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Dynamic Effects of Credit Shocks in a Data-Rich Environment

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Décembre 2017

Dynamic Effects of Credit Shocks in a Data-Rich Environment

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Dynamic Effects of Credit Shocks in a Data-Rich Environment*

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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 allows us to perform counterfactual experiments which suggest that credit spread shocks have largely contributed to the deterioration in economic conditions during the Great Recession. Recursive estimation of the model reveals relevant instabilities since 2007 and provides further evidence that monetary policy has partly offset the effects of credit shocks on economic activity.

JEL Classification: C55, C32, E32, E44

Keywords: Credit shocks, FAVAR, structural factor analysis.

*The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of Dallas, or the Federal Reserve System.

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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. Accord-

¹Other 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.

ingly, 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 minimize the risk of omitted variable bias discussed e.g. in Sims (1992) or Bernanke, Boivin and Elias (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.

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 (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 important 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 sizeable part of the decline in many activity and price series, as well as the federal funds rate in 2008 and 2009. Moreover, the significant drop in risk-free rates due to the adverse credit shocks tends to mitigate the effects on economic activity during the Great Recession.

Recursive estimation of the model reveals notable instabilities since 2007. As we progress through zero lower bound period, adverse credit shocks are found to result in a diminished response of the short rate, while the effects on economic activity appear larger. This pro-

vides further evidence that monetary policy can partly offset the effects of credit shocks on economic activity, when it can do so.

We consider a battery of specifications. Our benchmark FAVAR model is estimated using a mixed-frequencies monthly panel augmented with quarterly data. We impose two different recursive assumptions on a small number of data series to identify structural shocks. In the first ordering, the monetary policy cannot react on impact to a credit shock. The second recursive identification scheme 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. 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.

Our results are consistent with those obtained in studies using fully structural dynamic stochastic general equilibrium (DSGE) models, though our FAVAR analysis documents the effects of credit shocks on a much broader set of variables while imposing very few restrictions. For instance, in the model of Christiano, Motto and Rostagno (2014), which builds on Bernanke, Gertler and Gilchrist (1999), “risk shocks,” which capture the exogenously time-varying cross-sectional standard deviation of idiosyncratic productivity shocks, directly move credit spreads. Such shocks cause an increase in the external finance premium for borrowers, which leads to cuts in investments, production, employment, and are found to account for a large share of US GDP fluctuations.²

Section 2 presents the structural factor model and discusses various estimation and iden-

²Gilchrist, Ortiz and Zakrajšek (2009) estimate a similar model in which they introduce two financial shocks: a “risk shock” that directly affects the external finance premium, and a net worth shock affecting the balance sheet of a firm. Both shocks imply a persistent slowdown in economic activity and in investment.

tification issues. The main results are presented in Section 3. Section 4 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, robustness analysis, and the data set used. It also compares our results to those obtained from smaller-scale structural VAR models, to quantify the relevance of using large data sets. That section shows that the responses of key economic activity measures to credit shocks are significantly larger in our FAVAR model than in standard VARs, and, credit shocks generate a substantially larger share of economic fluctuations in our FAVAR models than in small-scale VARs. 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.

2 Econometric Framework in Data-Rich Environment

It is common to estimate the effects of identified macroeconomic shocks using small-scale vector autoregressions (VARs). However, 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. In addition, VARs allow us to produce impulse responses only for the relatively small set of variables included in the estimation.

One way to address 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.³ 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) and

³An 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).

Stock and Watson (2016) for an overview]. In particular, Bernanke et al. (2005) and Boivin et al. (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 model⁴

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

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

where X_t contains N economic and financial indicators, F_t represents K unobserved factors ($N \gg K$), 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).

2.1 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.⁵

The PCA 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.⁶ However,

⁴It 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(2016)].

⁵Stock and Watson (2002a) prove the consistency of such an estimator in the approximate factor model when both cross-section 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 $\sqrt{T}/N \rightarrow 0$. Inference should take into account the effect of generated regressors, except when T/N goes to zero.

⁶See, Doz, Giannone and Reichlin (2006). Moreover, Bernanke, Boivin and Elias (2005) estimated their model using both two-step principal components and single-step Bayesian likelihood methods, and obtained essentially the same results.

since the unobserved factors are first estimated and then included as regressors in the VAR equation (2), the two-step approach may suffer from the “generated regressors” problem. To get an accurate statistical inference on the impulse responses that accounts for uncertainty associated to factors estimation, we use the bootstrap procedure as in Bernanke et al. (2005).

2.2 Identification of structural shocks

To identify the structural shocks, we apply the contemporaneous timing restrictions procedure proposed in Stock and Watson (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 spreads⁷ — 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.⁸

We start by inverting the VAR process of factors (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 $B(L) \equiv \Lambda[I - \Phi(L)L]^{-1}$. Assuming the number of factors, K , is equal to the number of common shocks, and factor innovations e_t are linear combinations of structural shocks ε_t :

⁷In 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.

⁸In Bernanke et al. (2005) and Boivin et al. (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.

$$\varepsilon_t = He_t, \quad (4)$$

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

$$X_t = B^*(L)\varepsilon_t + u_t, \quad (5)$$

where $B^*(L) \equiv B(L)H^{-1} = \Lambda[I - \Phi(L)L]^{-1}H^{-1}$. 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 $B^*(0)$ in (5), so that it takes the form

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

where x stands for unrestricted elements. To estimate the matrix H , we proceed as in Stock and Watson (2016), noting that $B_{0:K}^* \varepsilon_t = B_{0:K} e_t$ implies $B_{0:K}^* B_{0:K}^{*'} = B_{0:K} \Sigma_e B_{0:K}'$, where $B_{0:K}$ contains the first K rows of $B_0 \equiv B(0) = \Lambda$, $B_{0:K}^* = B_{0:K} H^{-1}$, and Σ_e is the covariance matrix of e_t . Since $B_{0:K}^*$ 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.: $B_{0:K}^* = \text{Chol}(B_{0:K} \Sigma_e B_{0:K}')$. It follows that $H = (B_{0:K}^*)^{-1} B_{0:K}$, or

$$H = [\text{Chol}(B_{0:K} \Sigma_e B_{0:K}')]^{-1} B_{0:K}. \quad (7)$$

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^* 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

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

where

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

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 credit spread, sp_t , that load both on the activity and credit factors:

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

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 to the structural shocks as in (5):

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

and the impact response of the observables to structural shocks is

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

We identify the credit shock $\varepsilon_{2,t}$ by assuming, as in Stock and Watson (2016), 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, or $(1 - h_{12}h_{21})^{-1}(\lambda_{12} - \lambda_{11}h_{12}) = 0$.

From (8) and (9), credit conditions 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 $\lambda_{11}h_{12}$. Intuitively, the above restriction imply 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 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.⁹ Otherwise, 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 further shows in a Monte Carlo experiment that the identification strategy adopted is able to recover the true impulse response functions.

2.3 Data and main specifications

We estimate the FAVAR model on a large number of economic and financial indicators. The sample starts in 1959M01 and ends in 2016M12. All series are initially transformed to induce stationarity. The description of the series and their transformation is presented in Appendix.

Common proxies of the external finance premium of borrowing firms are the credit spreads for non-financial institutions. Our benchmark measure is the the difference between BAA corporate bond yields and 10-year Treasury bond yields, BSPREAD hereafter, although we considered as alternatives the spread between AAA bond yields and 10-year Treasury yields (ASPREAD), and the Gilchrist and Zakrajsek (2012) credit spread (GZ SPREAD). Figure 1 reveals clearly that credit spreads are positively correlated with the unemployment rate. This correlation confounds, however, both the effects of current economic conditions

⁹When 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 (2016) for details].

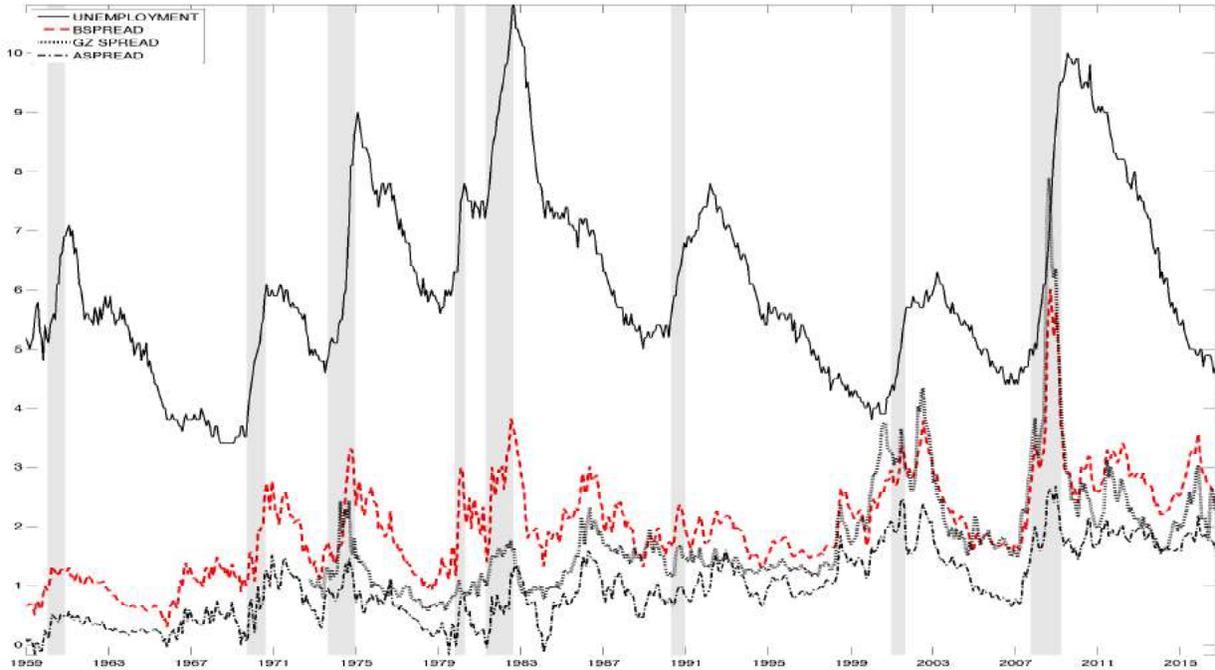


Figure 1: Measures of the external finance premium and unemployment

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 application, we use monthly and quarterly series. The monthly panel is an updated version of the data set in Bernanke, Boivin and Elias (2005) containing 141 U.S. economic series. It is augmented with 34 important quarterly U.S. macroeconomic series, mainly GDP components, to yield a mixed-frequencies monthly panel of 175 indicators, over the same period.¹⁰ 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.

Our first specification, labeled FAVAR 1, imposes a recursive structure on the following five economic indicators: $[\pi_{PCEPI}, UR, I, FFR, BSPREAD]$, where: π_{PCEPI} is the personal consumption expenditure price index (PCEPI) inflation rate; UR is unemployment

¹⁰The mixed-frequency panel is obtained using an EM algorithm as in Stock and Watson (2002b).

rate; I is real investment growth, and FFR is the federal funds rate. In practice, these indicators are listed first in data set X_t and we assume that the matrix B_0^* is of the form (6) in the structural moving-average representation (5). This assumption implies that $PCEPI$, UR , I and FFR are the only indicators that do not respond immediately to a surprise increase in $BSPREAD$, which is interpreted as the credit shock. The idea is that following credit shocks, it takes at least one month for the prices, unemployment and investment 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 note 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_{PCEPI} , UR , I and FFR may respond contemporaneously to the credit shock. 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 $BSPREAD$, after accounting for fluctuations in past common factors as well as in the current factors that explain the behavior of π_{PCEPI} , UR , I and FFR . The impact response of the $BSPREAD$ is equal to the standard deviation of the credit shock, which is a function of the relevant factor loadings in Λ and the corresponding elements in the matrix H .

Recent research has suggested that shocks to physical investment constitute a key source of business cycles fluctuations (see, e.g., 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.¹¹

In our second specification, labeled FAVAR 2, we assume a recursive structure in the following indicators $[\pi_{PCEPI}, UR, I, BSPREAD, FFR]$, where the credit shock is now ordered fourth ε_t . This identification scheme implies again that the inflation rate, the unemployment rate and the real investment growth do not respond in the same month to unexpected credit shocks. However, in contrast to our first specification, we let the federal funds rate respond immediately to all other shocks, including the credit shock. 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.

3 Results

In this section, we present empirical results from our benchmark FAVAR model with both recursive orderings discussed above. Both recursive identification scheme imply extracting five static factors from the data, X_t .¹² The lag order in VAR dynamics in (2) is set to 3

¹¹While 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 online Appendix, section 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, 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.

¹²Information criteria and tests in Amengual and Watson (2007), Bai and Ng (2002, 2007), Hallin and Liska (2007) and Onatski (2010) found between 2 and 8 static and dynamic shocks.

according to BIC. Finally, we report the 90% bootstrap confidence intervals.

3.1 Impulse responses to credit shocks

Figure 2 plots the impulse responses, estimated on full sample, of the level of key variables to the credit shock.¹³ The black line reports the point estimate of IRFs from FAVAR 2 recursive ordering where the credit spread is ordered before the FFR. The estimated IRFs from FAVAR 1 specification, where the short interest rate reaction is restricted to zero, are indicated by the dotted blue line. Both specifications produce very similar results.

On impact, the BSPREAD rises by 19 basis points from 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 1.2% within the first 12 months, before returning to its initial level. 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. Average weekly hours worked and capacity utilization fall significantly on impact. GDP and investment measures behave similarly to other real activity series, although total investment drops by more, falling by almost 3% 11 months after the shock.

On the credit side, we observe a significant and important decrease of consumer credit as well as of business and real estate loans. The total consumption decline is more muted than that of production and consumer credit, while the consumption of durables decreases significantly, which is in line with theories emphasizing the intertemporal smoothing of consumption.

The price indices based on the CPI, PCEPI, and PPI, show almost no change on impact and present a very persistent decline thereafter, settling four years later at a permanently

¹³While 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.

lower level than would have obtained without the credit shock. Note that while our identification restriction prevents the PCEPI-based inflation to change contemporaneously with the credit shock, other measures of inflation such as those based on the 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.

The federal funds rate is prevented from declining on impact in FAVAR 1, but is unrestricted in FAVAR 2. It does not react significantly on impact in the latter specification, but falls substantially in the subsequent months, reaching a drop of more than 30 basis points two years 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. However, the sample ends on 2016M12 and thus contain the whole zero lower bound period (ZLB) from 2009 to 2015 during which the FFR was not able to fall. But, according to Swanson and Williams (2014) the effective interest rates during that period are 1 to 3-year Treasury bonds since economic agents decisions depend on the entire yield curve. The figure 2 shows that 1-year and 3-year yields on Treasury securities fall markedly on impact and in years following the shock. Below, we will explore the stability of these results, particularly the impact response of monetary policy, since the beginning of Great Recession.

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.¹⁴ 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.

We have studied the robustness of our results to other identification strategies, recursive ordering and sign restrictions, to different lag orders as well as to using the Gilchrist-Zakrajsek credit spread (GZ SPREAD) instead of the BAA spread. The analysis is presented in the Appendix. Our findings are overall robust.

3.2 Importance of credit shocks

Table 1 shows the importance of credit shocks in explaining economic fluctuations during our 1959-2016 sample. The second column reports the contribution of the credit shock to the variance of the common component of the series at a 48-month horizon. The third column shows the fraction of the total variability of the series explained by the common component, the rest being explained by idiosyncratic component. The fourth column presents the contribution of the credit shock to the total variance of the series. It is simply the product of the second and third columns. The fifth and sixth columns show the results for the FAVAR 2 specification.

Both specifications produce very similar results. Interestingly, the credit shock has important effects on many crucial variables. It explains more than 50% of the variance of the common component of industrial production, and 40% of its total variability. Credit measures, capacity utilization rate, labor market series, some leading indicators and credit spreads are well explained by the credit shocks. Table 1 also shows that common disturbances explain overall a large fraction of fluctuations in key economic time series. Indeed, the third column of Table 1 shows that the common component explains a sizeable fraction of the variability in most of the indicators listed, especially for industrial production, prices, financial

¹⁴GYZ 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.

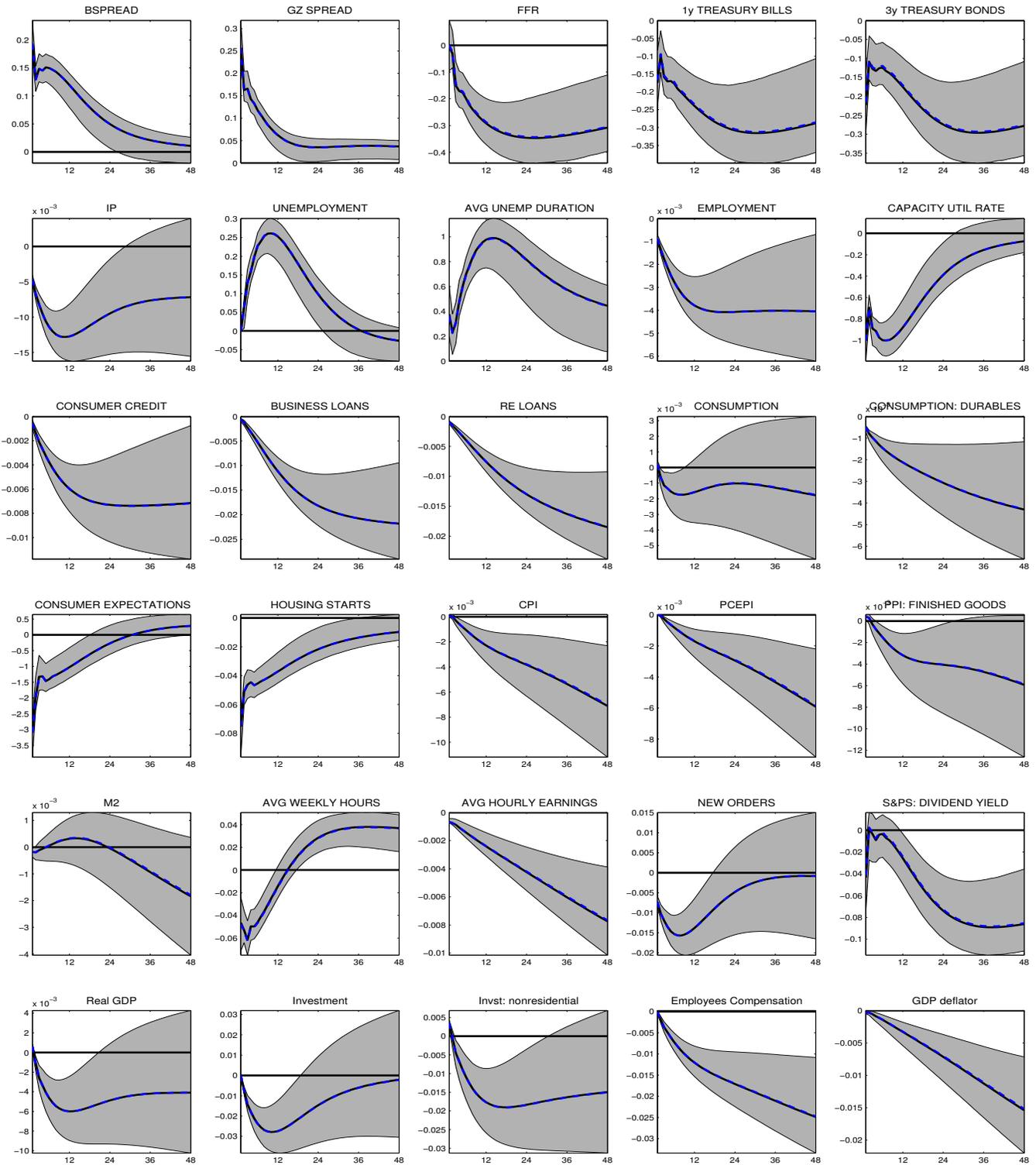


Figure 2: Dynamic responses of variables to credit shock in FAVAR 2

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified through the recursive identification scheme, $[\pi_{PCE}, UR, I, BSPREAD, FFR]$, 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 specification.

Table 1: Variance decomposition and R^2

Series	FAVAR 1			FAVAR 2	
	VD: common shocks	R2: common comp.	VD: total	VD: common shocks	VD: total
BSPREAD	0,67	0,64	0,43	0,67	0,43
GZ SPREAD	0,46	0,60	0,27	0,46	0,28
FFR	0,18	0,89	0,16	0,19	0,17
1y TREASURY BILLS	0,22	0,88	0,19	0,23	0,20
3y TREASURY BONDS	0,21	0,87	0,18	0,22	0,19
IP	0,51	0,78	0,40	0,51	0,39
UNEMPLOYMENT	0,26	0,76	0,20	0,26	0,20
AVG UNEMP DURATION	0,28	0,75	0,21	0,29	0,22
EMPLOYMENT	0,55	0,26	0,14	0,55	0,14
CAPACITY UTIL RATE	0,63	0,79	0,50	0,63	0,50
CONSUMER CREDIT	0,34	0,16	0,06	0,34	0,06
BUSINESS LOANS	0,46	0,33	0,15	0,46	0,15
RE LOANS	0,60	0,33	0,20	0,60	0,20
CONSUMPTION	0,06	0,53	0,03	0,06	0,03
CONSUMPTION: DURABLES	0,25	0,21	0,05	0,25	0,05
CONSUMER EXPECTATIONS	0,25	0,58	0,14	0,24	0,14
HOUSING STARTS	0,54	0,58	0,32	0,54	0,32
CPI	0,04	0,83	0,03	0,04	0,03
PCE PRICE INDEX	0,04	0,81	0,03	0,04	0,03
PPI: FINISHED GOODS	0,04	0,61	0,02	0,04	0,02
M2	0,09	0,08	0,01	0,09	0,01
AVG WEEKLY HOURS	0,27	0,52	0,14	0,26	0,14
AVG HOURLY EARNINGS	0,33	0,33	0,11	0,33	0,11
NEW ORDERS	0,45	0,32	0,15	0,45	0,14
S&PS: DIVIDEND YIELD	0,13	0,67	0,09	0,13	0,09
GDP	0,10	0,69	0,07	0,10	0,07
INVESTMENT	0,12	0,50	0,06	0,12	0,06
INVST: NONRESIDENTIAL	0,13	0,80	0,10	0,13	0,10
EMPLOYEES COMPENSATION	0,19	0,58	0,11	0,19	0,11
GDP DEFLATOR	0,08	0,56	0,04	0,08	0,05

Notes: The second column reports for key macroeconomic series, $x_{i,t}$, the contribution of the credit shock to the variance of the common component of the series at a 48-month horizon. The third column contains the fraction of the total variability of the series explained by the common component. The fourth column is the product of the previous two and represents the fraction of the total variance of the series. The fifth and the sixth columns show the results for the FAVAR 2 specification.

indicators, average unemployment duration, capacity utilization and consumer expectations.

3.3 How important were credit spreads in the Great Recession?

Given the assumption $\varepsilon_t = He_t$, we can rewrite the system (1)-(2) in its structural form

$$X_t = \Lambda^* F_t^* + u_t \quad (11)$$

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

where $F_t^* = HF_t$, $\Lambda^* = \Lambda H^{-1}$, and $\Phi^*(L) = H\Phi(L)H^{-1}$. Hence, given the estimates of F_t and H , we can obtain an estimate of the structural factors, $\hat{F}_t^* = \hat{H}\hat{F}_t$, associated with the structural shocks ε_t .¹⁵ 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 actual data (solid blue lines) from 2007M1 to 2009M6, the date at which the recession officially ended.¹⁶

Figure 3 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 7% and 3%, 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 almost 2 percentage points. 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.

¹⁵This gives “structural” factors as opposed to the statistically identified factors in Bai and Ng (2013).

¹⁶According to the NBER, the Great Recession lasted from December 2007 to June 2009. 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 2007M01 to 2009M06.

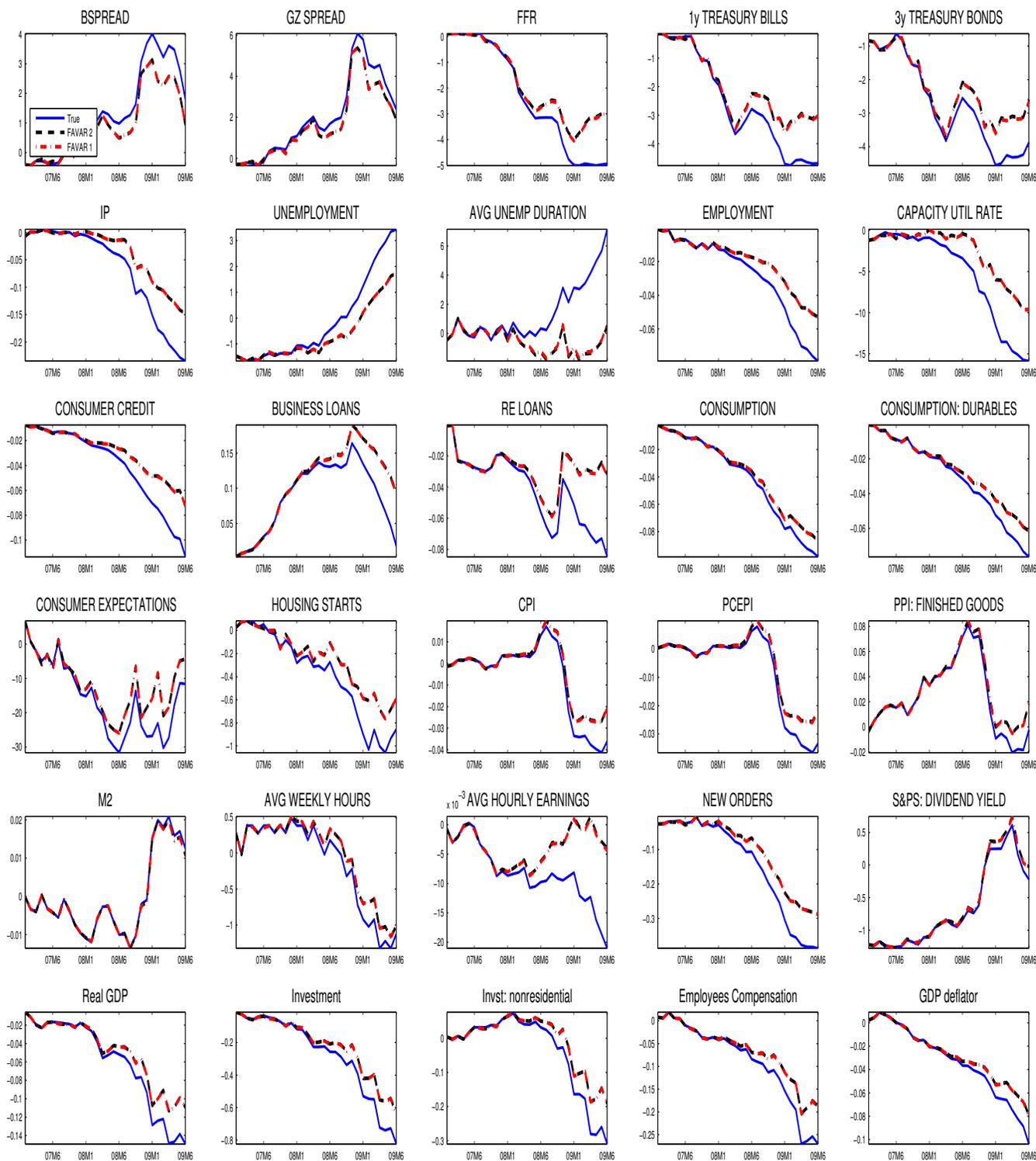


Figure 3: Importance of credit shocks during Great Recession

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. The credit shock is shut down from 2007M06.

3.4 Recursive estimation of impulse responses to credit shocks

Recursive estimation of the FAVAR model reveals notable instabilities since 2007. This should not be too surprising given the unusually large spike in spreads in 2008-09, and given the fact that conventional monetary policy has been constrained by the zero lower bound on nominal interest rates from the end of 2008 through the end of 2015.

Figure 4 plots the impulse responses to a credit shock in models estimated recursively over the samples 1959M04 – 2007M07 through 1959M04 – 2016M12, under the FAVAR 2 specification. We show the results for a subset of series in order to make them more easily readable. In contrast to the full sample specification, the federal funds rate declines significantly on impact for samples ending in 2007 through 2010. A closer look reveals that the response of the FFR becomes increasingly negative during the Great Recession, falling on impact by more than 50 basis points when the model is estimated on data through 2008M12. This results also in a larger impact response of 1 and 3-year Treasury yields.

Interestingly, the sharp drops in the federal funds rate and longer-term Treasury yields are associated with overall dampened responses of real economic activity, credit measures, and of leading indicators. In other words, the impulse responses of industrial production, the unemployment rate are mitigated and less persistent when monetary policy is able to respond to adverse credit shocks. Similarly, consumer credit, real estate loans, and leading indicators such as consumer expectations and housing starts also seem to react positively to the monetary stimulus. The fact that the federal funds rate could not decrease following the crisis as much as it did pre-2007 appears to have contributed to worsen the economic impact of credit shocks.

The structural instability in the factor model context has received some attention recently.¹⁷ While Stock and Watson (2012) argue that the factor structure is relatively stable during the Great Recession, Cheng et al. (2016) propose a procedure to detect structural

¹⁷Bates et al. (2013) show that the principal component estimation of the factor space is consistent under several types and magnitudes of structural breaks.

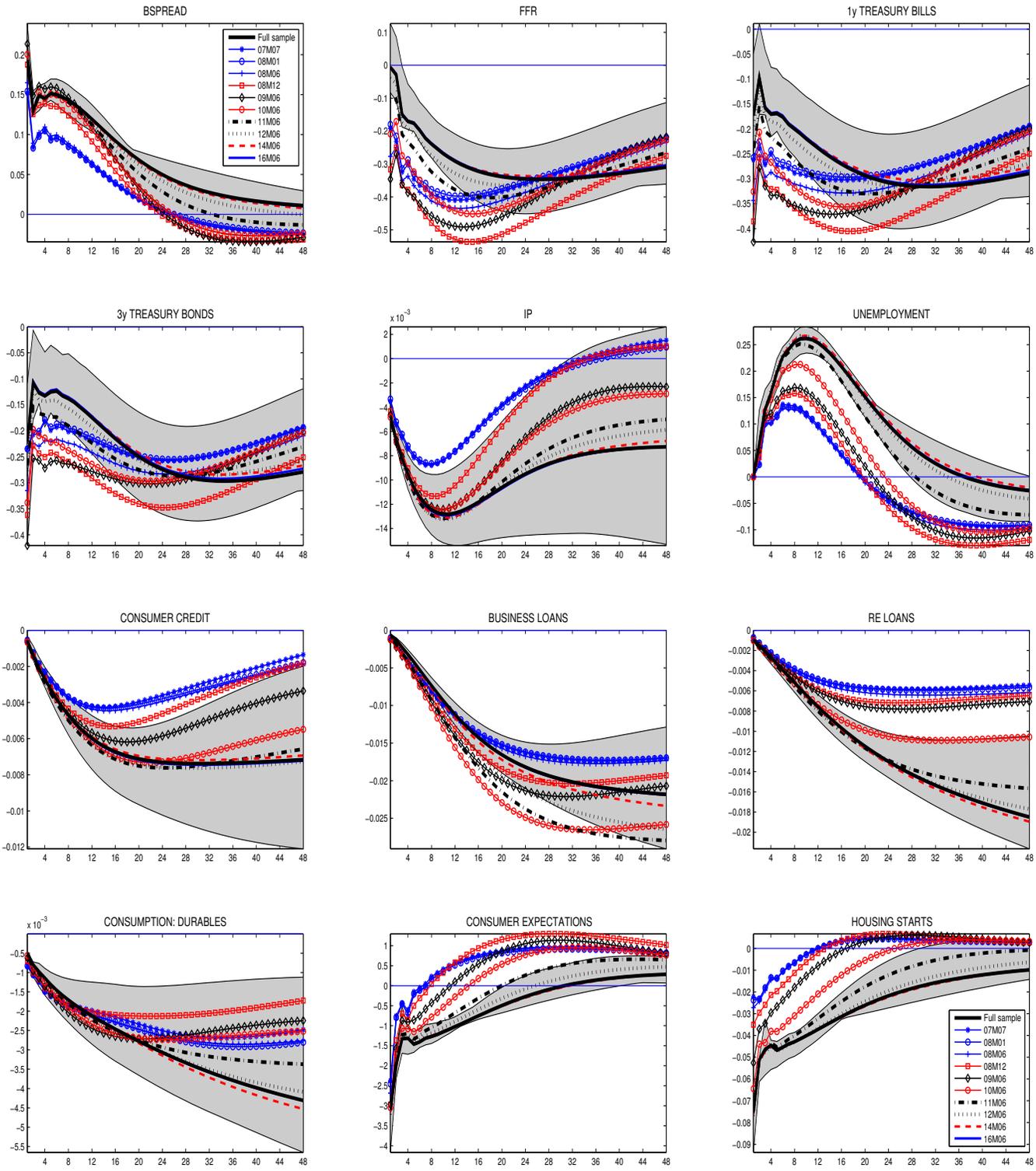


Figure 4: Recursively estimated dynamic responses to credit shock in FAVAR 2

Notes: The figure plots the impulse responses to a credit shock in models estimated recursively over the samples 1959M04 – 2007M07 through 1959M04 – 2016M12, under the FAVAR 2 specification. 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.

changes in factor loadings as well as in the number of factors, and find evidence of a new factor affecting financial variables during the last crisis. In the macro-finance context, some papers have documented instabilities using time-varying parameter (TVP) models.¹⁸

4 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.

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. The drop in yields of Treasury securities suggests that monetary policy has partly offset the effects of credit shocks on economic activity during the Great Recession.

Recursive estimation of the model reveals relevant instabilities since 2007. The fact that the federal funds rate was constrained by the zero lower bound after 2008 appears to have

¹⁸Aastveit et al. (2017) revisit the stability of standard small-scale VARs since the recent crisis. Prieto et al. (2016) measure the effects of credit spread, housing and stock price shocks in a TVP-VAR framework as well, and find that the contribution of financial shocks to GDP have increased substantially during the Great Recession. This finding is confirmed in Abbate et al. (2016) who study the international transmission of financial shocks in the TVP factor model context.

contributed to worsen the economic impact of credit shocks.

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. A variance decomposition analysis suggests that credit shocks have important effects on several real activity measures, price indicators, leading indicators, and credit spreads. A counterfactual experiment reveals that credit spread shocks have largely contributed to the deterioration in economic conditions during the Great Recession. Our results appear robust to different FAVAR specifications and identification schemes.

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Appendix A. Identification of impulse responses 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 2. The data generating process is the structural DFM:

$$X_t = \Lambda^* F_t^* + u_t \quad (13)$$

$$F_t^* = \Phi^*(L) F_{t-1}^* + \varepsilon_t \quad (14)$$

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

The coefficients in Λ , Φ and the matrix H , as well as the lag order in VAR dynamics are exactly the ones from the FAVAR 2 specification. The time and cross-section sizes are 693 and 175 respectively. The initial conditions on factors VAR are the first three periods of rotated factors from FAVAR 2.

Figure 5 plots impulse responses from the simulation experiment. The black line represents the true impulse response functions obtained from (13)-(14). 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.

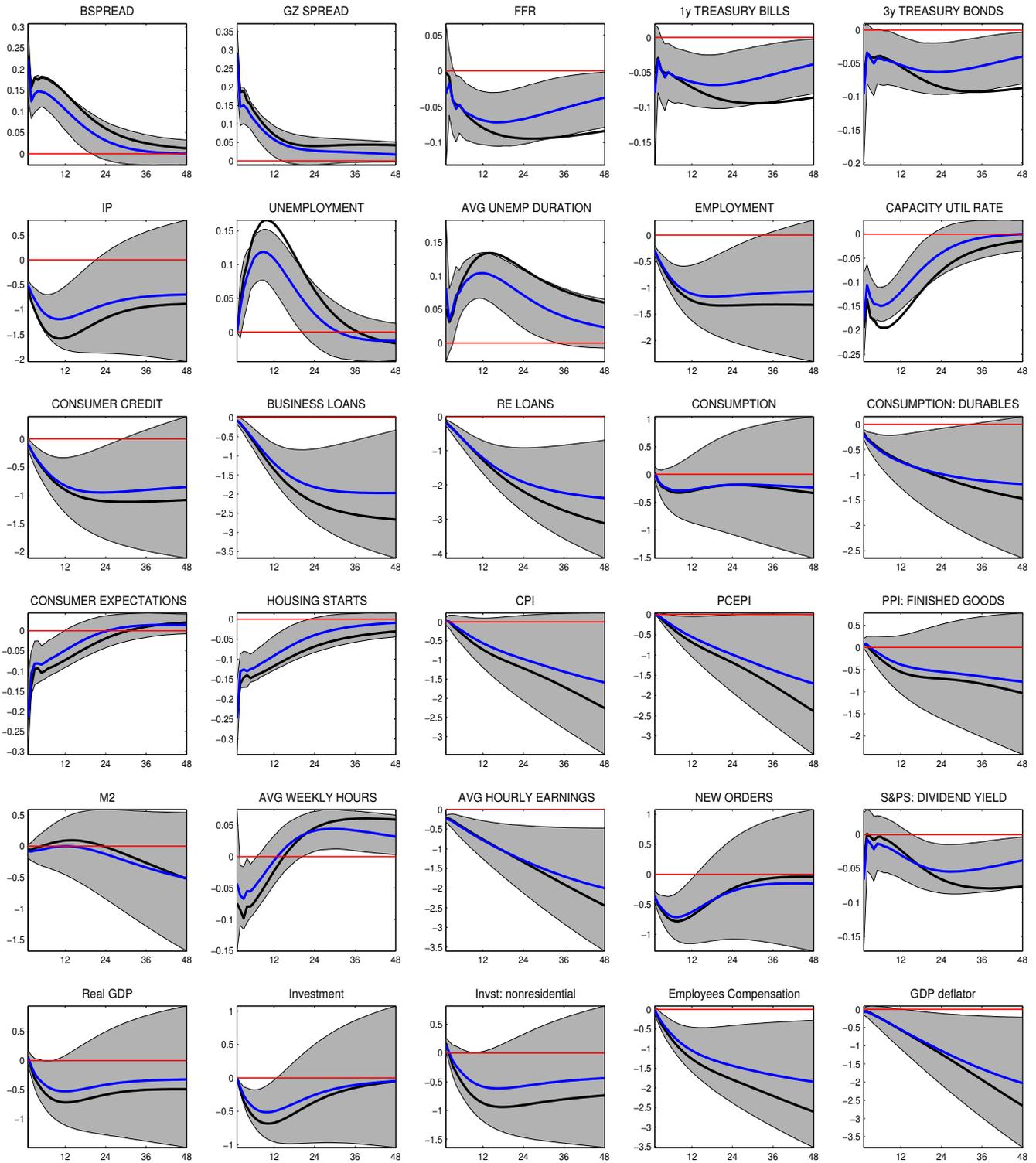


Figure 5: Calibrated simulation to FAVAR 2 model

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified in FAVAR 2 specification. The black line shows the true impulse response, the blue line reports the median simulated IRF and 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 figures 6 - 7 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.

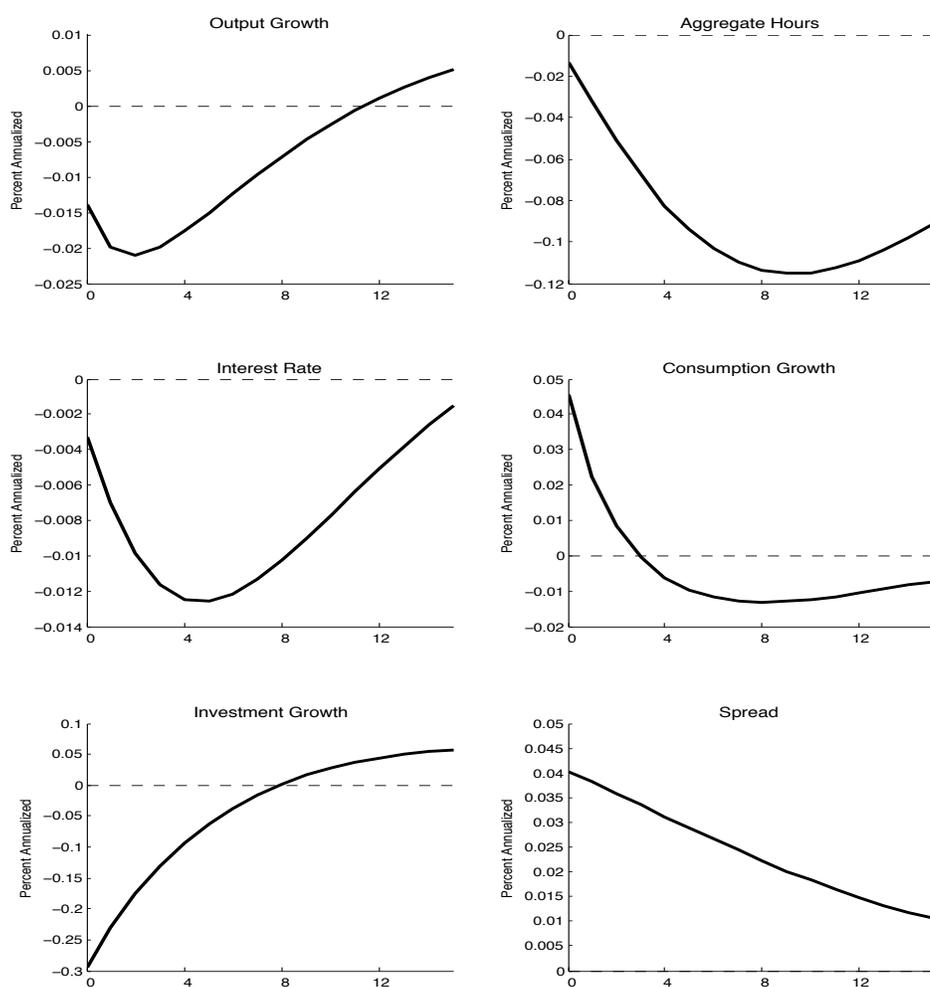


Figure 6: Dynamic responses to a spread shock in an estimated DSGE model

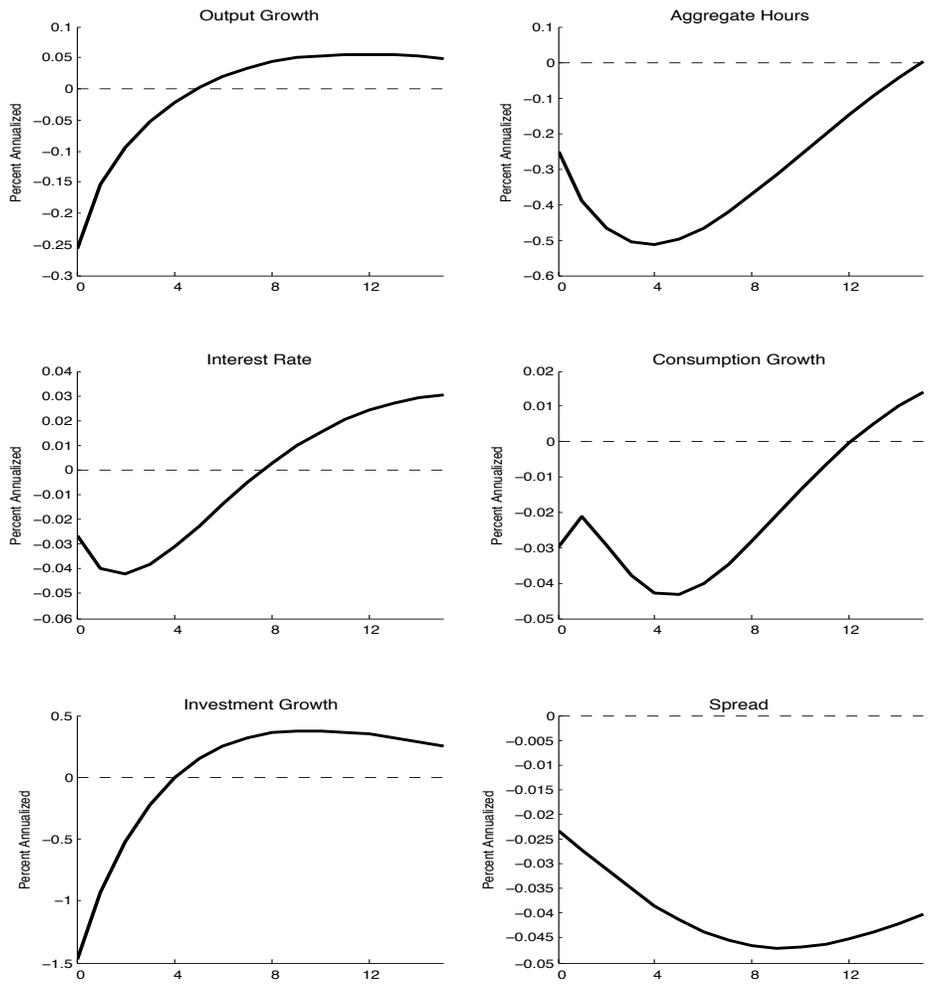


Figure 7: Dynamic responses to a shock to the marginal efficiency of investment in an estimated DSGE model

Appendix C. Robustness analysis

Appendix C.1 Robustness to lag selection

The Figure 8 compares the dynamic responses to credit shock obtained with difference lag structures on the factors' VAR process.

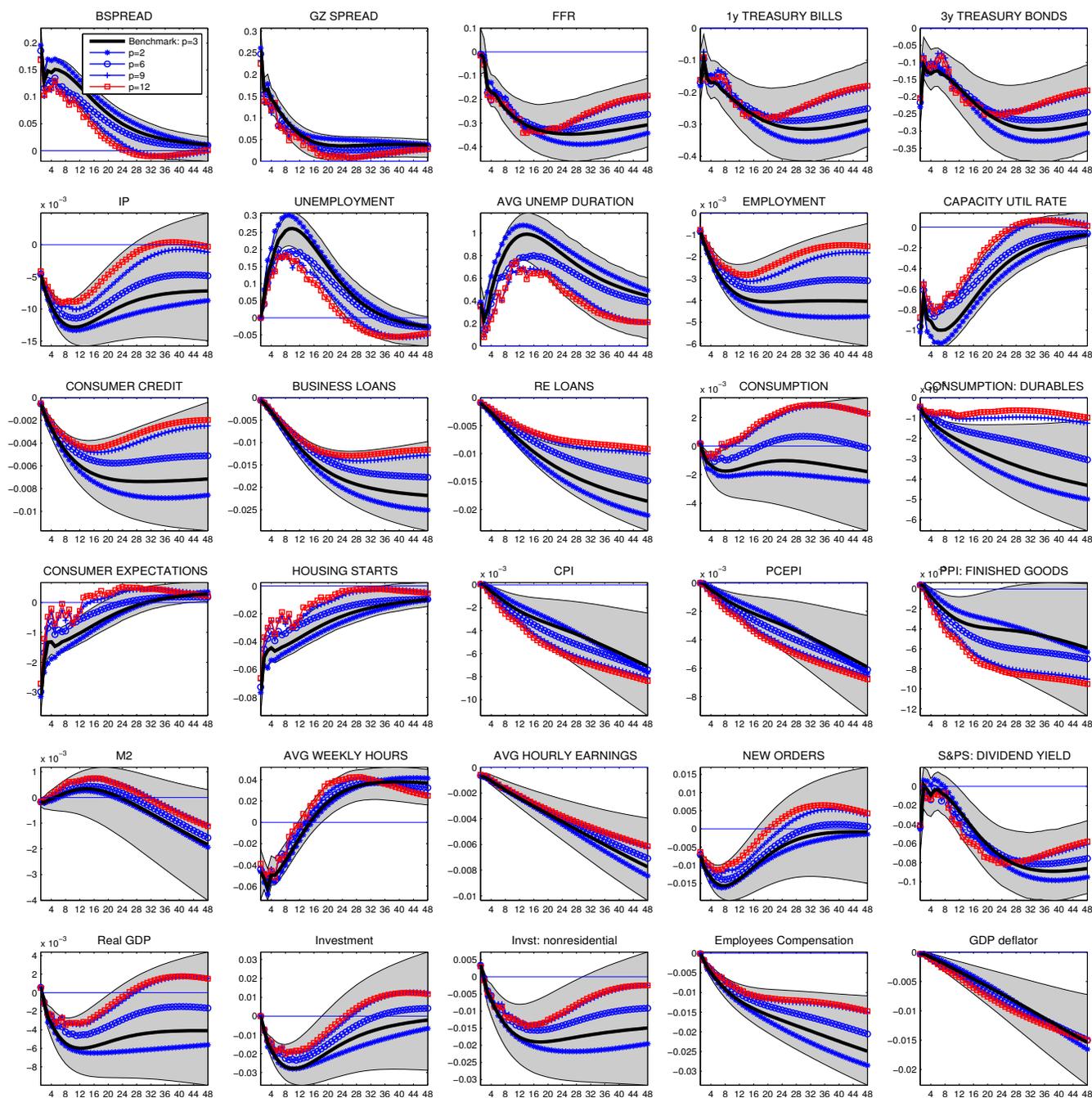


Figure 8: Dynamic responses to credit shock in FAVAR 2 with different lag structures

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified in FAVAR 2 specification.

The grey areas indicate the 90% confidence intervals computed using 5000 bootstrap replications for the benchmark model.

Appendix C.2: Comparison with GZ SPREAD

The Figure 9 compares the dynamic responses to credit shock identified using BSPREAD and GZ SPREAD of Gilchrist and Zakrajsek (2012).

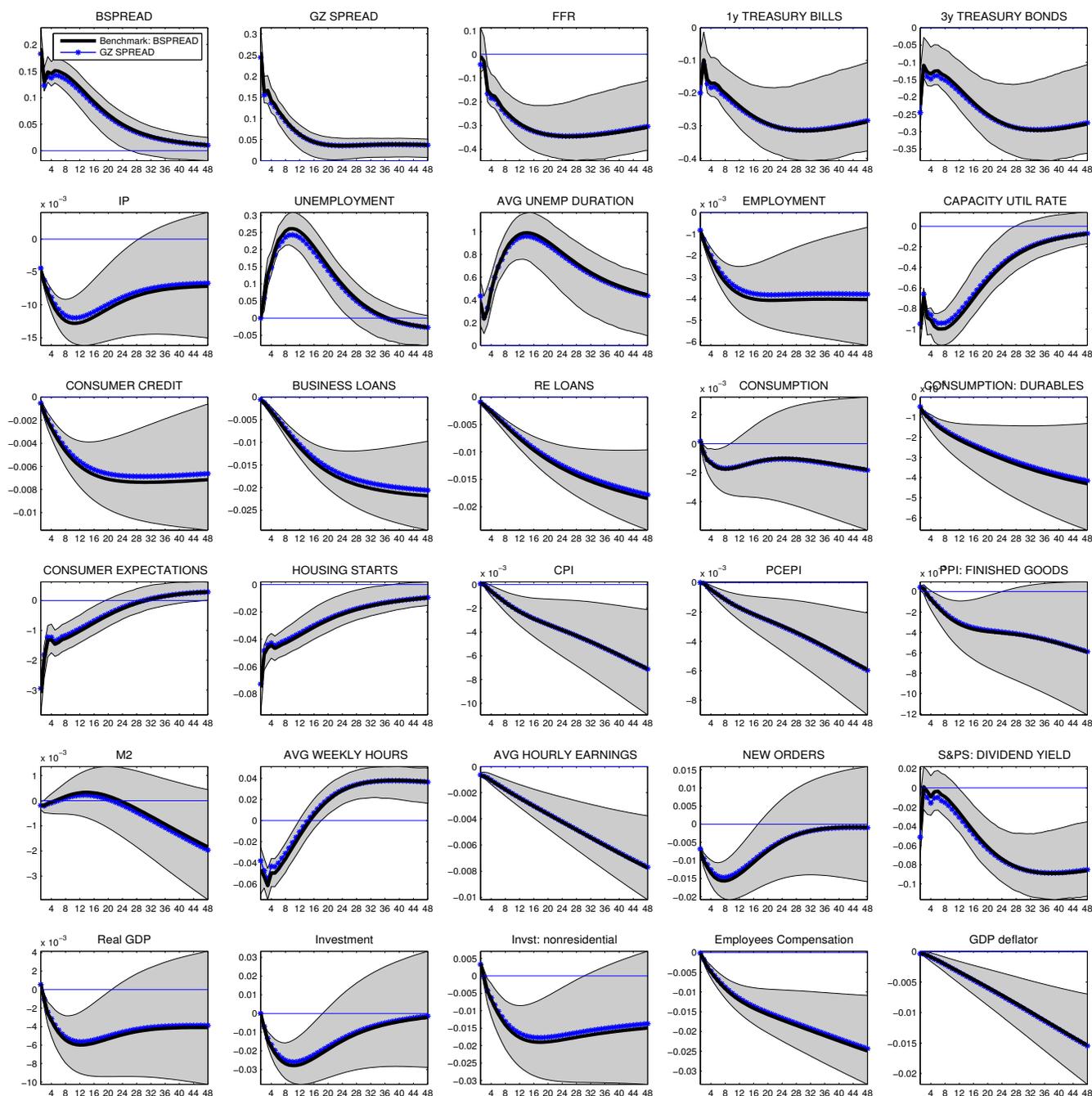


Figure 9: Dynamic responses of variables to credit shock using GZ spread in FAVAR 2

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified through the recursive identification scheme, $[\pi_{PCE}, UR, I, GZSPREAD, FFR]$, where GZ SPREAD is the Gilchrist-Zakrajsek credit spread and 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 the FAVAR 2 specification.

Appendix C.3 Robustness to ordering

The Figure 10 compare the dynamic responses to credit shock obtained with difference lag structures on the factors' VAR process.

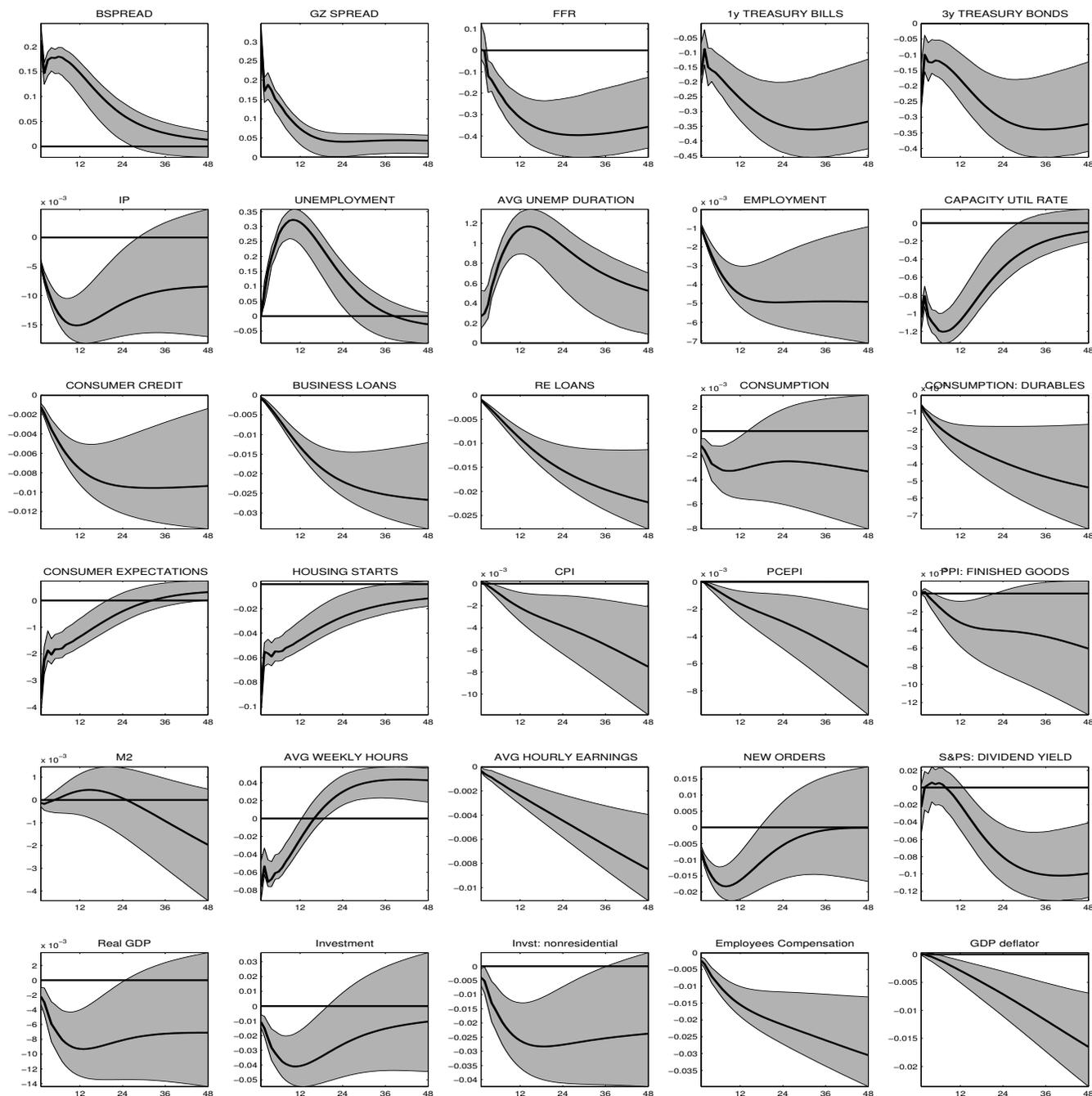


Figure 10: Dynamic responses to credit shock with alternative recursive ordering

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified in following recursive ordering: $[\pi_{PCE}, UR, BSPREAD, I, FFR]$. The credit shock is ordered third. The grey areas indicate the 90% confidence intervals computed using 5000 bootstrap replications for the benchmark model.

Appendix C.4 Robustness to sign restrictions

In this section we compare the dynamic responses identified using sign restrictions to our benchmark recursive identification in FAVAR 2. The sign restrictions are now widely used since the seminal work by Uhlig (2005). They have been used in FAVAR framework as well, Ahmadi and Uhlig (2015). This approach is meant to be less restrictive than Choleski decomposition, but has also received some criticism, see Fry and Pagan (2011). Nevertheless, it is of interest to see how our results compare to those from a more agnostic procedure. In the VAR setup, Prieto et al. (2016) found their recursive ordering robust to several identification schemes, including sign restrictions.

The inequality restrictions following a positive credit shock are imposed on the impact responses of few elements of the FAVAR 2 recursive ordering elements: $\pi_{PCE} \leq 0$, $UR \geq 0$, $I \leq 0$, $BSPREAD \geq 0$. The response of FFR is unrestricted. To implement the sign restrictions we first orthogonalize the common residuals using the Cholesky decomposition based on the recursive ordering in FAVAR 2. Then, we use QR decomposition to draw an orthonormal matrix Q that post-multiplies the Cholesky MA(∞) representation of the data. The rotated impulse responses satisfying the inequality restrictions are retained. We repeat the process 500,000 times. Around 5% of those matrices are retained.

The Figure 11 plots the median IRF as well as 68% and 90% of all impulse responses that satisfy the restrictions. We compare to recursive ordering identification in FAVAR 2 model. The results of our preferred specification are overall robust to those obtained through sign restrictions. Recall that grey areas in the figure do not represent the confidence intervals. They represent a subset of all models that satisfy the inequality restrictions that are set-identified. As is the case with partial identification, the confidence set should incorporate the model uncertainty around all retained impulse response functions. Therefore, we are pretty sure our recursive IRFs lie in the space spanned by the sign restrictions.

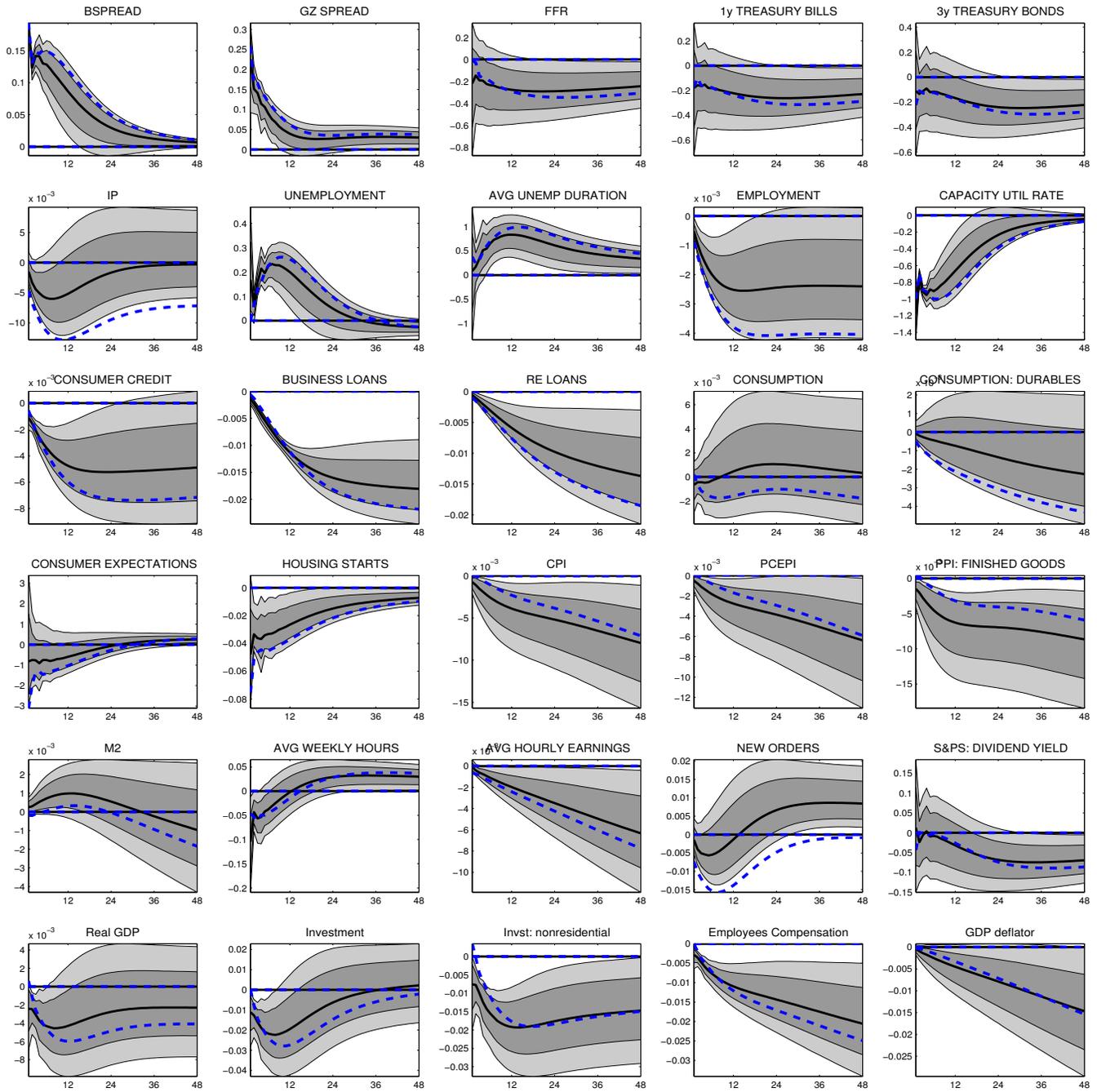


Figure 11: Dynamic responses to credit shock with sign restrictions

Notes: The figure plots the impulse responses of the level of key variables to the credit shock identified using sign restrictions. The black line is the median IRF. The light and the dark grey areas indicate respectively 90% and 68% of impulse responses that satisfy the inequality restrictions. The dotted blue line reports the point estimate of the FAVAR 2 model.

Appendix D. Other results

Appendix D.1 Interpretation of factors

An interesting feature of the identification approach is the matrix H which can be used to interpret the estimated factors. Recall that structural shocks are a linear combination of residuals, $\varepsilon_t = He_t$. This allows us to rewrite the model in its structural form

$$X_t = \Lambda^* F_t^* + u_t \quad (15)$$

$$F_t^* = \Phi^*(L)F_{t-1}^* + \varepsilon_t \quad (16)$$

where $F_t^* = HF_t$, $\Lambda^* = \Lambda H^{-1}$, and $\Phi^*(L) = H\Phi(L)H^{-1}$. Hence, given the estimates of F_t and H , we can obtain an estimate of the structural factors, $\hat{F}_t^* = \hat{H}\hat{F}_t$, associated with the structural shocks ε_t .¹⁹ The rotated factors and associated variables are plotted in Figure 12. The results reveal that the transformation by \hat{H} yields estimated structural factors very close to the observed indicators used in the recursive identification scheme.

The Figure 12 compares the dynamic responses to credit shock obtained with difference lag structures on the factors' VAR process.

¹⁹This gives “structural” factors as opposed to the statistically identified factors in Bai and Ng (2013).

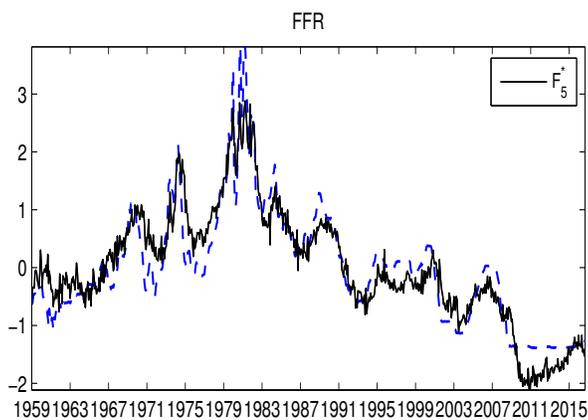
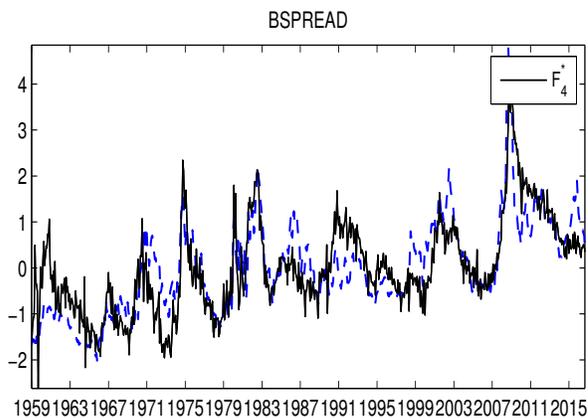
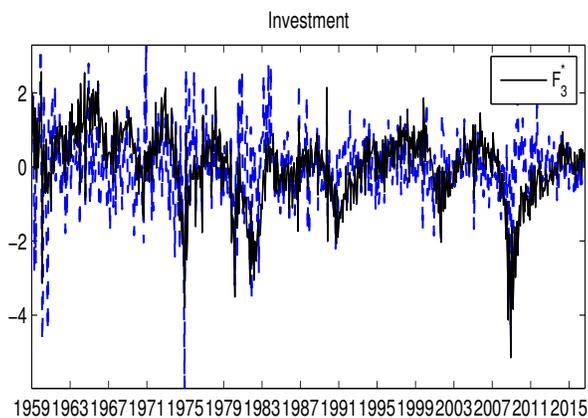
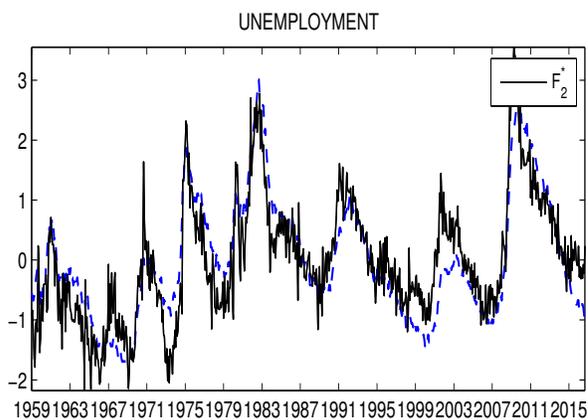
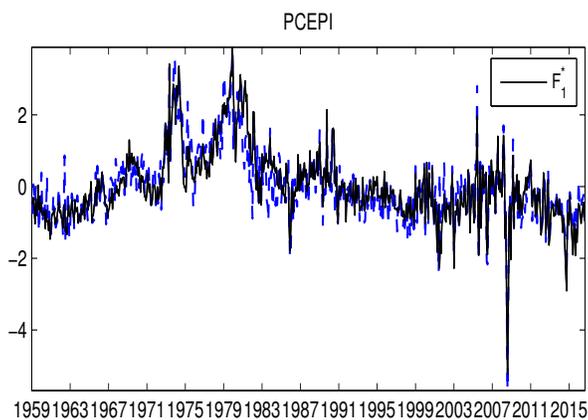


Figure 12: Interpretation of factors

Notes: The figure plots the estimated structural factors (blue dotted line) and variables (black line) in the recursive identification scheme in FAVAR 2.

Appendix D.2 Time series of credit shocks

The Figure 13 plots the time series of the identified credit shock from both FAVAR 1 and 2 specifications.

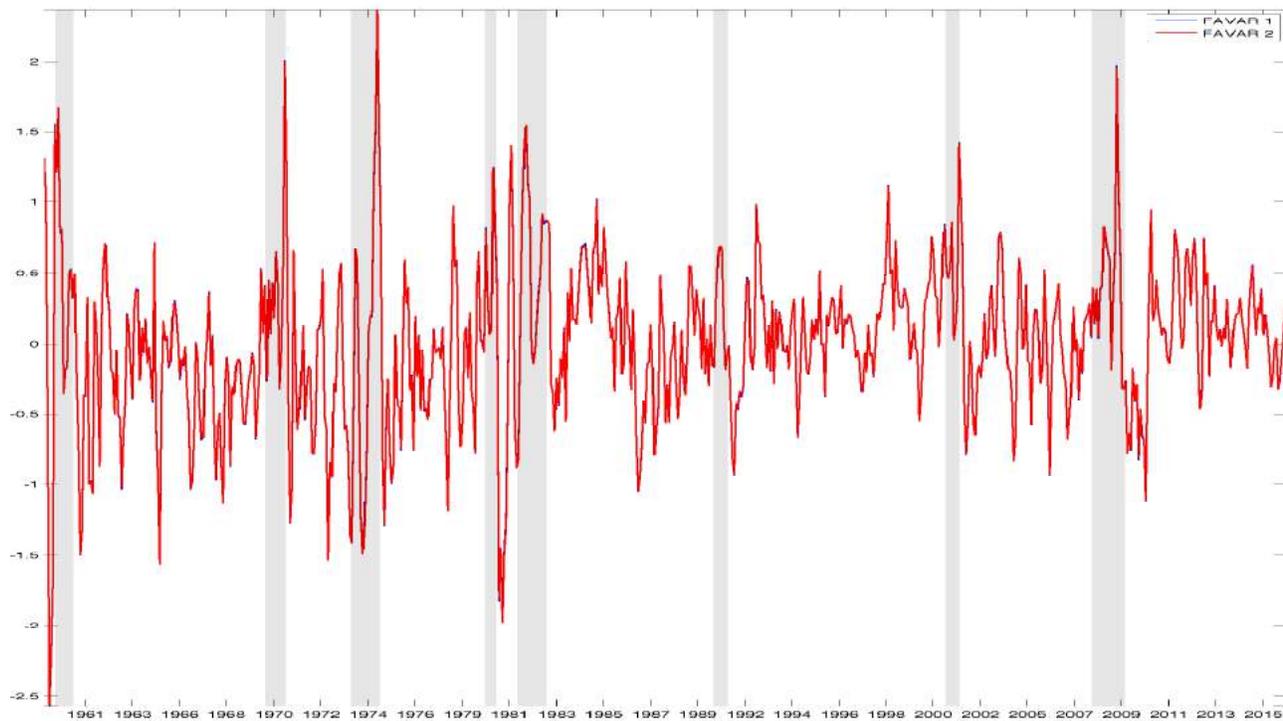


Figure 13: Time series of structural credit shocks

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.

Appendix D.3 Recursive estimation of dynamic responses to credit shocks

The figure 14 plots the dynamic responses to credit shocks estimated recursively from 2007M07 until the end of sample under FAVAR 2 specification. These are the same results as in the main text, but presented in a 3D plot which provides a complementary view of time instability in impulse responses during that period.

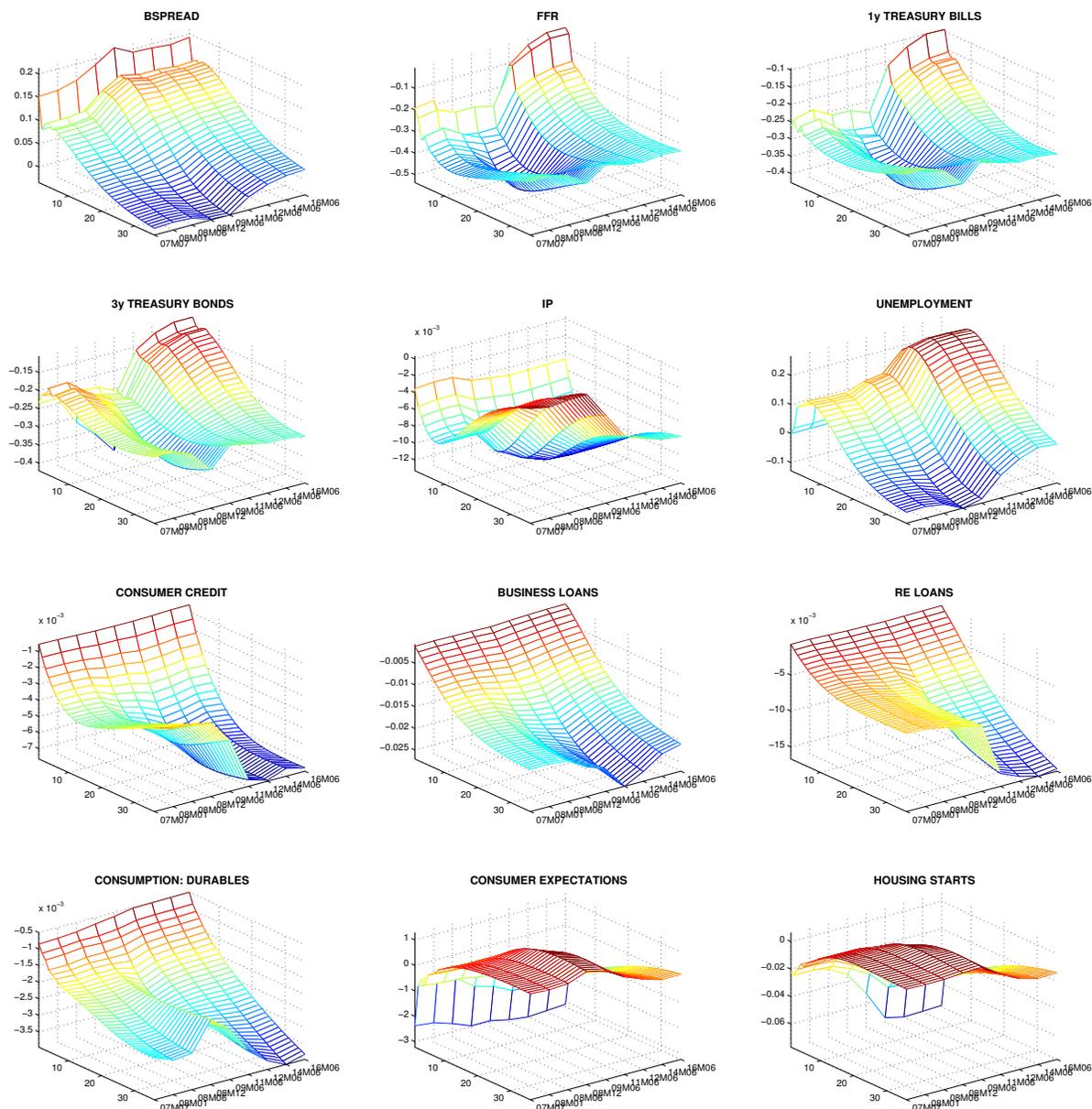


Figure 14: Dynamic responses to credit shock with sign restrictions

Notes: The figure plots the impulse responses to credit shocks estimated recursively from 2007M07 until the end of the sample, under FAVAR 2 specification. We show only a subset of series in order to make the differences easy to read.

Appendix E. 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 has the following recursive ordering $[\pi_{PCEPI}, UR, IFFR, BSPREAD]$ with 3 lags. Hence, inflation, unemployment, investment and the federal funds rate cannot respond in the same month to an unexpected increase in the credit spread. This identifying assumption is similar to 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. In other words, we consider those five series as factors.

Figure 15 shows the effects of an unexpected increase in the BSPREAD of 19 basis points, i.e., the same magnitude as the one considered in FAVAR 1. The shock causes a significant and persistent increase in the unemployment rate, a fall in the price level, and a persistent reduction of the federal funds rate. 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 the 10-year A-spread ($ASPREAD$). Table 2 lists all the structural VAR models considered, and Figure 15 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.

The FAVAR impulse responses to credit shocks are very different for the two real activity series, unemployment rate and investment. The credit disturbances cause a much bigger response during the first after the shock. 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. This is in line with Bernanke, Boivin and Elias (2005), who, in the context of monetary policy shocks, show important qualitative differences between VAR and FAVAR responses of many variables.

Table 3 reports the contribution of credit shocks to the total variance of these series. We have also considered Industrial Production (IP) instead of the unemployment rate. The VAR credit shocks, compared to FAVAR credit disturbances, contribute much less to fluctuations

in the PCEPI (between 1 and 3%), unemployment rate (5 to 14%) and industrial production (between 1% and 5%). These results indicate that credit shocks are indeed much more important in explaining economic fluctuations than the small-scale VAR models suggest.

Table 2: VAR models specifications

VAR models	Recursive ordering
Model 1	[<i>PCEPI, UR, I, FFR, BSPREAD</i>]
Model 2	[<i>PCEPI, UR, I, BSPREAD, FFR</i>]
Model 3	[<i>PCEPI, UR, I, FFR, ASPREAD</i>]

Notes: This table shows the VAR models used in the comparison.

Table 3: Variance decomposition: contribution of the credit shock in four VAR models

Variables	Model 1	Model 2	Model 3	Model 1*	Model 2*	Model 3*
PCE	0,02	0,03	0,02	0,02	0,02	0,01
UNEMPLOYMENT	0,14	0,12	0,06			
IP				0,08	0,08	0,03
INVESTMENT	0,02	0,02	0,01	0,02	0,02	0,01
FFR	0,11	0,17	0,10	0,12	0,17	0,10
BSREAD	0,90	0,89		0,87	0,86	
A SPREAD			0,90			0,89

*Notes: The columns two to five report the contribution of the credit shock to the variance of the of the series at a 48-month horizon. The model specifications are listed in table (2). In models with * we have replaced unemployment rate by industrial production.*

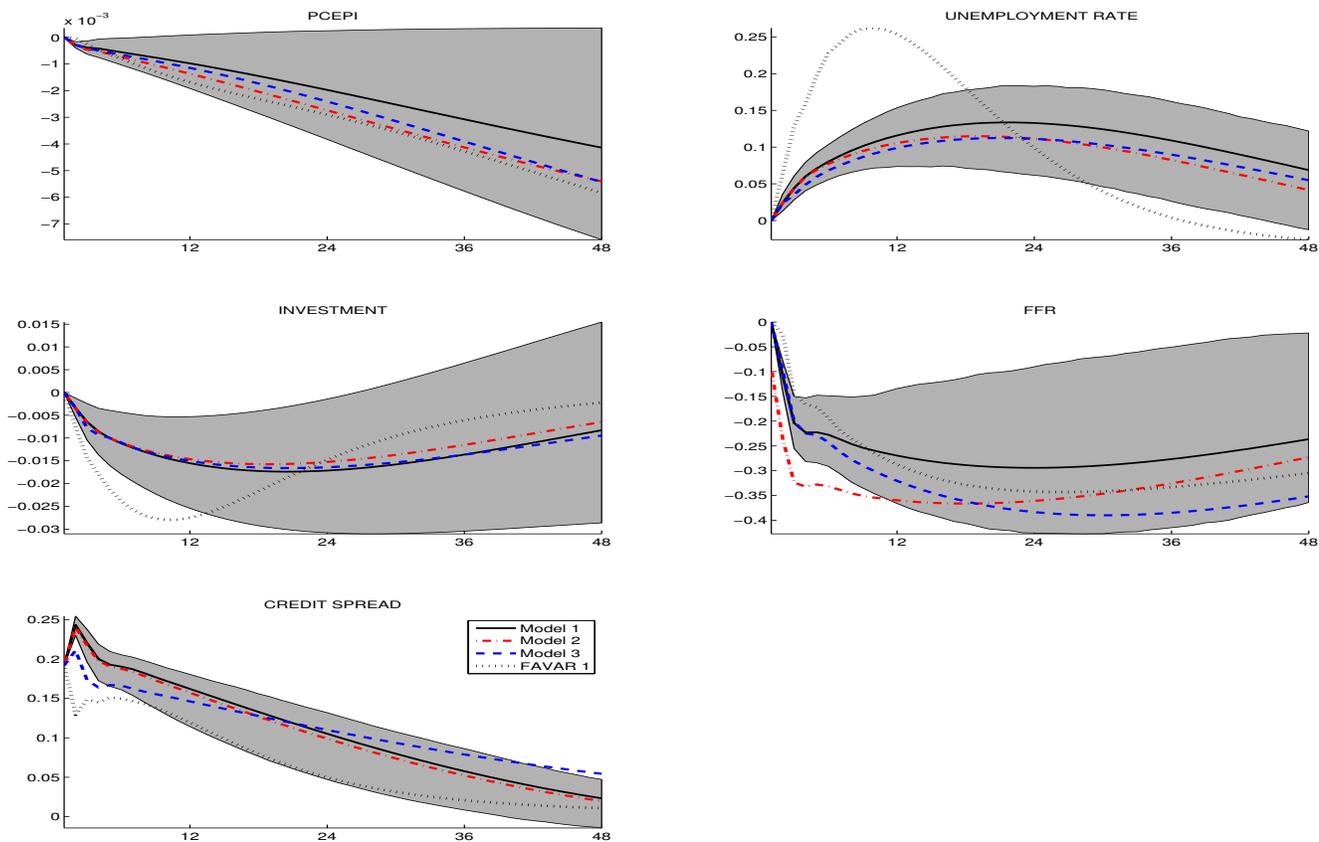


Figure 15: Dynamic responses to credit shock in SVAR models

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 (2). The grey areas indicate the 90% confidence intervals for the benchmark model (Model 1) computed using 5,000 bootstrap replications.

Appendix F: 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 # 176). A ** indicate a series that is deflated with the GDP deflator (series # 159).

No.	Series Code	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	Real Personal Income (2009), SAAR - United States
19	YPDR	5	Real Personal Income, Disposable Personal Income, Total (2009), SAAR - United States
20	YP@V00C	5	Personal Income Less Transfer Payments (2009), SAAR - United States
21	SAVPER	2	Nominal Personal Saving, SAAR - United States
22	SAVPRATE	1	Nominal Personal Income, Personal Saving as a Percentage of Disposable Personal Income, SAAR - United States
EMPLOYMENT AND HOURS			
23	LHEL	5	INDEX OF HELP WANTED
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	UNRATE	1	Civilian Unemployment Rate, Percent, Monthly, Seasonally Adjusted
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	Average Hourly Earnings of Production and Nonsupervisory Employees, Construction, SA - United States
36	AHPMF	5	Average Hourly Earnings of Production and Nonsupervisory Employees, Manufacturing, SA - United States
37	PMEMP	1	NAPM EMPLOYMENT INDEX (PERCENT)
38	CES002	5	EMPLOYEES, NONFARM - TOTAL PRIVATE
39	CES003	5	EMPLOYEES, NONFARM - GOODS-PRODUCING
40	CES004	5	EMPLOYEES, NONFARM - NATURAL RESOURCES & MINING
41	CES011	5	EMPLOYEES, NONFARM - CONSTRUCTION
42	CES014	5	EMPLOYEES, NONFARM - MFG
43	CES017	5	EMPLOYEES, NONFARM - DURABLE GOODS
44	CES033	5	EMPLOYEES, NONFARM - NONDURABLE GOODS
45	CES046	5	EMPLOYEES, NONFARM - SERVICE-PROVIDING
46	CES048	5	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES
47	CES049	5	EMPLOYEES, NONFARM - WHOLESALE TRADE
48	CES053	5	EMPLOYEES, NONFARM - RETAIL TRADE
49	CES088	5	EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES
50	CES140	5	EMPLOYEES, NONFARM - GOVERNMENT
51	CES151	1	AVG WKLY HOURS, PROD WRKRS, NONFARM - GOODS-PRODUCING
52	CES153	1	AVG WKLY HOURS, PROD WRKRS, NONFARM - CONSTRUCTION
53	CES154	1	AVG WKLY HOURS, PROD WRKRS, NONFARM - MFG
54	CES155	1	AVG WKLY OVERTIME HOURS, PROD WRKRS, NONFARM - MFG
55	CES156	1	AVG WKLY HOURS, PROD WRKRS, NONFARM - DURABLE GOODS
56	CES275	5	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - GOODS-PRODUCING
57	CES277	5	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION
58	CES278	5	AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG
REAL CONSUMPTION			
59	JQCR	5	Real Personal Consumption Expenditures Quantity Index, Total (2009), SA - United States
60	JQCNR	5	Real Personal Consumption Expenditures Quantity Index, Goods, Nondurable Goods (2009), SA - United States
61	JQCDR	5	Real Personal Consumption Expenditures Quantity Index, Goods, Durable Goods (2009), SA - United States
62	JQCSVR	5	Real Personal Consumption Expenditures Quantity Index, Services (2009), SA - United States
160	UJQCDMVR.M	5	REAL PCE-DUR-MV&PARTS,QTY INDEX (2000=100),SA,SA-US
161	JQCDFHER.M	5	REAL PCE-DUR-FURN&HH EQUIP,QTY INDEX (2000=100),SA,SA-US
162	JQCDOR.Q	5	REAL PCE-DUR-OTH,QTY INDEX (2000=100),SA,SA-US
163	JQCNFR.Q	5	REAL PCE-NDUR-FOOD,QTY INDEX (2000=100),SA,SA-US
164	JQCNSR.Q	5	REAL PCE-NDUR-CLO&SHOES,QTY INDEX (2000=100),SA,SA-US
165	JQCNER.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS,QTY INDEX (2000=100),SA,SA-US
166	JQCNEGAOR.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS-GASOLINE&OIL,QTY INDEX (2000=100),SAAR-US
167	JQCNEFACR.Q	5	REAL PCE-NDUR-GASOLINE FUEL OIL&OTH ENERGY GDS-FUEL OIL&COAL,QTY INDEX (2000=100),SAAR-U.S.
168	JQCNROR.Q	5	REAL PCE-NDUR-OTH,QTY INDEX (2000=100),SA,SA-US
169	JQCSVHSR.Q	5	REAL PCE-SVC-HOUSING,QTY INDEX (2000=100),SA,SA-US
170	JQCSVTSR.Q	5	REAL PCE-SVC-TRNSPRT,QTY INDEX (2000=100),SA,SA-US
171	JQCSVMR.Q	5	REAL PCE-SVC-MEDICAL CARE,QTY INDEX (2000=100),SA,SA-US
172	JQCSVRECR.Q	5	REAL PCE-SVC-RECR,QTY INDEX (2000=100),SA,SA-US
173	JQCSVOR.Q	5	REAL PCE-SVC-OTH,QTY INDEX (2000=100),SA,SA-US
174	JQCENERGYR.Q	5	REAL PCE-ENERGY GDS&SVC,QTY INDEX (2000=100),SAAR-US
175	JQCXFAER.Q	5	REAL PCE EX FOOD&ENERGY,QTY INDEX (2000=100),SAAR-US
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 and Construction, New Privately Owned Housing Units Started, Total, SAAR - United States
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	EXCHANGE RATE (FRB): CANADA (CANADIAN \$ PER USD)
75	EXRUK	5	EXCHANGE RATE (FRB): UNITED KINGDOM (CENTS PER POUND)
76	EXRUS	1	UNITED STATES -EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.) IMF
			PRICE INDEXES
77	PMCP	1	NAPM COMMODITY PRICES INDEX (PERCENT)
78	WTISPLC	5	Spot Crude Oil Price: West Texas Intermediate (WTI), Dollars per Barrel, Not Seasonally Adjusted
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	PUS3	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)
94	PCEPI	5	Personal Consumption Expenditures: Chain-type Price Index, Index 2009=100, Seasonally Adjusted
			STOCK PRICES
95	FSDJ	5	Index, Equity, Dow Jones, 30 Industrial Average, Close Price - United States
96	FSDXP	1	S&P's COMPOSITE COMMON STOCK: DVIDEND YIELD (% PER ANNUM)
97	FSPCOM	5	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)
98	FSPIN	5	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)
99	FSPXE	5	S&P's COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (% , NSA)
			MONEY AND CREDIT AGGREGATES
100	FM1	5	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL\$,SA)
101	FM2	5	MONEY STOCK:M2(M1+O'NITE RPS,EUROS\$,G/P&B/D MMMFS&SAV&SM TIME DEP)(BIL\$,
102	CCINRV	5	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)
103	BUSLOANS	5	Commercial and Industrial Loans, All Commercial Banks, Billions of U.S. Dollars, Seasonally Adjusted
104	REALLN	5	Real Estate Loans, All Commercial Banks, Billions of U.S. Dollars, Monthly, Seasonally Adjusted
			SENTIMENTS
105	U0M083	1	Survey and Diffusion Indexes, Leading Economic Indicators, Consumer Expectations, NSA - United States
			INTEREST RATES AND BONDS
106	FYGM3	1	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)
107	FYGM6	1	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)
108	FYGT1	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
109	FYGT10	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
110	FYGT20	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,20-YR.(% PER ANN,NSA)
111	FYGT3	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,3-YR.(% PER ANN,NSA)
112	FYGT5	1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)
113	FYPR	1	PRIME RATE CHG BY BANKS ON SHORT-TERM BUSINESS LOANS(% PER ANN,NSA)
114	FYAAAC	1	BOND YIELD: MOODY's AAA CORPORATE (% PER ANNUM)
115	GZ SPREAD	1	Gilchrist-Zakrasjek Credit Spread
116	FYBAAC	1	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)
117	SFYGM3	1	FYGM3 - FYFF
118	SFYGM6	1	FYGM6 - FYFF
119	SFYGT1	1	FYGT1 - FYFF
120	SFYGT5	1	FYGT5 - FYFF
121	SFYGT10	1	FYGT10 - FYFF
122	SFYAAAC	1	FYAAAC - FYFF
123	SFYBAAC	1	FYBAAC - FYFF
124	FYFF	1	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)
125	BSPREAD	1	FYBAAC - FYGT10
No.			QUARTERLY GDP COMPONENTS
126	GDPRC@US.Q	5	NIA REAL GROSS DOMESTIC PRODUCT (CHAINED-2009), SA - U.S.
127	GDPGDR.Q	5	Real Personal Consumption Expenditures: Goods (SAAR, Bil.Chn.2009)
128	GDPSVR.Q	5	Real Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2009)
129	GDPSR.Q	5	Real Private Nonresidential Investment: Structures (SAAR, Bil.Chn.2009)
130	WS@US.Q	5**	NIA NOMINAL TOTAL COMPENSATION OF EMPLOYEES, SA - U.S.
131	CGRC@US.Q	5	REAL GOVERNMENT CONSUMPTION EXPENDITURE & GROSS INVESTMENT (CHAINED-2000)

132	I.Q	5*	GROSS PRIV DOM INVEST,BILLIONS OF \$,SAAR-US
133	IF.Q	5*	GROSS PRIV DOM INVEST-FIXED,BILLIONS OF \$,SAAR-US
134	IFNRE.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES,BILLIONS OF \$,SAAR-US
135	IFNRES.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES-STRUC,BILLIONS OF \$,SAAR-US
136	IFNRESC.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-COML&HEALTH CARE,BILLIONS OF \$,SAAR-US
137	IFNRESMFG.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-MFG,BILLIONS OF \$,SAAR-US
138	IFREE.Q	5*	PRIV FIXED INVEST-EQUIP,BILLIONS OF \$,SAAR-US
139	IFRESPEMF.Q	5*	PRIV FIXED INVEST-RES-STRUC-MFAM,BILLIONS OF \$,SAAR-US
140	IFRESPEF.Q	5*	PRIV FIXED INVEST-RES-STRUC-1 FAM,BILLIONS OF \$,SAAR-US
141	IFRESPE.Q	5*	PRIV FIXED INVEST-RES-STRUC-PERMANENT SITE,BILLIONS OF \$,SAAR-US
142	IFRES.Q	5*	PRIV FIXED INVEST-RES-STRUC,BILLIONS OF \$,SAAR-US
143	IFRE.Q	5*	GROSS PRIV DOM INVEST-FIXED RES,BILLIONS OF \$,SAAR-US
144	IFNREEO.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-OTH,BILLIONS OF \$,SAAR-US
145	IFNREET.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-TRNSPRT,BILLIONS OF \$,SAAR-US
146	IFNREEIND.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-IND,BILLIONS OF \$,SAAR-US
147	IFNREEIPO.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-INFO PROC&SW-OTH,BILLIONS OF \$,SAAR-US
148	IFNREEIPCS.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-SW,BILLIONS OF \$,SAAR-US
149	IFNREEIPCC.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-COMP&PERI,BILLIONS OF \$,SAAR-US
150	IFNREEIP.Q	5*	GROSS PRIV DOM INVEST-FIXED-NONRES-EQUIP&SW-INFO PROC,BILLIONS OF \$,SAAR-US
151	IFNREE.Q	5*	GROSS PRIV DOM INVEST-FIXED NONRES-EQUIP#&SW,BILLIONS OF \$,SAAR-US
152	IFNRESO.Q	5*	PRIV FIXED INVEST-NONRES-OTH STRUC,BILLIONS OF \$,SAAR-US
153	IFNRESMI.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-MINING EXPLORATION,SHAFTS,&WELLS,BILLIONS OF \$,SAAR-US
154	IFNRESP.Q	5*	PRIV FIXED INVEST-NONRES-STRUC-POWER&COMM,BILLIONS OF \$,SAAR-US
155	II.Q	1	GROSS PRIV DOM INVEST-CH IN PRIV INVENT,BILLIONS OF \$,SAAR-US
156	IIF.Q	1	GROSS PRIV DOM INVEST-CH IN PRIV INVENT-FARM,BILLIONS OF \$,SAAR-US
157	M.Q	5**	IMPORTS OF GDS&SVC,BILLIONS OF \$,SAAR-US
158	X.Q	5**	EXPORTS OF GDS&SVC,BILLIONS OF \$,SAAR-US
159	PGDP@US.Q	5	NIA PRICE DEFLATOR - GROSS DOMESTIC PRODUCT, SA - U.S.
176	USCEN:PDII.Q	0	GROSS PRIV DOM INVESTMENT PRICE DEFLATOR, SA - U.S.