INDEX (200=100), SAAR
62	JQCSVR	5	REAL PERSONAL CONS EXP-SERVICES QUANTITY INDEX (200=100), SAAR
			Real inventories and orders
63	MOCMQ	5	NEW ORDERS (NET) - CONSUMER GOODS & MATERIALS, 1996 DOLLARS (BCI)

64	MSONDQ	5	NEW ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 DOLLARS (BCI)
65	PMDEL	1	NAPM VENDOR DELIVERIES INDEX (PERCENT)
66	PMNO	1	NAPM NEW ORDERS INDEX (PERCENT)
67	PMNV	1	NAPM INVENTORIES INDEX (PERCENT)
			Housing starts
68	HUSTSZ	4	HOUSING STARTS: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)
69	HSFR	4	HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA
70	HSMW	4	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.
71	HSNE	4	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.
72	HSSOU	4	HOUSING STARTS:SOUTH (THOUS.U.)S.A.
73	HSWST	4	HOUSING STARTS:WEST (THOUS.U.)S.A.
			Exchange rates
74	EXRCAN	5	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)
75	EXRUK	5	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)
76	EXRUS	5	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)
			Price indexes
77	PMCP	1	NAPM COMMODITY PRICES INDEX (PERCENT)
78	PW561	5	PRODUCER PRICE INDEX: CRUDE PETROLEUM (82=100,NSA)
79	PWCMSA	5	PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)
80	PWFCSA	5	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)
81	PWFSA	5	PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)
82	PWIMSA	5	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)
83	PUNEW	5	CPI-U: ALL ITEMS (82-84=100,SA)
84	PUS	5	CPI-U: SERVICES (82-84=100,SA)
85	PUXF	5	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)
86	PUXHS	5	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)
87	PUXM	5	CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)
88	PUXX	5	CPI-U: ALL ITEMS LESS FOOD AND ENERGY (82-84=100,SA)
89	PUC	5	CPI-U: COMMODITIES (82-84=100,SA)
90	PUCD	5	CPI-U: DURABLES (82-84=100,SA)
91	PU83	5	CPI-U: APPAREL & UPKEEP (82-84=100,SA)
92	PU84	5	CPI-U: TRANSPORTATION (82-84=100,SA)
93	PU85	5	CPI-U: MEDICAL CARE (82-84=100,SA)
			Stock prices
94	FSDJ	5	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE
95	FSDXP	1	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
96	FSPCOM	5	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)
97	FSPIN	5	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)
98	FSPXE	1	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)
			Money and credit quantity aggregates
99	FM1	5	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)
100	FM2	5	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,
101	CCINRV	5	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)
			Miscellaneous
102	UOMO83	1	COMPOSITE INDEXES LEADING INDEX COMPONENT INDEX OF CONSUMER EXPECTATIONS UNITS: 1966.1=100 NSA, CONFBOARD AND U.MICH.
			Interest rates and bonds
103	FYGM3	1	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)
104	FYGM6	1	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)
105	FYGT1	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
106	FYGT10	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
107	FYGT20	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,20-YR.(% PER ANN,NSA)
108	FYGT3	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,3-YR.(% PER ANN,NSA)
109	FYGT5	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)
110	FYPR	1	PRIME RATE CHG BY BANKS ON SHORT-TERM BUSINESS LOANS(% PER ANN,NSA)
111	FYAAAC	1	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)
112	FYAAAM	1	BOND YIELD: MOODY'S AAA MUNICIPAL (% PER ANNUM)
113	FYAC	1	BOND YIELD: MOODY'S A CORPORATE (% PER ANNUM,NSA)
114	FYAVG	1	BOND YIELD: MOODY'S AVERAGE CORPORATE (% PER ANNUM)
115	FYBAAC	1	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)
116	SFYGM3	1	FYGM3-FYFF
117	SFYGM6	1	FYGM6-FYFF
118	SFYGT1	1	FYGT1-FYFF
119	SFYGT5	1	FYGT5-FYFF
120	SFYGT10	1	FYGT10-FYFF
121	SFYAAAC	1	FYAAAC-FYFF
122	SFYBAAC	1	FYBAAC-FYFF
123	FYFF	1	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)
124	Bspread10Y	1	FYBAAC-FYGT10
			Quarterly indicators
125	GDPRC@US.Q	5	NIA REAL GROSS DOMESTIC PRODUCT (CHAINED-2000), SA - U.S.
126	GDPGDR.Q	5	REAL GDP-GDS,BILLIONS OF CH (2000) $,SAAR-US
127	GDPSVR.Q	5	REAL GDP-SVC,BILLIONS OF CH (2000) $,SAAR-US
128	GDPSR.Q	5	REAL GDP-STRUC,BILLIONS OF CH (2000) $,SAAR-US
129	WS@US.Q	5**	NIA NOMINAL TOTAL COMPENSATION OF EMPLOYEES, SA - U.S.
130	CR.Q	5	REAL PCE,BILLIONS OF CH (2000) $,SAAR-US
131	JQCDR.Q	5	REAL PCE-DUR,QTY INDEX (2000=100),SA,SA-US
132	UJQCDMVR.Q	5	REAL PCE-DUR-MV&PARTS,QTY INDEX (2000=100),SA,SA-US
133	JQCDFHER.Q	5	REAL PCE-DUR-FURN&HH EQUIP,QTY INDEX (2000=100),SA,SA-US
134	JQCDOR.Q	5	REAL PCE-DUR-OTH,QTY INDEX (2000=100),SA,SA-US
135	JQCNR.Q	5	REAL PCE-NDUR,QTY INDEX (2000=100),SA,SA-US
136	JQCNFR.Q	5	REAL PCE-NDUR-FOOD,QTY INDEX (2000=100),SA,SA-US
137	JQCNCSR.Q	5	REAL PCE-NDUR-CLO&SHOES,QTY INDEX (2000=100),SA,SA-US
138	JQCNER.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS,QTY INDEX (2000=100),SA,SA-US
139	JQCNEGAOR.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS-GASOLINE&OIL,QTY INDEX (2000=100),SAAR-US
140	JQCNEFACR.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS-FUEL OIL&COAL,QTY INDEX (2000=100),SAAR-U
141	JQCNOR.Q	5	REAL PCE-NDUR-OTH,QTY INDEX (2000=100),SA,SA-US
142	JQCSVR.Q	5	REAL PCE-SVC,QTY INDEX (2000=100),SA,SA-US
143	JQCSVHSR.Q	5	REAL PCE-SVC-HOUSING,QTY INDEX (2000=100),SA,SA-US

144	JQCSVHOPR.Q	5	REAL PCE-SVC-HH OPS,QTY INDEX (2000=100),SA,SA-US
145	JQCSVHOPEAGR.Q	5	REAL PCE-SVC-HH OPS-ELEC&GAS,QTY INDEX (2000=100),SA,SA-US
146	JQCSVHOPOR.Q	5	REAL PCE-SVC-OTH HH OPS,QTY INDEX (2000=100),SA,SA-US
147	JQCSVTSR.Q	5	REAL PCE-SVC-TRNSPRT,QTY INDEX (2000=100),SA,SA-US
148	JQCSVMR.Q	5	REAL PCE-SVC-MEDICAL CARE,QTY INDEX (2000=100),SA,SA-US
149	JQCSVRECR.Q	5	REAL PCE-SVC-RECR,QTY INDEX (2000=100),SA,SA-US
150	JQCSVOR.Q	5	REAL PCE-SVC-OTH,QTY INDEX (2000=100),SA,SA-US
151	JQCENERGYR.Q	5	REAL PCE-ENERGY GDS&SVC,QTY INDEX (2000=100),SAAR-US
152	JQCXFAER.Q	5	REAL PCE EX FOOD&ENERGY,QTY INDEX (2000=100),SAAR-US
153	CGRC@US.Q	5	NIA REAL GOVERNMENT CONSUMPTION EXPENDITURE & GROSS INVESTMENT (CHAINED-2000), SA - U.S.
154	I.Q	5*	GROSS PRIV DOM INVEST,BILLIONS OF $,SAAR-US
155	IF.Q	5*	GROSS PRIV DOM INVEST-FIXED,BILLIONS OF $,SAAR-US
156	IFNRE.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES,BILLIONS OF $,SAAR-US
157	IFNRES.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES-STRUC,BILLIONS OF $,SAAR-US
158	IFNRESC.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-COML&HEALTH CARE,BILLIONS OF $,SAAR-US
159	IFNRESMFG.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-MFG,BILLIONS OF $,SAAR-US
160	IFREE.Q	5*	PRIV FIXED INVEST-EQUIP,BILLIONS OF $,SAAR-US
161	IFRESPEMF.Q	5*	PRIV FIXED INVEST-RES-STRUC-MFAM,BILLIONS OF $,SAAR-US
162	IFRESPESF.Q	5*	PRIV FIXED INVEST-RES-STRUC-1 FAM,BILLIONS OF $,SAAR-US
163	IFRESPE.Q	5*	PRIV FIXED INVEST-RES-STRUC-PERMANENT SITE,BILLIONS OF $,SAAR-US
164	IFRES.Q	5*	PRIV FIXED INVEST-RES-STRUC,BILLIONS OF $,SAAR-US
165	IFRE.Q	5*	GROSS PRIV DOM INVEST-FIXED RES,BILLIONS OF $,SAAR-US
166	IFNREEO.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-OTH,BILLIONS OF $,SAAR-US
167	IFNREET.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-TRNSPRT,BILLIONS OF $,SAAR-US
168	IFNREEIND.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-IND,BILLIONS OF $,SAAR-US
169	IFNREEIPO.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-INFO PROC&SW-OTH,BILLIONS OF $,SAAR-US
170	IFNREEIPCS.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-SW,BILLIONS OF $,SAAR-US
171	IFNREEIPCC.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-COMP&PERI,BILLIONS OF $,SAAR-US
172	IFNREEIP.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-INFO PROC,BILLIONS OF $,SAAR-US
173	IFNREE.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES-EQUIP#&SW,BILLIONS OF $,SAAR-US
174	IFNRESO.Q	5*	PRIV FIXED INVEST-NONRES-OTH STRUC,BILLIONS OF $,SAAR-US
175	IFNRESMI.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-MINING EXPLORATION,SHAFTS,&WELLS,BILLIONS OF $,SAAR-US
176	IFNRESP.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-POWER&COMM,BILLIONS OF $,SAAR-US
177	II.Q	1	GROSS PRIV DOM INVEST-CH IN PRIV INVENT,BILLIONS OF $,SAAR-US
178	IIF.Q	1	GROSS PRIV DOM INVEST-CH IN PRIV INVENT-FARM,BILLIONS OF $,SAAR-US
179	M.Q	5	IMPORTS OF GDS&SVC,BILLIONS OF $,SAAR-US
180	X.Q	5	EXPORTS OF GDS&SVC,BILLIONS OF $,SAAR-US
181	PGDP@US.Q	5	NIA PRICE DEFLATOR - GROSS DOMESTIC PRODUCT, SA - U.S.
182	PCP@US.Q	5	NIA PRICE DEFLATOR - PRIVATE CONSUMPTION EXPENDITURE, SA - U.S.
183	USCEN:PDII.Q	0	GROSS PRIV DOM INVESTMENT PRICE DEFLATOR, SA - U.S.