PRELIMINARY

IMPLICATIONS OF DYNAMIC FACTOR MODELS FOR VAR ANALYSIS

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1. Introduction

A fundamental contribution of Sims (1980) was his constructive argument that many of the "incredible" identifying restrictions underlying the structural macroeconometric models of the 1960s and 1970s are unnecessary either for forecasting or for certain types of policy analysis. Instead of imposing large numbers of identifying restrictions that permitted system estimation by two- or three-stage least squares, Sims proposed that the system dynamics be left completely free. His key insight was that the effect of policy interventions – an autonomous increase in the money supply or an autonomous decrease in government spending – could be analyzed by examining the moving average representation relating macroeconomic reality (outcome variables of interest) directly to the structural economic shocks. To identify these policy effects, one simply needed to identify the structural economic shocks; then the dynamic policy effects could be computed as the impulse response function obtained by inverting the vector autoregressive (VAR) representation of the data, linearly transformed to yield the moving average representation with respect to the structural shock. No restrictions on the dynamic structure were required (nor desired!) – all that was needed was some scheme to sort through the VAR forecast errors, or innovations, in just the right way so that one can deduce the structural economic shock or shocks desired for undertaking the policy analysis.

This final requirement – moving from the VAR innovations to the structural shocks – is the hardest part of so-called structural VAR (SVAR) analysis, for it requires first that the structural shocks can in theory be obtained from the innovations, and second that there be some economic rationale justifying how, precisely, to distill the structural shocks from the innovations. The first of these requirements can be thought of as requiring that there is no omitted variable bias: if a variable is known to individuals, firms, and policy-makers and that variable contains information about a structural economic shocks distinct from what is already included in the VAR, then omitting that variable means that the VAR innovations will not in general span the space of the structural shocks, so the structural shocks cannot in general be deduced from the VAR innovations. This difficulty has long been recognized and indeed has been pointed to as the source of both practical problems in early VARs, including the “price puzzle” of Sims (1992) (see Christiano, Eichenbaum, and Evans (1999) for a discussion), and theoretical problems, such as the specter of noninvertibility (e.g. Lippi and Reichlin (1994)). The key to addressing these problems is to increase the amount of information in the VAR so that the innovations span the space of structural disturbances. For example, as recounted by Sims (1993), disappointing forecasts of inflation from the earliest real-time VAR forecasting exercises at the Federal Reserve Bank of Minnesota led Robert Litterman to add the trade-weighted exchange rate, the S&P 500, and a commodity price index to the original six-variable Minnesota VAR. This line of reasoning has led Sims and coauthors to consider yet larger VARs, such as the 13- and 18-variable VAR in Leeper, Sims, and Zha (1996). But increasing the number of variables in a VAR leads to significant technical problem, for the number of unrestricted VAR coefficients increases as the square of the number of variables in the system.

One approach to handling the resulting proliferation of parameters, spearheaded by Sims and his students, is to impose Bayesian restrictions and to estimate or calibrate the hyperparameters, so that the VAR is estimated by (possibly informal) empirical Bayes methods (see Doan, Litterman, and Sims (1984), Litterman (1986), Sims (1993), Leeper, Sims, and Zha (1996)). This is not a line of work for the computationally challenged. More importantly, because of the quadratic increase in complexity it is unclear that it can be pushed much beyond systems with a score or two of variables without, in effect, imposing the incredible (now statistical) identifying restrictions that SVAR analysis was designed to eschew. What if 18 variables are not enough to span the space of structural shocks? After all, in reality Fed economists track hundreds if not thousands of variables as they prepare for upcoming meetings of the Open Market Committee. Unless the staff economists are wasting their time, one must assume that these hundreds of variables help them isolate the structural shocks currently impacting the economy.

In this paper, we examine VAR methods that can be used to identify the space of structural shocks when there are hundreds of economic time series variables that potentially contain information about these underlying shocks. This alternative approach is based on dynamic factor analysis, introduced by John Geweke in his Ph.D. thesis (published as Geweke (1977)) under the supervision of Sims. The premise of the dynamic factor model (DFM) is that there are a small number of unobserved common dynamic factors that produce the observed comovements of economic time series. These common dynamic factors are driven by the common structural economic shocks, which are the relevant shocks that one must identify for the purposes of conducting policy analysis. Even if the number of common shocks is small, because the dynamic factors are unobserved this model implies that the innovations from conventional VAR analysis with a small or moderate number of variables will fail to span the space of the structural shocks to the dynamic factors. Instead, these shocks are only revealed when one looks at a very large number of variables and distills from them the small number of common sources of comovement.

There is a body of empirical evidence that the dynamic factor model, with a small number of factors, captures the main comovements of postwar U.S. macroeconomic time series data. Sims and Sargent (1977) examine a small system and conclude that two dynamic factors can explain 80% or more of the variance of major economic variables, including the unemployment rate, industrial production growth, employment growth, and wholesale price inflation; moreover, one of these dynamic factors is primarily associated with the real variables, while the other is primarily associated with prices. Empirical work using methods developed for many-variable systems has supported the view that only a few – perhaps two – dynamic factors explain much of the predictable variation in major macroeconomic aggregates (e.g. Stock and Watson (1999, 2002a), Giannone, Reichlin, and Sala (2004)). These new methods for estimating and analyzing dynamic factor models, combined with the empirical evidence that perhaps only a few dynamic factors are needed to explain the comovement of macroeconomic variables, has motivated recent research on how best to integrate factor methods into VAR and SVAR analysis (Bernanke and Boivin (2003), Bernanke, Boivin, and Eliasz (2005; BBE hereafter), Favero and Marcellino (2001), Favero, Marcellino, and Neglia (2004), Giannone, Reichlin, and Sala (2002, 2004), and Forni, Giannone, Lippi, and Reichlin (2004)); we return to this recent literature in Sections 2 and 5.

This paper has three objectives. The first is to provide a unifying framework that explicates the implications of DFMs for VAR analysis, both reduced-form (including forecasting applications) and structural. In particular we list a number of testable overidentifying restrictions that are central to the simplifications provided by introducing factors into VARs.

Our second objective is to examine empirically these implications of the DFM for VAR analysis. Is there support for the exact factor model restrictions or, if not, for an approximate factor model such as that of Chamberlain and Rothschild (1983)? If so, how many factors are needed: two, as suggested by Sargent and Sims (1977) and more recent literature, or more? Another implication of the DFM is that, once factors are included in the VAR, impulse responses with respect to structural shocks should not change upon the inclusion of additional observable variables; but is this borne out empirically?

Our third objective is to provide a framework and some new econometric methods for structural VAR analysis using dynamic factors. This framework facilitates a discussion of the factor VAR (FAVAR) identification schemes used by BBE and Favero, Marcellino, and Neglia (2004). The use of factors simplifies structural VAR analysis by reducing the dimension of the VAR needed to span the space of structural shocks; this said, the fundamental economic questions of how to identify those shocks with economically meaningful concepts remains.

We have four main empirical findings, which are based on an updated version of the Stock-Watson (2002a) data set (the current version has 132 monthly U.S. variables, 1959 – 2003). First, it appears that the number of dynamic factors present in our data set exceeds two; we estimate the number to be seven. Second, we find that many of the implications of the DFM for the full 132-variable VAR are rejected, however these rejections are almost entirely associated with coefficients that are statistically significantly different from zero but are very small in an economic or practical sense. Moreover, it is possible that these many rejections and many small estimated coefficients are a consequence of finite-sample departures from asymptotic distribution theory. Third, perhaps because these departures from the VAR implications of the DFM are small, we find that impulse responses and variance decompositions computed using an identification scheme similar to BBE's are insensitive to specification changes that relax some of the DFM restrictions.

The remainder of the paper is organized as follows. Section 2 lays out the DFM and its implications for reduced-form VAR analysis. Sections 3 and 4 examine these implications empirically using the 132-variable data set. Section 5 provides a treatment of structural factor VARs and illustrates these methods by providing an alternative approach to implementation of the BBE identification scheme. Section 6 concludes.

2. The Dynamic Factor Model in VAR Form

This section summarizes the restrictions imposed by the dynamic factor model on the VAR representation of the variables. We do this by first summarizing the so-called static representation of the DFM, a representation of interest in its own right because it leads to estimation of the space spanned by the dynamic factors using principal components when n is large. The static representation of the DFM is then used to derive two VAR form of the DFM, expressed in terms of the (readily estimated) static factors.

2.1 The DFM and Reduced-Form VARs

Let X_t be a $n\times 1$ vector of stationary time series variables observed for $t = 1,\ldots,T$.

The dynamic factor model. The DFM expresses X_t as a distributed lag of a small number of unobserved common factors, plus an idiosyncratic disturbance that itself might be serially correlated:

$$X_{it} = \tilde{\lambda}_i(\mathrm{L})f_t + u_{it},\ i = 1,\ldots,n, \tag{2.1}$$

$$u_{it} = \delta_i(\mathrm{L})u_{it-1} + \nu_{it}, \tag{2.2}$$

where f_t is the $q\times 1$ vector of unobserved dynamic factors, $\tilde{\lambda}_i(\mathrm{L})$ is a $1\times q$ vector lag polynomial, called the "dynamic factor loadings," and u_{it} is the idiosyncratic disturbance which we model as following an autoregression. The factors and idiosyncratic disturbances are assumed to be uncorrelated at all leads and lags, that is, $E(f_t u_{is}) = 0$ for all i, t, s.

Chamberlain and Rothschild (1983) introduced a useful distinction between exact and approximate DFMs. In the exact DFM of Geweke (1977) and Sargent and Sims (1978), the idiosyncratic terms are mutually uncorrelated at all leads and lags, that is,

$$E(u_{it}u_{js}) = 0 \text{ for all } t, s \text{ and for } i \neq j \tag{2.3}$$

In the approximate DFM, this assumption is relaxed to allow for a limited amount of correlation among the idiosyncratic terms (see the survey by Stock and Watson (2004) for technical conditions). We return to the distinction between the exact and approximate DFM when discussing the VAR restrictions implied by the DFM.

For our purposes it is convenient to work with a DFM in which the idiosyncratic errors are serially uncorrelated. This is achieved by multiplying both sides of (2.1) by $1 - \delta_i(\mathrm{L})\mathrm{L}$, which yields

$$X_{it} = \lambda(\mathrm{L})f_t + \delta_i(\mathrm{L})X_{it} + \nu_{it}, \tag{2.4}$$

where $\lambda_i(\mathrm{L}) = (1-\delta_i(\mathrm{L})\mathrm{L})\tilde{\lambda}_i(\mathrm{L})$.

We model the unobserved factors as following a VAR,

$$f_t = \Gamma(\mathrm{L})f_{t-1} + \eta_t, \tag{2.5}$$

where $\Gamma(\mathrm{L})$ is a matrix lag polynomial and η_t is a $q\times 1$ disturbance vector, where $\mathrm{E}\eta_t \nu_{is} = 0$ for all i, t, s.

The DFM consists of (2.4) and (2.5). The DFM assumptions imply that the spectral density of X has a factor structure:

$$S_X(\omega) = \tilde{\lambda}(e^{i\omega})S_f(\omega)\tilde{\lambda}(e^{-i\omega}) + S_u(\omega), \tag{2.6}$$

where $S_X(\omega)$, $S_F(\omega)$, and $S_u(\omega)$ are the spectral density matrices of X, f, and u at frequency ω, S_u is diagonal, and $\tilde{\lambda}(z) = [\tilde{\lambda}_1(z) \ldots \tilde{\lambda}_n(z)]'$.

The unknown coefficients of the DFM (2.4) and (2.5) (with additional lag length and normalization restrictions) can be estimated by Gaussian maximum likelihood using the Kalman Filter (Engle and Watson (1981), Stock and Watson (1989, 1991), Sargent (1989), and Quah and Sargent (1993)). When n is very large, however, this method is at best computationally cumbersome. For this reason, alternative methods for estimation of the factors and DFM coefficients have been developed for large n. One approach is to use Brillinger's (1964, 1981) dynamic principal components; the theory of applying this method when n is large is developed by Forni, Hallin, Lippi, and Reichlin (2000). However dynamic principal components analysis produces two-sided estimates of the factors and thus these estimates are not suitable for forecasting or for structural VAR analysis in which information set timing assumptions are used to identify shocks. This problem of two-sided estimates of the dynamic factors can be avoided by recasting the DFM in so-called static form.

The DFM in static form. In the static form of the DFM (Stock and Watson (2002)), there are r static factors that consist of current and (possibly) lagged values of the q dynamic factors. Suppose that $\lambda(L)$ has finite degree $p - 1$, and let $F_t = [f_t' \;\; f_{t-1}' \ldots f_{t-p+1}']'$ or a subset of these lags of f_t if not all dynamic factors appear with p lags. Let the dimension of F_t be r, where $q \le r \le qp$. Then the DFM (2.4) and (2.5) can be written,

$$X_{it} = \Lambda_i F_t + \delta_i(L) X_{it-1} + \nu_{it} \tag{2.7}$$

$$F_t = \Phi(L) F_{t-1} + G\eta_t, \tag{2.8}$$

where Λ_i is a $1 \times r$ row vector consisting of the coefficients of $\lambda_i(L)$, $\Phi(L)$ consists of the coefficients of $\Gamma(L)$ and zeros, and G is $r \times q$. If the order of $\Gamma(L)$ is at most p, then the VAR for F_t has degree one and $\Phi(L) = \Phi$. The representation (2.7) and (2.8) is called the "static" form of the DFM because F_t appears in the X equation without any lags, as it does in classical factor analysis in cross-sectional data.

The static form of the DFM implies that the variance of prefiltered X_t has a conventional factor structure. Let $\tilde{X}_{it} = (1 - \delta_i(\mathrm{L})\mathrm{L})X_{it}$, $\Lambda = [\Lambda_1' \ldots \Lambda_n']'$ be the matrix of (static) factor loadings, $\tilde{X}_t = [\tilde{X}_{1t} \ \ldots \ \tilde{X}_{nt}]'$, $\nu_t = [\nu_{1t} \ldots \nu_{nt}]'$, and let $\Sigma_{\tilde{X}}$, Σ_F, and Σ_ν be the covariance matrices of $\tilde{X}_t$, F_t and ν_t. Then

$$\Sigma_{\tilde{X}} = \Lambda\Sigma_F\Lambda' + \Sigma_\nu. \tag{2.9}$$

This is the usual variance decomposition of classical factor analysis.

The DFM in VAR form. The VAR form of the DFM obtains by substituting (2.8) into (2.7) and collecting terms. The equation for X_{it} in the VAR is,

$$X_{it} = \Lambda_i\Phi(\mathrm{L})F_{t-1} + \delta_i(\mathrm{L})X_{it-1} + \varepsilon_{X_it} \tag{2.10}$$

where $\varepsilon_{X_it} = \Lambda_i G\eta_t + \nu_{it}$ and $\varepsilon_{Ft} = G\eta_t$. Combining (2.10) with the factor evolution equation yields the complete DFM in VAR form:

$$\begin{bmatrix} F_t \\ X_t \end{bmatrix} = \begin{bmatrix} \Phi(\mathrm{L}) & 0 \\ \Lambda\Phi(\mathrm{L}) & D(\mathrm{L}) \end{bmatrix}\begin{bmatrix} F_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Ft} \\ \varepsilon_{Xt} \end{bmatrix} \tag{2.11}$$

where $\varepsilon_{Xt} = [\varepsilon_{X_1t} \ \ldots \ \varepsilon_{X_nt}]'$ and

$$D(\mathrm{L}) = \begin{bmatrix} \delta_1(\mathrm{L}) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \delta_n(\mathrm{L}) \end{bmatrix}. \tag{2.12}$$

The DFM implies that the one-step ahead forecast errors $\varepsilon_t \equiv [\varepsilon_{Ft}' \ \varepsilon_{Xt}']'$ are given by

$$\begin{bmatrix} \varepsilon_{Ft} \\ \varepsilon_{Xt} \end{bmatrix} = \begin{bmatrix} I \\ \Lambda \end{bmatrix} G\eta_t + \begin{bmatrix} 0 \\ \nu_t \end{bmatrix} \tag{2.13}$$

where $\nu_t = [\nu_{1t} \ldots \nu_{nt}]'$, with covariance matrix

$$\mathrm{E}\varepsilon_t\varepsilon_t' \equiv \Sigma_\varepsilon = \begin{bmatrix} G\Sigma_\eta G' & \Sigma_\eta G'\Lambda' \\ \Lambda G\Sigma_\eta & \Lambda G\Sigma_\eta G\Lambda' + \Sigma_\nu \end{bmatrix} \tag{2.14}$$

where $\Sigma_\eta = \mathrm{E}\eta_t\eta_t'$.

A disciple of Sims (1980) might quibble with our use of the term "VAR form" for (2.11) – (2.13), for two reasons. First, this form imposes many restrictions on the lag dynamics and on the structure of the covariance matrix of the one-step ahead forecast errors; in contrast Sims (1980) introduced VARs as a way to avoid making any such restrictions and the term "VAR" typically refers to unrestricted structures. This said, the restrictions studied here are akin to the Bayesian restrictions, developed by Sims and his students, in which prior parametric restrictions are used to control the proliferation of parameters in high-dimensional VARs. Second, the F_t variables in the VAR are unobserved, however because n is large the factors are consistently estimable so we proceed as if they are observable.

Impulse response functions and variance decompositions. Inverting the VAR representation (2.11) – (2.13) yields the moving average representation for X_t in terms of current and lagged innovations η_t to the dynamic factors and the idiosyncratic disturbances ν_t:

$$X_t = B(\mathrm{L})G\eta_t + u_t, \tag{2.15}$$

where $B(\mathrm{L}) = (\mathrm{I} - D(\mathrm{L})\mathrm{L})^{-1}\Lambda(\mathrm{I} - \Phi(\mathrm{L})\mathrm{L})^{-1}$ and $u_t = (\mathrm{I} - D(\mathrm{L})\mathrm{L})^{-1}\nu_t$. This moving average representation delivers impulse response functions and forecast error variance decompositions for X_{t+h} as a function of the horizon h.

The impulse responses and variance decompositions based on (2.15) can be thought of as the factor version of impulse responses and variance decompositions with respect to Cholesky factorizations of conventional VAR innovations, in the sense that η_t is identified using an arbitrary statistical normalization (like that produced by principal components analysis), not an economic model of structural shocks. In Section 5, we take up the further step from the moving average representation in terms of η_t to the structural impulse response function in terms of dynamic factor structural shocks.

2.3 Summary of VAR Restrictions Implied by the DFM

The static form and VAR form of the DFM incorporates several overidentifying restrictions.

1. **Factor structure of X_t.** The covariance matrix Σ_X has the factor structure (2.9), where the rank of $\Lambda\Sigma_F\Lambda'$ is r, the number of static factors. This restriction (under the weaker conditions of an approximate dynamic factor model) is used by the Bai-Ng (2002) information criteria methods for estimation of r.
2. **Reduced rank of ε_{Ft}.** The rank of $\mathrm{E}\varepsilon_{Ft}\varepsilon_{Ft}'$ (the (1,1) block of (2.14)) is q, the number of dynamic factors. Giannone, Reichlin, and Sala (2004) use this restriction to make inferences about q.
3. **Factor structure of ε_{Xt}.** The innovations in X_t, ε_{Xt}', obey a classical factor model, that is, they are serially uncorrelated and the (2,2) block of (2.14) has a factor structure, where the number of factors is the number of dynamic factor innovations, q. In Section 3, we use this restriction to estimate the number of dynamic factors q.
4. ***X* does not predict *F* given lagged *F*.** That is, the upper right block in (2.11) is zero, a restriction tested in Section 4.

5. X_j **does not predict** X_i **given lagged** F**.** That is, D(L) in (2.12) is diagonal, so $E(X_{it}|F_{t-1}, F_{t-2},\ldots X_{it-1}, X_{it-2},\ldots, X_{jt-1}, X_{jt-2},\ldots) = E(X_{it}|F_{t-1}, F_{t-2},\ldots, X_{it-1}, X_{it-2},\ldots)$. This restriction is tested Section 4.
6. X_j **does not explain** X_i **given current** F**.** That is, X_j does not appear in (2.7), so $E(X_{it}|F_t, X_{it-1}, X_{it-2},\ldots, X_{jt}, X_{jt-1},\ldots) = E(X_{it}|F_t, X_{it-1}, X_{it-2},\ldots)$. This is a key implication for SVAR analysis using factors because it says that, given the factors, the VAR need not include any other X's except the X of interest, that is, excluding other observable variables from the VAR does not produce omitted variable bias. This restriction is tested Section 4.
7. **Cross-equation restrictions in the** X **equations.** If Φ(L) has degree one or more, there are overidentifying cross-equation restrictions across the rows in the lower left block of (2.11). If however F_t follows a VAR(1) so $\Phi(L) = \Phi$ then there are no overidentifying restrictions. Because of the sensitivity of this restriction to subsidiary lag restrictions we do not examine this restriction empirically.

2.4 Estimation of Static Factors, Restricted VAR Coefficients, and Dynamic Factor Innovations

In principle the coefficients of the VAR representation (with additional lag length restrictions and normalizations) could all be estimated by restricted quasi-maximum likelihood estimation. However that would be computationally cumbersome and we instead adopt a stepwise approach that first entails estimation of the static factors, then estimation of the VAR coefficients, and finally estimation of the dynamic factor innovations.

Estimation of static factors and the number of static factors. The static factors F_t can be estimated as the principal components of the filtered observables $\tilde{X}_t$ (where X_t is standardized to have sample mean zero and unit standard deviation). Specifically the estimators of $\{F_t\}$ and Λ solve the minimization problem,

$$\min_{F_1,\ldots,F_T,\Lambda,\delta_1(L),\ldots,\delta_n(L)} T^{-1}\sum_{t=1}^{T}[(I-D(L)L)X_t-\Lambda F_t]'[I-D(L)L)X_t-\Lambda F_t] \qquad (2.16)$$

where D(L) is given in (2.12). The maximization in (2.15) is conveniently done iteratively. Given a preliminary estimator of D(L), $\{F_t\}$ can be computed as the first r principal components of $(I - D(\mathrm{L})\mathrm{L})X_t$; given the estimate of $\{F_t\}$, $\delta_i(\mathrm{L})$ and Λ are estimated by n individual regressions of X_{it} on (F_t, X_{it-1},…, X_{it-m_i+1}), where m_i is the order of $\delta_i(\mathrm{L})$. Each step of this procedure reduces (does not increase) the sum of squares in (2.16) and the procedure can be iterated to convergence.[1] This produces estimators $\hat{F}_t$, $\hat{\Lambda}$, and $\hat{D}(\mathrm{L})$, the diagonal matrix with i^{th} diagonal element $\hat{\delta}_i(\mathrm{L})$ (for results on consistency and distribution theory see Stock and Watson (2002b) and Bai (2003)).

The number of static factors can be estimated using the Bai-Ng (2002) information criteria. These can be applied either to the sample covariance matrix of X_t (the method proposed by Bai and Ng (2002)) or alternatively to the covariance matrix of $(I - \hat{D}(\mathrm{L})\,\mathrm{L})X_t$.

Estimation of restricted VAR coefficients. Given the estimates $\hat{F}_t$, the restricted VAR coefficients are estimated by first regressing $\hat{F}_t$ onto the desired number of lags to obtain the estimator of $\Phi(\mathrm{L})$, $\hat{\Phi}(\mathrm{L})$, then using $\hat{\Phi}(\mathrm{L})$, $\hat{\Lambda}$, and $\hat{D}(t)$ to construct the restricted VAR coefficient matrix in (2.11).

Estimation of space spanned by dynamic shocks. Restriction #3 in Section 2.3 can be used to estimate consistently the number of dynamic factors and the dynamic factor innovations. First, the innovations in X_t, ε_{Xt}, are estimated by $\hat{\varepsilon}_{Xt}$, constructed using (2.11) and the estimated restricted VAR coefficients so that $\hat{\varepsilon}_{Xt} = X_t - \hat{\Lambda}\hat{\Phi}(\mathrm{L})\hat{F}_{t-1} - \hat{D}(L)\,X_{t-1}$. Second, the number of dynamic factors q is estimated by applying the Bai-Ng (2002) procedure to the sample covariance matrix of $\hat{\varepsilon}_{Xt}$, yielding an estimator $\hat{q}$.

The dynamic factor innovations now can be estimated in several ways. The algorithm used here chooses G such that the innovations are uncorrelated and that they maximize the trace R^2 of X, ordered so that the first dynamic factor makes the largest

[1]This estimator modifies the static principal components estimator of Stock and Watson (2002), in which $\delta_i(\mathrm{L}) = 0$ in the notation here.

variance reduction, the second the second-largest, and so forth. Specifically, use equation (2.15) and normalize $\Sigma_\eta = I$ so that tr($\sum_{j=0}^{\infty} B_j G \Sigma_\eta G' B_j'$) = tr($\sum_{j=0}^{\infty} B_j G G' B_j'$) = tr($G'\left(\sum_{j=1}^{\infty} B_j B_j'\right)G$). Then

$$\mathrm{tr}(\Sigma_X) = \mathrm{tr}\left(G'\left(\sum_{j=1}^{\infty} B_j B_j'\right)G\right) + \mathrm{tr}(\Sigma_u) \tag{2.17}$$

so that choosing G to maximize the trace R^2 explained by the factors is equivalent to choosing G to be the eigenvectors of $\sum_{j=1}^{\infty} B_j B_j'$ that correspond to the largest q eigenvalues. The estimator of G, $\hat{G}$, is the sample analog of this matrix of eigenvectors, computed using the estimator of $B(z)$ based on $\hat{\Phi}(\mathrm{L})$, $\hat{\Lambda}$, and $\hat{D}(t)$.

Another way to estimate the dynamic factor innovations, which we do not use, is to estimate them as the first $\hat{q}$ principal components of $\hat{\varepsilon}_{Xt}$. In this case, the dynamic factor innovations sequentially maximize the trace R^2 of $\hat{\varepsilon}_{Xt}$.

3. Empirical Results I: Number of Factors and Reduced-Form Variance Decompositions

We begin the empirical analysis by estimating the number of factors, the number of dynamic factors, and the dynamic factor innovations, and by computing forecast error variance decompositions with respect to the dynamic factor innovations, using the methods of Section 2.4.

3.1 The Data and Transformations

The data set consists of monthly observations on 132 U.S. macroeconomic time series from 1959:1 through 2003:12. The predictors include series in 14 categories: real output and income; employment and hours; real retail, manufacturing and trade sales; consumption; housing starts and sales; real inventories; orders; stock prices; exchange rates; interest rates and spreads; money and credit quantity aggregates; price indexes;

average hourly earnings; and miscellaneous. The series are transformed by taking logarithms and/or differencing so that the transformed series are approximately stationary. In general, first differences of logarithms (growth rates) are used for real quantity variables, first differences are used for nominal interest rates, and second differences of logarithms (changes in growth rates) for price series. Specific transformations and the list of series is given in the Appendix.

Both outlier-adjusted and outlier-unadjusted versions of the series were used. The outlier adjustment entailed replacing observations of the transformed series with absolute median deviations larger than 6 times the inter quartile range by with the median value of the preceding 5 observations. The outlier-adjusted series were used for the estimation of the number of static and dynamic factors, the estimation of the static factors, and the estimation of the matrix G relating the dynamic and static factor innovations. All other analysis (VAR estimation, impulse responses, exclusion tests, etc.) was conducted using the outlier-unadjusted series.

3.2 Number of Static and Dynamic Factors

Number of static factors. The Bai-Ng information criteria IC_{p1} and IC_{p2} were computed both for the sample covariance matrix of X_t and for the sample covariance matrix of the filtered X_t, $(I - \hat{D}(\mathrm{L})\,\mathrm{L})X_t$, where the filter was computed using 6 lags for $\delta_i(\mathrm{L})$ ($m_i = 6$ for all i). When applied to X_t, the Bai-Ng criteria estimated there to be 7 static factors, although the criteria are nearly flat for $6 \leq q \leq 10$. When applied to the filtered X_t, the criteria estimate 9 static factors, and again the criterion is nearly flat for $6 \leq q \leq 10$. These results are robust to using 4 lags in $D(\mathrm{L})$ instead of 6. Our interest is in the space of dynamic factors, not the number of static factors, so to be conservative we choose the larger of these two estimates and adopt $\hat{q} = 9$ static factors.

Number of dynamic factors. Following the procedure of Section 2.4, the Bai-Ng information criteria IC_{p2} was used to estimated the number of dynamic factors from the innovation matrix of $\hat{\varepsilon}_{Xt}$. The results are summarized in Table 1 for the baseline case in which F_t follows a VAR(2) ($\Phi(\mathrm{L})$ has degree one) and $D(\mathrm{L})$ has degree 5 ($m = 6$). For 7 or fewer static factors, the number of static and dynamic factors are estimated to be the same, however for more than 7 static factors, the number of dynamic factors is estimated to be 7. These results are robust to using a VAR(1) for F_t or 4 lags in D(L).

3.3. Reduced-Form Variance Decompositions

Our estimates of the number of static and dynamic factors exceeds those typically found in the literature (discussed in Section 1) and exceeds those we have found when we have focused on forecasting the main macroeconomic aggregates (Stock and Watson (1999, 2002a)). Where do these extra factors come from? Is the Bai-Ng procedure simply detecting factor structure that is perhaps present in a statistical sense but is unimportant economically?

We examine these questions by computing variance decompositions with respect to the different factor innovations. If only two of these factor innovations were important in an economic sense, the remaining five innovations ought to have a negligible role in explaining the variation of X_t.

The results are summarized in Table 2, which presents forecast error variance decompositions for the X variables at the 24 month horizon (similar results obtain at the 48 month horizon, and for a bandpass-filtered component over business cycle frequencies). Several features of these variance decompositions stand out. By this measure, the first factor explains nearly all the variation in the major aggregates measuring production and hours; for example, the first factor explains 93% of the 24-month ahead forecast error variance of total industrial production, 91% of this quantity for capacity utilization, and 94% of this quantity for total employment. In contrast, this dynamic factor explains very little of the variation in inflation or stock returns at this horizon. The variation in inflation is mainly explained by the second and third factors: taken together, these account for 66% of the forecast error variance of overall CPI inflation and 57% of the variance of the PCE deflator. The fourth factor is mainly associated with movements in long-term interest rates (but not spreads). The fifth factor is associated with swings in long-term unemployment, and the sixth factor mainly affects exchange rates and stock returns. The seventh dynamic factor has a negligible effect on most variables, and mainly explains movements in average hourly earnings and exchange rates. On average, the first three dynamic factors explain 45% of variance of the 24-

month ahead forecast error, and the remaining four dynamic factors explain an additional 11%. Finally, although the factors explain much or most of the forecast error variance of most series, some series appear to be simply unrelated to these overall economic and financial factors. For example, employment in mining, housing starts, inflation in medical prices and services prices, and growth of the monetary base are in the main unrelated to the overall economic conditions measured by the seven dynamic factors.

Figure 1 plots, for selected series, the business cycle component (computed using a bandpass filter with pass band of 24 – 96 months) and that part explained by various factors. These graphs confirm that the first factor explains most of the medium-run variation in industrial production, and the second and third factor explain most of the variation in price inflation. The fourth factor explains much of the variation of the 10-year T-bond rate, and the sixth factor explains much of the variation in the trade-weighted exchange rate (although there are evident exceptions).

These results provide a more nuanced view of the general findings, surveyed in the introduction, that only two or three factors are needed to explain the covariation in U.S. economic time series. For the main measures of real economic activity and prices, this appears to be true. Starting with Sargent and Sims (1977), many of the papers in this literature have focused on these main series. In addition, for the purposes of forecasting either inflation or output growth, these forecast error variance decompositions suggest that perhaps only two or three factors are needed, a result consistent with the small number of factors in Stock and Watson (1999, 2002). The role of the additional dynamic factors is to account for the movements of the remaining series, which are mainly financial series such as interest rates, stock returns, and exchange rates. For the purposes of forecasting, it may suffice to use a small number of dynamic (and possibly static) factors, but for the purpose of structural VAR modeling the dimension of the space of dynamic factor innovations appears to be larger seven (or, perhaps, six).

For the rest of the empirical analysis, we adopt a baseline specification of 9 static factors and 7 dynamic factors.

4. Empirical Results II: Testing VAR exclusion restrictions

This section examines empirically the restrictions on the reduced-form factor VAR: that X does not predict F given lagged F, that X_j does not predict X_i given lagged F, and that X_j does not explain X_i given current F.

4.1 Restriction #4: *X* does not predict *F* given lagged *F*

We examine this restriction by sequentially including X_j in (2.8), so that the factor prediction equation is,

$$F_t = \Phi(\mathrm{L})F_{t-1} + \Psi_j(\mathrm{L})X_{jt-1} + \varepsilon_{Ft}, \tag{4.1}$$

where $\Psi_j(\mathrm{L})$ is a 9×1 vector lag polynomial of degree five (so each row of $\Psi_j(\mathrm{L})$ has six unrestricted coefficients). Restriction #4 is that $\Psi_j(\mathrm{L}) = 0$, $j = 1,\ldots, 132$. For each of the nine equations in (4.1), we computed the six degree-of-freedom heteroskedasticity-robust chi-squared test of the hypothesis that the relevant row of $\Psi_j(\mathrm{L})$ is zero, along with the marginal R^2 (the increase in the R^2) from including $X_{jt-1}, \ldots, X_{jt-6}$. We do not report p-values for full test of $\Psi_j(\mathrm{L}) = 0$ because of doubts about accuracy of large-sample distribution theory in approximating the distribution of this test, which has 54 degrees of freedom.

The results of these exclusion tests are summarized in Figure 2, which presents the empirical cumulative distribution function (cdf) of the p-values of the 132 six degree-of-freedom tests, with the results for each factor (each equation in (4.1)) presented in a different panel. Under the null hypothesis that $\Psi_j(\mathrm{L}) = 0$ for all $j = 1,\ldots, 132$ series, one would expect 5% of the tests to reject at the 5% significance level and so forth. Thus under the null the expected cdf of the p-values would be the 45° line, and a cdf above the 45° line indicates more rejections among the 132 series than would be expected under the null hypothesis.

All the panels in Figure 2 show p-value cdfs above the 45° line, and in several of the panels (especially for factors 1 –4) the plots indicate a substantial excess of rejections. The individual test statistics, and thus the p-values, are not independent, so for example the Kolmogorov-Smirnov test cannot be applied to test whether the p-values fall along the 45° line. Still, at least for some of the factors, these results suggest that at least some of the individual X series help to predict at least some of the Fs, in contradiction to the implications of the DFM.

Table 3 presents the marginal R^2s associated with adding the six lags of each variable, one variable at a time. The first nine numerical columns report the marginal R^2s for each of the nine factor equations; the final column of Table 3 is discussed in the next subsection. Inspection of the entries in Table 3 reveals that almost all the marginal R^2s are all small. For example, the restricted VAR regression for factor #1 has an R^2 of .569, but the marginal R^2s from adding six lags of the candidate variable are less than .02 for all but ten of the 132 variables, and the average marginal R^2 from adding a variable is .009. Because the number of observations is large (540), small marginal R^2s are consistent with the many rejections of the null hypothesis that individual rows of $\Psi_j(L) = 0$. The one notably large set of marginal R^2s occurs for the spreads as predictors of the second factor: most of these marginal R^2s exceeds .07.

We continue the discussion of these results in Section 4.3, after examining the other VAR exclusion restrictions.

4.2 Restriction #5: X_j does not predict X_i given lagged F

We examine this restriction by augmenting (2.10) with lagged values of X_{jt}:

$$X_{it} = \Lambda_i\Phi(L)F_{t-1} + \delta_i(L)X_{it-1} + \delta_{ij}(L)X_{jt-1} + \varepsilon_t \tag{4.2}$$

Restriction #5 is that $\delta_{ij}(L) = 0$, $i, j = 1,\ldots, 132$, $i \neq j$.

We examined this restriction by estimating equation (4.2) for different dependent variables where, for each dependent variable, six lags of the remaining 131 X's were included sequentially, yielding 131 separate heteroskedasticity-robust chi-squared statistics and marginal R^2s. Instead of considering all 132 possible dependent variables, we focus on seven dependent variables of particular interest: industrial production, nonfarm private employment, the unemployment rate, CPI inflation, PCE deflator inflation, the 90-day T-bill rate, and the 10-year T-bond rate.

The results are given in Figures 3 and 4 and in Table 4. Figure 3 presents the cdfs of the p-values of these exclusion tests, with the tests for each of the seven dependent variables presented in a different panel. Also plotted are the p-values of the test of whether X_{jt} Granger-causes the dependent variable, that is, the p-value testing the coefficients on $X_{jt-1},\ldots, X_{jt-6}$ in (4.2) when the lags of F_t are omitted. As in Figure 2, cdfs above the 45° line indicate more rejections than one would expect by random chance if the null hypothesis were true.

Figure 4 is a scatterplot of the marginal R^2s for these regressions, where the horizontal axis is the marginal R^2 obtained by including six lags of X_{jt} when lags of F_t are excluded, and the vertical axis is the marginal R^2 obtained by including X_{jt} when two lags of F_t are included.

Table 4 provides numerical values of the marginal R^2s obtained by including X_{jt} when lags of F_t are included, where the dependent variable is given in the column heading for the first seven columns. In addition, the final column reports the average marginal R^2 resulting from including the row variable, averaged over all 131 regressions for each of the possible 131 dependent variables.

Several findings are evident from Figures 3 and 4 and Table 4. With all the p-value cdfs above the 45° line, clearly there are more rejections of the null hypothesis that $\delta_{ij}(\mathrm{L}) = 0$ than one would expect simply by chance under the null. This said, there is less statistically significant evidence of predictability if the factors are included in the regressions than if the factors are excluded.

Despite this evidence of statistically significant departures from the null, these departures are estimated to be quantitatively small. The increase in the R^2s that arise by adding the additional variables are quite small, in most instances less than .02 and in almost all instances less than .03. Averaged across all dependent variables (the final column of Table 4), there is no single variable or set of variables with sizeable average marginal R^2s. The extent to which the marginal R^2s are smaller when F is included than when it is not differs from one dependent variable to another. For the real variables and PCE inflation, including lags of F_t substantially reduces the marginal predictive content of the remaining Xs. For long term interest rates and CPI inflation (for some predictors at least), the marginal R^2 is comparable whether or not lags of F_t are included, however in these instances the marginal R^2s are already small (typically .02 or less). Of the 7×131 = 924 instances considered here, the only patterns of marginal R^2s of .05 or more occur when other interest rates are used to predict the 10-year Treasury bond rate. This suggests that the estimated factors might not fully capture the dynamics of interest rate spreads.

4.3 Restriction #6: X_j does not explain X_i given current F

If this restriction fails, then equation (2.7) becomes

$$X_{it} = \Lambda_i^j F_t + \delta_i^j(L) X_{it} + \alpha_{ij}(\mathrm{L})X_{jt} + \nu_{it}^j, \tag{4.3}$$

where the superscript j distinguishes these coefficients from those in (2.7) without X_j. Restriction #6 is that $\alpha_{ij}(\mathrm{L}) = 0$, which we examine by computing heteroskedasticity-robust chi-squared tests of the hypothesis that $X_{jt-1},.., X_{jt-6}$ do not enter equation (4.3).

Figure 5 presents the cdfs of the p-values for the tests that $X_{jt-1},.., X_{jt-6}$ do not enter equation (4.3) and, for comparison purposes, the p-values for these test when the factors are omitted from the equations.[2] As was seen in Figure 4, there are an excess of rejections of $\alpha_{ij}(\mathrm{L}) = 0$ over what would be expected under the null. At the same time, there are substantially fewer rejections of the X_j exclusion restrictions, once the factors are included in the regression.

The importance of restriction 6 is that, if it holds, the impulse responses with respect to dynamic factor structural shocks can be computed without including any other lags of X in the VAR. Restriction 6, however, is sufficient but not necessary to justify the exclusion of X_{jt} from (4.3). The necessary condition is simply that $\Lambda_i^j = \Lambda_i$, in which case the impulse responses and variance decompositions with respect to the dynamic

[2] Because X_{jt} enters (4.3) contemporaneously, if X_{jt} is a subaggregate of X_{it} – for example, X_{it} is industrial production and X_{jt} is industrial production for consumer goods – ν_{it} would contain the idiosyncratic innovation in X_{jt} so $\alpha_{ij}(\mathrm{L})$ would be nonzero. We do not view this as a violation of the factor model, but instead an implication of including series with different levels of aggregation in our data set. Accordingly, when the other X's include subaggregates of the dependent variable, the p-values of their tests of $\alpha_{ij}(\mathrm{L}) = 0$ are excluded from Figures 5 and 6.

factor structural shocks will not change upon inclusion of X_{jt-1} in the VAR even if $\alpha_{ij}(L) \neq 0$.

We therefore test directly the hypothesis that $\Lambda_i^j = \Lambda_i$ for the same predictors and dependent variables as in Figure 5; the results (p-values for heteroskedasticity-robust Hausman tests) are summarized in Figure 6. Strikingly, there are no excess rejections of this hypothesis for any of the dependent variables. Together, Figures 5 and 6 suggest that there is statistically significant evidence against the X_j exclusion restrictions in the factor equations, but that these departures from the exact DFM do not result in statistically significant changes in the coefficients on the factors in these equations nor, by implication, do the impulse response functions with respect to the dynamic factor structural shocks change if X_j is included in (4.3).

4.4 Discussion

Taken at face value, the results of this section indicate widespread rejection of the exclusion restrictions of the DFM, yet at the same time the economic importance of these violations – as measured by marginal R^2s or statistically significant changes in the factor loadings Λ upon including observable variables in the X_j equations – is quite small.

In interpreting these results, it is useful to consider the two possibilities that these tests are simply statistical artifacts and in fact the DFM restrictions hold, or alternatively that these tests have correctly found violations of the DFM restrictions. We consider these possibilities in turn.

There are three reasons to be concerned that these apparent violations might in fact be statistical artifacts. First, these regressions all involve estimated factors. Although the factor estimates are consistent, in finite samples the factors will contain estimation error. Standard errors-in-variables reasoning suggests that the estimation of the factors will reduce their predictive content and as a result the individual variables will retain some predictive content, even if in population they follow an exact DFM. This interpretation is consistent with the large fraction of rejections combined with the small marginal R^2s when individual X's are included in either the F or X static DFM equations.

Second, most of these regressions contain quite a few regressors, which raises concerns about the applicability of conventional large-sample asymptotic theory.

Third, although some of the predictive relations uncovered by these tests – such as short rates having additional predictive content for long rates, given the factors – make economic sense, many do not. For example, residential building permits in the South has a relatively large marginal R^2 for predicting the first factor, but building permits in the Northeast or the Midwest, or housing starts in the south, do not. Although building permits in the South might in fact contain special information useful for forecasting this aggregate real output factor, its relatively high in-sample marginal R^2 could just be a statistical artifact.

These concerns notwithstanding, it is important to consider the other possibility that these tests have correctly detected violations of DFM restrictions. In this regard, we make three comments.

First, if X_{jt} enters the F_t equation only with a lag (restriction #4 fails), then this can still be consistent with estimating 9 static factors using the Bai-Ng (2002) criterion. Specifically, consider the modified model (2.7) and (4.1), where $\varepsilon_{Ft} = G\eta_t$. Then $\mathrm{E}F_t\nu_t$ = 0 and the covariance matrix of $\tilde{X}_t$ still has the factor structure (2.9) and the Bai-Ng (2002) will estimate the dimension of the factor matrix to be r, the number of static factors. However, the spectral density matrix of X_t does not have a factor structure at every frequency and in this sense the DFM fails. Moreover, the covariance matrix of X_t (as opposed to $\tilde{X}_t$) does not have a factor structure, so the estimated number of factors should differ, possibly substantially, depending on whether the series are filtered. But our estimates of the number of static factors are comparable whether the series are filtered or not, in fact they are slightly less (not more) when the series are not filtered.

Second, if current or lagged X_{jt} enters the X_{it} equation after conditioning on F_t (restriction #5 fails), then neither the covariance matrices of X_t nor that of $\tilde{X}_t$ will have a factor structure. In this case statistically significant evidence against restriction #5 is inconsistent with estimation of a small number of factors, at least in large samples. If there are only a few observable variables that predict F_t, then then those variables would be observable static factors; however the rejections are widespread, so this interpretation is not consistent with the empirical evidence.

Third, perhaps the series in fact obey a DFM but the Bai-Ng (2002) procedure has identified too few static factors. This would be consistent with the widespread rejections, and would indicate a difference between the Bai-Ng (2002) information criterion approach to the estimation of the factors and the significance testing approach of this section. But changing the number of static factors in this analysis does not substantially change the number of rejections of the DFM restrictions, so this explanation also is not fully consistent with the empirical results.

Taken together, these considerations lead us to the preliminary conclusion that the approximation of the DFM model appears to be imperfect, and that many of its restrictions might violated. These violations are small, however, in an economic or quantitative sense, leaving open the possibility that the DFM still might be a useful approximation either for forecasting (the subject of other work) or for structural VAR analysis using dynamic factor structural shocks. We therefore now turn to structural factor VAR analysis and to its sensitivity to departures from the DFM restrictions.

5. Empirical Results III: The BBE Structural FAVAR

5.1 The BBE FAVAR identification scheme

Structural VAR analysis requires deducing one or more structural shocks from the VAR innovations, and the same requirement arises here, where those innovations and structural shocks are to the dynamic factors instead of to observable variables. Write the relation between the q reduced form dynamic factor innovations η_t and the q dynamic factor structural shocks ζ_t as,

$$\zeta_t = H\eta_t \tag{5.1}$$

where H is an invertible $q\times q$ matrix. In this notation, the task of structural factor VAR analysis is to identify H or, if one is interested in just one economic shock, a row of H.

In general there are two ways to approach the problem of identifying *H*: either full system identification as in Blanchard-Watson (1986), in which we strive to identify all elements of *H*, or single-equation identification as in much of the recent literature, in which we focus on identifying only a single row of *H*. Here we follow BBE and Favero, Marcellino, and Neglia (2004) and focus on single-equation identification, in particular, identification of the monetary policy shock.

The BBE identification scheme. BBE's identification procedure is a factor generalization of the familiar Wold causal ordering used to identify monetary policy shocks. In this procedure, there are a set of 'slow moving" variables that are ordered first in a Wold causal chain; the monetary policy instrument (the Federal Funds Rate) is ordered after these slow moving variables; and there are a set of additional variables "fast moving" that are ordered after the monetary policy instrument[3]. Specifically, our implementation of the BBE identification scheme consists of the following assumptions, which suffice to identify ζ_t^R:

1. There is a known subset of the variables, called slow-moving variables, that are affected by a subset of q^S of the structural shocks, which we shall denote by the $q^S \times 1$ vector ζ_t^S. In particular, the monetary policy shock does not affect these slow-moving variables, such as price inflation and output, within the month.
2. The scalar monetary policy shock, ζ_t^R, is a shock to the dynamic factors.
3. Within the month, the only dynamic factor structural shocks to affect the Federal Funds rate are the slow-moving shocks – this reflects the rule-based response of the Fed to the economy – and the monetary policy shock. The Fed Funds rate might also include some idiosyncratic error, for example arising from movements in 25 basis point increments.[4]

[3] In a precursor to this large-*n* approach, Leeper, Sims, and Zha (1996) identify the monetary policy shock as not affected by a large number of "sluggish" private sector variables in their 13- and 18-variable VARs.

[4] In this regard, our implementation differs from that used by BBE. They model the federal funds rate as a observable factor so that there is not idiosyncratic error in the federal funds rate equation.

4. The remaining variables, the fast-moving variables (such as exchange rates and stock returns), are affected within the quarter by ζ_t^S, ζ_t^R, and, in addition, the $q^F \times 1$ vector of fast-moving structural shocks, ζ_t^F.

5. The shocks ζ_t^S, ζ_t^R, and ζ_t^F, are mutually uncorrelated.

We now lay out this identification scheme mathematically. Assumption 1 lets us partition X_t and its one-step ahead innovation ε_{Xt} into three blocks, slow-moving variables, the federal funds rate R_t, and fast-moving variables:

$$X_t = \begin{bmatrix} X_t^S \\ R_t \\ X_t^F \end{bmatrix} \text{ and } \varepsilon_{Xt} = \begin{bmatrix} \varepsilon_{Xt}^S \\ \varepsilon_t^R \\ \varepsilon_{Xt}^F \end{bmatrix} \tag{5.2}$$

where we have used obvious notation for the different groups. From (2.13), the innovation in F_t is $\varepsilon_{Ft} = G\eta_t = C\zeta_t$, where $C = GH^{-1}$, and the innovations ε_{Xt} are given by $\varepsilon_{Xt} = \Lambda\, G\eta_t + v_t = \Lambda C\zeta_t + v_t$. Assumptions 1 – 4 imply that the innovations ε_{Xt} are related to the dynamic factor structural shocks by

$$\begin{aligned} \varepsilon_{Xt}^S &= \Lambda_S C_S \zeta_t^S + v_t^S \\ \varepsilon_{Xt}^R &= \Lambda_R C_S \zeta_t^S + \Lambda_R C_R \zeta_t^R + v_t^R \\ \varepsilon_{Xt}^F &= \Lambda_F C_S \zeta_t^S + \Lambda_F C_R \zeta_t^R + \Lambda_F C_F \zeta_t^F + v_t^F \end{aligned} \tag{5.3}$$

where Λ is matrix of factor loadings in (2.7), conformably partitioned as $\Lambda = [\Lambda_S' \; \Lambda_R' \; \Lambda_F']'$, and C is conformably partitioned as $[C_S \;\; C_R \;\; C_F]$.

The identification argument proceeds as follows. First, because ζ_t^S spans the space of factor innovations of ε_{Xt}^S, $\Lambda_S\varepsilon_{Ft} = \Lambda_S C_S \zeta_t^S$, ζ_t^S can be identified up to a nonsingular transformation as $E(\varepsilon_{Xt}^S | \varepsilon_{Ft}) = \Lambda_S C_S \zeta_t^S$. Second, the monetary policy shock can be determined up to scale as the residual from the projection of the factor component of ε_{Xt}^R (= $\Lambda_R C_S \zeta_t^S + \Lambda_R C_R \zeta_t^R$) onto the nonsingular transformation of ζ_t^S computed in the first step. Finally, for completeness the space spanned by ζ_t^F can be identified as the residual from the projection of the factor component of ε_{Xt}^F onto the non-singular transformations of ζ_t^S and ζ_t^R computed in the first two steps.

Econometric implementation of the BBE identification scheme. Our estimation algorithm follows the foregoing discussion of identification. We estimate the *BBE* monetary policy shock in three steps.[5]

1. Estimate the factor model as in Section 2. Let $\widehat{\Lambda}$, $\hat{\Sigma}_v$, and $\hat{\Sigma}_{\varepsilon_F}$ denote the estimates of Λ, and the covariance matrices of v and ε_{Ft}.
2. Estimate the reduced rank regression of ε_{Xt}^S onto ε_{Ft} as $\widehat{\Pi}\hat{\zeta}_t^S$, where $\widehat{\Pi} = \hat{\Lambda}_S\hat{\Sigma}_{\varepsilon_F}^{1/2}R$, $\hat{\zeta}_t^S = R'\hat{\Sigma}_{\varepsilon_F}^{-1/2}\hat{\varepsilon}_{Ft}$ and R is an $q\times q^s$ matrix with columns given by the eigenvectors of $\hat{\Sigma}_{\varepsilon_F}^{1/2'}\hat{\Lambda}'\Sigma_v^{-1}\hat{\Lambda}\hat{\Sigma}_{\varepsilon_F}^{1/2}$ corresponding the to its q^s largest eigenvalues. $\hat{\zeta}_t^S$ is an estimate of (a non-singular transformation of) ζ_t^S.
3. Regress $\hat{\Lambda}_R\hat{\eta}_t$ onto $\hat{\zeta}_t^S$. The residual from this regression is $\hat{\zeta}_t^R$, an estimate of (a scaled version of) ζ_t^R.

The Favero and Marcellino (2005)/Favero, Marcellino, Neglia (2004) identification scheme. These authors first estimate the static factors using a large panel of data, then include these static factors along with additional variables (in Favero, Marcellino, and Neglia (2004)), the output gap, inflation, commodity price inflation, and an exchange rate) plus the monetary policy instrument (the short rate) in an unrestricted VAR. The monetary policy shock is identified by ordering interest rates last in a

[5] Our econometric implementation differs from BBE's. BBE estimate the monetary policy component in three steps. First, they obtain the first three principal components from the full data set and the first three from the slow-moving series. Next, they regress each the principal components from the full data set onto the federal funds rate, R_t, and the principal components from the slow-moving variables. Third, the construct modified factors, $\overline{F}_t$, that are the full-sample factors, minus the part explained by R_t in the preceding regressions. Finally, they estimate a VAR in $\overline{F}_t$, some observable variables (IP and the CPI, both of which they treat as observable factors), and R_t, with R_t ordered last to yield the monetary policy shock.

Cholesky decomposition. In terms of Section 2, this scheme drops the DFM implications and is equivalent to allowing the variables in the VAR to be observable (static) factors. In terms of (5.3)the Favero, Marcellino, and Neglia (2004) scheme orders both slow- and fast-moving shocks ahead of the monetary policy shock, and assumes that there is no idiosyncratic or measurement error component ν_t^R.

5.2 Baseline empirical results

Following BBE, our slow-moving variables are output, employment, inventories, and broad-based price indexes (for a total of 65 slow-moving variables) and the fast-moving variables are interest rates, exchange rates, commodity prices, and stock returns (68 fast-moving variables). Details are given in the Appendix.

The first step is to estimate the number of dynamic factors among the slow-moving variables, q^S. Like the estimation of the total number of dynamic factors (reported in Table 1), this was done by applying the Bai-Ng (2002) IC_{p2} criterion to the sample covariance matrix of the estimated innovations $\hat{\varepsilon}_{Xt}^S$ in the slow-moving variables. The results are summarized in Table 5. If fewer than four static factors are used, q^S is estimated to be the number of static factors; if four or more static factors are used, q^S is estimated to be 4. The Bai-Ng (2004) criterion is fairly flat in the region of $2 \le q^S \le 4$ so these results are consistent with the Sims-Sargent (1977) finding of only two quantitatively important dynamic factors among the slow-moving variables. These estimates were computed for a VAR(1) for F and 6 lags for D(L), and are robust to using either a VAR(2) for F or 4 lags for D(L).

For the baseline results, we set the number of slow-moving dynamic factors to four. The monetary policy shock, impulse responses, and variance decompositions were computed using the algorithm described in Section 5.1.

Figure 7 plots the year-upon-year change of the Federal Funds rate ($FF_t - FF_{t-12}$) and its orthogonal decomposition into the components attributed to the monetary policy shock, the slow-moving shocks, the fast-moving shocks, and the idiosyncratic component. Most of the changes in the Federal Funds rate are estimated to be responses to the first four structural innovations (such as through a monetary policy rule), or associated with idiosyncratic shocks. There are substantial changes in the Federal Funds rate that are associated with the monetary policy shock in the 1970s and 1980s, but less fluctuations of the monetary policy shock component in the 1990s.

Figures 8 and 9 respectively present the impulse responses and forecast error variance decompositions, by horizon, of selected variables with respect to the monetary policy shock. Results for two specifications are presented, the baseline case of $q^S = 4$ factors and an alternative specification with $q^S = 2$. Numerical values of the monetary policy shock impulse responses and forecast error variance decompositions are given in Table 6 for all 132 series at selected horizons.

Although we use a somewhat different identification strategy and a different estimation method, the results in Figures 8 and 9 and in Table 6 generally accord with those of BBE and (as do theirs) with standard theory. A monetary policy shock that initially increases the Fed Funds rate by 100 basis points is estimated to be highly persistent, with the Fed Funds rate still elevated by 80 basis points after three years. The monetary shock also results in an initial slowdown in the growth of the money supply (all measures), which moderates after one or two years. This 100 basis point monetary policy shock has a contractionary effect on output and employment, with total employment falling by 0.4%, and IP falling by 0.8% after three years, relative to the no-shock benchmark. The contraction is felt more strongly in some sectors, for example construction and goods-producing sectors, than in others, for example finance and services. The PCE deflator, which has a negligible initial response to the monetary shock but eventually declines by 0.3 percent. The CPI inflation rate is estimated to increase for the first few months after the shock before falling by 0.2 percentage points, however, it remains to ascertain whether this small remaining "price puzzle" for the CPI (but not for the PCE deflator) is statistically significant. The monetary contraction is associated with a temporary inversion of the yield curve: the 10 year T-bond/Fed Funds spread initially falls by 0.4 percentage points, but half of this gap disappears within one year. In response to the monetary contraction, the S&P is estimated to fall (relative to the benchmark) initially by 1.9% and to continue to fall over the next six months, for a total 6-month decline of 5.6%.

The fraction of the variance explained by the monetary policy shock is estimated to be small for most of the real quantity variables and for prices. These results are consistent with similarly small estimates found using conventional (observable variable) SVAR analysis. The monetary policy shocks are estimated to account for a substantial fraction of the variability of interest rates and, at horizons of one to three years, for substantial fractions of the variability of retail sales, residential building permits, and the growth of M2. These results (both variance decompositions and impulse responses) are robust to using only two slow-moving dynamic factors ($q^S = 2$) instead of four.

5.3 Sensitivity to adding observable variables to the VAR

The analysis of Section 4 pointed to a considerable number of small violations of the DFM restrictions. We now turn to an examination of whether relaxing some of these restrictions substantively changes the conclusions of the analysis. In particular, we relax restrictions 4, 5, and 6 so that an observable variable X_{jt} (and five of its lags) appears in equation (2.7), and two lags of X_{jt} appear in each equation in (2.8). This has the effect of treating X_{jt} as an observable factor since it affects all X_{it} contemporaneously and is useful in predicting the other factors. Aside from this expanded specification of the factors, all other aspects of the model and its estimation are as in Section 5.2.

The results are summarized in Table 7, which reports impulse responses and forecast error variance decompositions for selected series with respect to the monetary policy shock at the 24-month horizon. The results for the systems augmented with the observable factors are very close to those for the benchmark model of Section 5.2. For example, in Section 4 the spread was found to have substantial marginal predictive content for the second factor; however, when the spread is included as an observable factor, the impulse responses and variance decompositions change negligibly, even for the price series for which the second and third factors play major explanatory roles. Overall, these conclusions are consistent with the Hausman test results of Section 4 in which the additional variables enter statistically significantly, but do not substantially change the estimate of Λ and therefore do not change substantially the structural impulse responses or variance decompositions.

6. Summary

These results pose two puzzles. First, we estimate that there are a relatively large number of dynamic factors that account for the movements in these data: between two and four that account for the movement in output, employment, and price inflation, and between 3 and 5 more that account for additional movements in financial variables. These are many more factors than have been found by previous researchers, starting with Sims and Sargent (1977). A partial resolution of this conflict is that early researchers, including Sims and Sargent (1977), mainly focused on output, employment, and inflation, for which a small number of factors is plausible, but conflicts remain between our results and those of researchers (e.g. Giannone, Reichlin, and Sala (2004)) who have also used large data sets with a diverse range of variables.

Second, there is evidence that the factor model innovations might not span the space of structural shocks, yet this seems not to matter empirically for the structural FAVAR analysis. There is evidence against the VAR restrictions implied by the DFM. Although many of these violations are estimated to be small from an economic perspective, a few of them are large enough that they seem to indicate some misspecification in our base model. Yet when the structural FAVAR model is used to identify a monetary policy shock and to estimate its empirical implications, the results appear to be robust to deviations from these restrictions, in particular to allowing structural shocks to be other than the shocks identified through the dynamic factor model. Moreover, the impulse responses accord with conventional theory and in particular do not exhibit price, exchange rates, or other substantial "puzzles." The rejections suggest that the estimated innovations do not span the space of structural shocks, yet the structural FAVAR results are insensitive to expanding that space by adding more variables to the VAR. Additional work is needed on the empirical and statistical issues raised in Section 4 before the promising results of Section 5 can be interpreted as an endorsement of the structural FAVAR approach.

Data Appendix

Table A.1 lists the short name of each series, its mnemonic (the series label used in the source database), the transformation applied to the series, and a brief data description. All series are from the Global Insights Basic Economics Database, unless the source is listed (in parentheses) as TCB (The Conference Board's Indicators Database) or AC (author's calculation based on Global Insights or TCB data). In the transformation column, ln denotes logarithm, Δln and Δ^2ln denote the first and second difference of the logarithm, lv denotes the level of the series, and Δlf denotes the first difference of the series.

Table A.1 Data sources, transformations, and definitions

Short name	Mnemonic	Fast or Slow?	Tran	Description
PI	a0m052	F	Δln	Personal Income (AR, Bil. Chain 2000 $) (TCB)
PI less transfers	a0m051	F	Δln	Personal Income Less Transfer Payments (AR, Bil. Chain 2000 $) (TCB)
Consumption	a0m224_r	F	Δln	Real Consumption (AC) a0m224/gmdc (a0m224 is from TCB)
M&T sales	a0m057	S	Δln	Manufacturing And Trade Sales (Mil. Chain 1996 $) (TCB)
Retail sales	a0m059	S	Δln	Sales Of Retail Stores (Mil. Chain 2000 $) (TCB)
IP: total	ips10	S	Δln	Industrial Production Index - Total Index
IP: products	ips11	S	Δln	Industrial Production Index - Products, Total
IP: final prod	ips299	S	Δln	Industrial Production Index - Final Products
IP: cons gds	ips12	S	Δln	Industrial Production Index - Consumer Goods
IP: cons dble	ips13	S	Δln	Industrial Production Index - Durable Consumer Goods
IP: cons nondble	ips18	S	Δln	Industrial Production Index - Nondurable Consumer Goods
IP: bus eqpt	ips25	S	Δln	Industrial Production Index - Business Equipment
IP: matls	ips32	S	Δln	Industrial Production Index - Materials
IP: dble matls	ips34	S	Δln	Industrial Production Index - Durable Goods Materials
IP: nondble matls	ips38	S	Δln	Industrial Production Index - Nondurable Goods Materials
IP: mfg	ips43	S	Δln	Industrial Production Index - Manufacturing (Sic)
IP: res util	ips307	S	Δln	Industrial Production Index - Residential Utilities
IP: fuels	ips306	S	Δln	Industrial Production Index - Fuels
NAPM prodn	pmp	S	lv	Napm Production Index (Percent)
Cap util	a0m082	S	Δlv	Capacity Utilization (Mfg) (TCB)
Help wanted indx	lhel	S	Δlv	Index Of Help-Wanted Advertising In Newspapers (1967=100;Sa)
Help wanted/emp	lhelx	S	Δlv	Employment: Ratio; Help-Wanted Ads:No. Unemployed Clf
Emp CPS total	lhem	S	Δln	Civilian Labor Force: Employed, Total (Thous.,Sa)
Emp CPS nonag	lhnag	S	Δln	Civilian Labor Force: Employed, Nonagric.Industries (Thous.,Sa)
U: all	lhur	S	Δlv	Unemployment Rate: All Workers, 16 Years & Over (%,Sa)
U: mean duration	lhu680	S	Δlv	Unemploy.By Duration: Average(Mean)Duration In Weeks (Sa)
U < 5 wks	lhu5	S	Δln	Unemploy.By Duration: Persons Unempl.Less Than 5 Wks (Thous.,Sa)
U 5-14 wks	lhu14	S	Δln	Unemploy.By Duration: Persons Unempl.5 To 14 Wks (Thous.,Sa)
U 15+ wks	lhu15	S	Δln	Unemploy.By Duration: Persons Unempl.15 Wks + (Thous.,Sa)
U 15-26 wks	lhu26	S	Δln	Unemploy.By Duration: Persons Unempl.15 To 26 Wks (Thous.,Sa)
U 27+ wks	lhu27	S	Δln	Unemploy.By Duration: Persons Unempl.27 Wks + (Thous,Sa)
UI claims	a0m005	S	Δln	Average Weekly Initial Claims, Unemploy. Insurance (Thous.) (TCB)
Emp: total	ces002	S	Δln	Employees On Nonfarm Payrolls: Total Private
Emp: gds prod	ces003	S	Δln	Employees On Nonfarm Payrolls - Goods-Producing
Emp: mining	ces006	S	Δln	Employees On Nonfarm Payrolls - Mining
Emp: const	ces011	S	Δln	Employees On Nonfarm Payrolls - Construction
Emp: mfg	ces015	S	Δln	Employees On Nonfarm Payrolls - Manufacturing
Emp: dble gds	ces017	S	Δln	Employees On Nonfarm Payrolls - Durable Goods
Emp: nondbles	ces033	S	Δln	Employees On Nonfarm Payrolls - Nondurable Goods
Emp: services	ces046	S	Δln	Employees On Nonfarm Payrolls - Service-Providing
Emp: TTU	ces048	S	Δln	Employees On Nonfarm Payrolls - Trade, Transportation, And Utilities
Emp: wholesale	ces049	S	Δln	Employees On Nonfarm Payrolls - Wholesale Trade
Emp: retail	ces053	S	Δln	Employees On Nonfarm Payrolls - Retail Trade
Emp: FIRE	ces088	S	Δln	Employees On Nonfarm Payrolls - Financial Activities
Emp: Govt	ces140	S	Δln	Employees On Nonfarm Payrolls - Government

Emp-hrs nonag	a0m048	S	Δln	Employee Hours In Nonag. Establishments (AR, Bil. Hours) (TCB)
Avg hrs	ces151	S	lv	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing
Overtime: mfg	ces155	S	Δlv	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Mfg Overtime Hours
Avg hrs: mfg	aom001	S	lv	Average Weekly Hours, Mfg. (Hours) (TCB)
NAPM empl	pmemp	S	lv	Napm Employment Index (Percent)
Starts: nonfarm	hsfr	S	ln	Housing Starts:Nonfarm(1947-58);Total Farm&Nonfarm(1959-)(Thous.,Saar)
Starts: NE	hsne	F	ln	Housing Starts:Northeast (Thous.U.)S.A.
Starts: MW	hsmw	F	ln	Housing Starts:Midwest(Thous.U.)S.A.
Starts: South	hssou	F	ln	Housing Starts:South (Thous.U.)S.A.
Starts: West	hswst	F	ln	Housing Starts:West (Thous.U.)S.A.
BP: total	hsbr	F	ln	Housing Authorized: Total New Priv Housing Units (Thous.,Saar)
BP: NE	hsbne*	F	ln	Houses Authorized By Build. Permits:Northeast(Thou.U.)S.A
BP: MW	hsbmw*	F	ln	Houses Authorized By Build. Permits:Midwest(Thou.U.)S.A.
BP: South	hsbsou*	F	ln	Houses Authorized By Build. Permits:South(Thou.U.)S.A.
BP: West	hsbwst*	F	ln	Houses Authorized By Build. Permits:West(Thou.U.)S.A.
PMI	pmi	F	lv	Purchasing Managers' Index (Sa)
NAPM new ordrs	pmno	F	lv	Napm New Orders Index (Percent)
NAPM vendor del	pmdel	F	lv	Napm Vendor Deliveries Index (Percent)
NAPM Invent	pmnv	F	lv	Napm Inventories Index (Percent)
Orders: cons gds	a0m008	F	Δln	Mfrs' New Orders, Consumer Goods And Materials (Bil. Chain 1982 $) (TCB)
Orders: dble gds	a0m007	F	Δln	Mfrs' New Orders, Durable Goods Industries (Bil. Chain 2000 $) (TCB)
Orders: cap gds	a0m027	F	Δln	Mfrs' New Orders, Nondefense Capital Goods (Mil. Chain 1982 $) (TCB)
Unf orders: dble	a1m092	F	Δln	Mfrs' Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000 $) (TCB)
M&T invent	a0m070	F	Δln	Manufacturing And Trade Inventories (Bil. Chain 2000 $) (TCB)
M&T invent/sales	a0m077	F	Δlv	Ratio, Mfg. And Trade Inventories To Sales (Based On Chain 2000 $) (TCB)
M1	fm1	F	Δ^2ln	Money Stock: M1(Curr,Trav.Cks,Dem Dep,Other Ck'able Dep)(Bil$,Sa)
M2	fm2	F	Δ^2ln	Money Stock:M2(M1+O'nite Rps,Euro$,G/P&B/D Mmmfs&Sav&Sm Time Dep(Bil$,Sa)
M3	fm3	F	Δ^2ln	Money Stock: M3(M2+Lg Time Dep,Term Rp's&Inst Only Mmmfs)(Bil$,Sa)
M2 (real)	fm2dq	F	Δln	Money Supply - M2 In 1996 Dollars (Bci)
MB	fmfba	F	Δ^2ln	Monetary Base, Adj For Reserve Requirement Changes(Mil$,Sa)
Reserves tot	fmrra	F	Δ^2ln	Depository Inst Reserves:Total, Adj For Reserve Req Chgs(Mil$,Sa)
Reserves nonbor	fmrnba	F	Δ^2ln	Depository Inst Reserves:Nonborrowed,Adj Res Req Chgs(Mil$,Sa)
C&I loans	fclnq	F	Δ^2ln	Commercial & Industrial Loans Oustanding In 1996 Dollars (Bci)
ΔC&I loans	fclbmc	F	lv	Wkly Rp Lg Com'l Banks:Net Change Com'l & Indus Loans(Bil$,Saar)
Cons credit	ccinrv	F	Δ^2ln	Consumer Credit Outstanding - Nonrevolving(G19)
Inst cred/PI	a0m095	F	Δlv	Ratio, Consumer Installment Credit To Personal Income (Pct.) (TCB)
S&P 500	fspcom	F	Δln	S&P's Common Stock Price Index: Composite (1941-43=10)
S&P: indust	fspin	F	Δln	S&P's Common Stock Price Index: Industrials (1941-43=10)
S&P div yield	fsdxp	F	Δlv	S&P's Composite Common Stock: Dividend Yield (% Per Annum)
S&P PE ratio	fspxe	F	Δln	S&P's Composite Common Stock: Price-Earnings Ratio (%,Nsa)
Fed Funds	fyff	F	Δlv	Interest Rate: Federal Funds (Effective) (% Per Annum,Nsa)
Comm paper	cp90	F	Δlv	Cmmercial Paper Rate (AC)
3 mo T-bill	fygm3	F	Δlv	Interest Rate: U.S.Treasury Bills,Sec Mkt,3-Mo.(% Per Ann,Nsa)
6 mo T-bill	fygm6	F	Δlv	Interest Rate: U.S.Treasury Bills,Sec Mkt,6-Mo.(% Per Ann,Nsa)
1 yr T-bond	fygt1	F	Δlv	Interest Rate: U.S.Treasury Const Maturities,1-Yr.(% Per Ann,Nsa)
5 yr T-bond	fygt5	F	Δlv	Interest Rate: U.S.Treasury Const Maturities,5-Yr.(% Per Ann,Nsa)
10 yr T-bond	fygt10	F	Δlv	Interest Rate: U.S.Treasury Const Maturities,10-Yr.(% Per Ann,Nsa)
Aaa bond	fyaaac	F	Δlv	Bond Yield: Moody's Aaa Corporate (% Per Annum)
Baa bond	fybaac	F	Δlv	Bond Yield: Moody's Baa Corporate (% Per Annum)
CP-FF spread	scp90	F	lv	cp90-fyff (AC)
3 mo-FF spread	sfygm3	F	lv	fygm3-fyff (AC)
6 mo-FF spread	sfygm6	F	lv	fygm6-fyff (AC)
1 yr-FF spread	sfygt1	F	lv	fygt1-fyff (AC)
5 yr-FF spread	sfygt5	F	lv	fygt5-fyff (AC)
10 yr-FF spread	sfygt10	F	lv	fygt10-fyff (AC)
Aaa-FF spread	sfyaaac	F	lv	fyaaac-fyff (AC)
Baa-FF spread	sfybaac	F	lv	fybaac-fyff (AC)
Ex rate: avg	exrus	F	Δln	United States;Effective Exchange Rate(Merm)(Index No.)
Ex rate: Switz	exrsw	F	Δln	Foreign Exchange Rate: Switzerland (Swiss Franc Per U.S.$)
Ex rate: Japan	exrjan	F	Δln	Foreign Exchange Rate: Japan (Yen Per U.S.$)
Ex rate: UK	exruk	F	Δln	Foreign Exchange Rate: United Kingdom (Cents Per Pound)
EX rate: Canada	exrcan	F	Δln	Foreign Exchange Rate: Canada (Canadian $ Per U.S.$)
PPI: fin gds	pwfsa	F	Δ^2ln	Producer Price Index: Finished Goods (82=100,Sa)

PPI: cons gds	pwfcsa	F	Δ^2ln	Producer Price Index: Finished Consumer Goods (82=100,Sa)
PPI: int mat'ls	pwimsa	F	Δ^2ln	Producer Price Index:I ntermed Mat.Supplies & Components(82=100,Sa)
PPI: crude mat'ls	pwcmsa	F	Δ^2ln	Producer Price Index: Crude Materials (82=100,Sa)
Spot market price	psccom	F	Δ^2ln	Spot market price index: bls & crb: all commodities(1967=100)
Sens mat'ls price	psm99q	F	Δ^2ln	Index Of Sensitive Materials Prices (1990=100)(Bci-99a)
NAPM com price	pmcp	F	lv	Napm Commodity Prices Index (Percent)
CPI-U: all	punew	S	Δ^2ln	Cpi-U: All Items (82-84=100,Sa)
CPI-U: apparel	pu83	S	Δ^2ln	Cpi-U: Apparel & Upkeep (82-84=100,Sa)
CPI-U: transp	pu84	S	Δ^2ln	Cpi-U: Transportation (82-84=100,Sa)
CPI-U: medical	pu85	S	Δ^2ln	Cpi-U: Medical Care (82-84=100,Sa)
CPI-U: comm.	puc	S	Δ^2ln	Cpi-U: Commodities (82-84=100,Sa)
CPI-U: dbles	pucd	S	Δ^2ln	Cpi-U: Durables (82-84=100,Sa)
CPI-U: services	pus	S	Δ^2ln	Cpi-U: Services (82-84=100,Sa)
CPI-U: ex food	puxf	S	Δ^2ln	Cpi-U: All Items Less Food (82-84=100,Sa)
CPI-U: ex shelter	puxhs	S	Δ^2ln	Cpi-U: All Items Less Shelter (82-84=100,Sa)
CPI-U: ex med	puxm	S	Δ^2ln	Cpi-U: All Items Less Midical Care (82-84=100,Sa)
PCE defl	gmdc	S	Δ^2ln	Pce, Impl Pr Defl:Pce (1987=100)
PCE defl: dlbes	gmdcd	S	Δ^2ln	Pce, Impl Pr Defl:Pce; Durables (1987=100)
PCE defl: nondble	gmdcn	S	Δ^2ln	Pce, Impl Pr Defl:Pce; Nondurables (1996=100)
PCE defl: service	gmdcs	S	Δ^2ln	Pce, Impl Pr Defl:Pce; Services (1987=100)
AHE: goods	ces275	S	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing
AHE: const	ces277	S	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Construction
AHE: mfg	ces278	S	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Manufacturing
Consumer expect	hhsntn	F	Δlv	U. Of Mich. Index Of Consumer Expectations(Bcd-83)

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Table 1
Estimation of the Number of Dynamic Factors q

# dynamic factors (q)	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6	r = 7	r = 8	r = 9	r = 10
1	**-0.577**	-0.589	-0.593	-0.604	-0.615	-0.624	-0.630	-0.637	-0.642	-0.649
2	.	**-0.637**	-0.641	-0.649	-0.659	-0.664	-0.668	-0.677	-0.680	-0.686
3	.	.	**-0.676**	-0.683	-0.694	-0.699	-0.703	-0.710	-0.714	-0.719
4	.	.	.	**-0.693**	-0.704	-0.708	-0.713	-0.720	-0.724	-0.730
5	.	.	.	.	**-0.712**	-0.717	-0.722	-0.729	-0.733	-0.739
6	.	.	.	.	.	**-0.719**	-0.723	-0.731	-0.735	-0.741
7	.	.	.	.	.	.	**-0.726**	**-0.734**	**-0.738**	**-0.744**
8	.	.	.	.	.	.	.	-0.732	-0.738	-0.743
9	.	.	.	.	.	.	.	.	-0.734	-0.740
10	.	.	.	.	.	.	.	.	.	-0.736

Notes: Entries are the Bai-Ng (2002) IC_{p2} criterion, evaluated using the sample covariance matrix of the estimated innovations in X_t from the restricted VAR implied by the DFM. Each entry reports the IC_{p2} for the number of static factors r given in the column heading and the number of dynamic factors q given in the row. Estimates of q given r (the column maximum of IC_{p2}) are presented in bold.

Table 2
Forecast Error Variance Decompositions of All 132 Series with Respect to the Dynamic Factor Innovations: 24-month horizon

X_i Series	Idiosyncratic	Cumulative fraction of the variance explained by dynamic factors 1, …, *q*:						
		q = 1	*q* = 2	*q* = 3	*q* = 4	*q* = 5	*q* = 6	*q* = 7
PI	0.54	0.40	0.40	0.41	0.42	0.44	0.46	0.46
PI less transfers	0.41	0.55	0.55	0.56	0.56	0.57	0.59	0.59
Consumption	0.32	0.48	0.62	0.63	0.63	0.66	0.67	0.68
M&T sales	0.12	0.81	0.86	0.87	0.87	0.88	0.88	0.88
Retail sales	0.30	0.47	0.62	0.63	0.63	0.68	0.68	0.70
IP: total	0.02	0.93	0.94	0.94	0.95	0.97	0.97	0.98
IP: products	0.03	0.92	0.93	0.93	0.95	0.96	0.97	0.97
IP: final prod	0.04	0.89	0.89	0.89	0.93	0.94	0.95	0.96
IP: cons gds	0.07	0.76	0.77	0.77	0.83	0.88	0.91	0.93
IP: cons dble	0.12	0.73	0.73	0.74	0.78	0.84	0.84	0.88
IP: cons nondble	0.38	0.44	0.44	0.45	0.52	0.53	0.62	0.62
IP: bus eqpt	0.15	0.82	0.82	0.82	0.83	0.84	0.84	0.85
IP: matls	0.10	0.84	0.85	0.85	0.86	0.89	0.89	0.90
IP: dble matls	0.11	0.81	0.82	0.82	0.83	0.86	0.86	0.89
IP: nondble matls	0.24	0.74	0.74	0.75	0.75	0.76	0.76	0.76
IP: mfg	0.02	0.94	0.94	0.95	0.96	0.97	0.97	0.98
IP: res util	0.78	0.00	0.01	0.02	0.06	0.06	0.18	0.22
IP: fuels	0.88	0.03	0.04	0.11	0.11	0.12	0.12	0.12
NAPM prodn	0.35	0.56	0.60	0.60	0.62	0.64	0.64	0.65
Cap util	0.03	0.91	0.91	0.92	0.93	0.96	0.96	0.97
Help wanted indx	0.30	0.65	0.67	0.67	0.69	0.69	0.70	0.70
Help wanted/emp	0.18	0.77	0.78	0.78	0.79	0.81	0.81	0.82
Emp CPS total	0.12	0.76	0.77	0.77	0.78	0.85	0.85	0.88
Emp CPS nonag	0.12	0.76	0.77	0.77	0.78	0.85	0.85	0.88
U: all	0.07	0.85	0.85	0.85	0.86	0.92	0.92	0.93
U: mean duration	0.30	0.31	0.32	0.33	0.33	0.64	0.64	0.70
U < 5 wks	0.49	0.47	0.47	0.48	0.48	0.49	0.49	0.51
U 5-14 wks	0.21	0.73	0.74	0.74	0.74	0.79	0.79	0.79
U 15+ wks	0.06	0.69	0.70	0.70	0.70	0.92	0.92	0.94
U 15-26 wks	0.14	0.67	0.67	0.67	0.67	0.84	0.84	0.86
U 27+ wks	0.14	0.58	0.58	0.59	0.59	0.83	0.84	0.86
UI claims	0.22	0.71	0.74	0.75	0.75	0.77	0.77	0.78
Emp: total	0.04	0.94	0.94	0.94	0.95	0.95	0.95	0.96
Emp: gds prod	0.05	0.94	0.94	0.95	0.95	0.95	0.95	0.95
Emp: mining	0.94	0.03	0.04	0.04	0.04	0.04	0.04	0.06
Emp: const	0.24	0.66	0.66	0.67	0.68	0.68	0.71	0.76
Emp: mfg	0.07	0.91	0.92	0.92	0.92	0.93	0.93	0.93
Emp: dble gds	0.10	0.88	0.89	0.89	0.89	0.89	0.89	0.90
Emp: nondbles	0.19	0.77	0.78	0.78	0.78	0.80	0.80	0.81
Emp: services	0.20	0.73	0.73	0.73	0.73	0.74	0.75	0.80
Emp: TTU	0.15	0.79	0.79	0.79	0.80	0.81	0.82	0.85
Emp: wholesale	0.23	0.71	0.72	0.72	0.73	0.76	0.76	0.77
Emp: retail	0.26	0.64	0.65	0.65	0.66	0.66	0.67	0.74
Emp: FIRE	0.79	0.17	0.17	0.17	0.17	0.18	0.18	0.21
Emp: Govt	0.91	0.00	0.01	0.02	0.02	0.03	0.03	0.09
Emp-hrs nonag	0.11	0.84	0.84	0.85	0.85	0.86	0.86	0.89
Avg hrs	0.33	0.62	0.63	0.64	0.65	0.66	0.66	0.67
Overtime: mfg	0.36	0.61	0.62	0.62	0.62	0.63	0.63	0.64
Avg hrs: mfg	0.30	0.66	0.67	0.68	0.68	0.70	0.70	0.70
NAPM empl	0.28	0.66	0.68	0.68	0.69	0.70	0.70	0.72
Starts: nonfarm	0.57	0.21	0.31	0.34	0.36	0.40	0.42	0.43
Starts: NE	0.80	0.08	0.11	0.12	0.12	0.15	0.17	0.20
Starts: MW	0.72	0.17	0.21	0.22	0.24	0.24	0.27	0.28
Starts: South	0.64	0.18	0.25	0.27	0.29	0.34	0.36	0.36
Starts: West	0.79	0.10	0.16	0.18	0.19	0.20	0.20	0.21
BP: total	0.63	0.12	0.25	0.29	0.30	0.36	0.37	0.37
BP: NE	0.71	0.19	0.23	0.24	0.25	0.27	0.28	0.29

BP: MW	0.64	0.12	0.21	0.29	0.29	0.33	0.35	0.36
BP: South	0.74	0.05	0.13	0.16	0.18	0.25	0.26	0.26
BP: West	0.80	0.06	0.16	0.17	0.17	0.19	0.19	0.20
PMI	0.29	0.58	0.61	0.62	0.65	0.68	0.69	0.71
NAPM new ordrs	0.37	0.47	0.51	0.52	0.55	0.60	0.60	0.63
NAPM vendor del	0.65	0.31	0.32	0.32	0.33	0.33	0.34	0.35
NAPM Invent	0.61	0.35	0.37	0.37	0.38	0.39	0.39	0.39
Orders: cons gds	0.12	0.80	0.82	0.83	0.83	0.85	0.85	0.88
Orders: dble gds	0.16	0.78	0.80	0.81	0.81	0.81	0.81	0.84
Orders: cap gds	0.46	0.49	0.49	0.50	0.50	0.52	0.53	0.54
Unf orders: dble	0.52	0.41	0.43	0.43	0.43	0.44	0.45	0.48
M&T invent	0.43	0.39	0.43	0.44	0.46	0.56	0.57	0.57
M&T invent/sales	0.16	0.55	0.67	0.69	0.70	0.83	0.83	0.84
M1	0.80	0.06	0.09	0.10	0.11	0.11	0.20	0.20
M2	0.65	0.12	0.16	0.17	0.19	0.19	0.34	0.35
M3	0.85	0.03	0.04	0.04	0.06	0.06	0.15	0.15
M2 (real)	0.52	0.07	0.22	0.32	0.38	0.38	0.48	0.48
MB	0.90	0.01	0.02	0.02	0.02	0.02	0.09	0.10
Reserves tot	0.93	0.01	0.03	0.03	0.04	0.04	0.06	0.07
Reserves nonbor	0.83	0.04	0.05	0.05	0.09	0.10	0.15	0.17
C&I loans	0.87	0.10	0.10	0.12	0.12	0.13	0.13	0.13
ΔC&I loans	0.92	0.04	0.05	0.06	0.07	0.07	0.07	0.08
Cons credit	0.78	0.16	0.18	0.18	0.18	0.19	0.19	0.22
Inst cred/PI	0.80	0.06	0.08	0.08	0.08	0.16	0.19	0.20
S&P 500	0.22	0.05	0.48	0.52	0.65	0.65	0.77	0.78
S&P: indust	0.22	0.06	0.47	0.50	0.66	0.66	0.77	0.78
S&P div yield	0.26	0.02	0.48	0.53	0.64	0.64	0.73	0.74
S&P PE ratio	0.47	0.02	0.31	0.35	0.44	0.45	0.53	0.53
Fed Funds	0.30	0.48	0.58	0.63	0.66	0.69	0.70	0.70
Comm paper	0.22	0.42	0.60	0.68	0.77	0.78	0.78	0.78
3 mo T-bill	0.21	0.39	0.54	0.60	0.77	0.77	0.79	0.79
6 mo T-bill	0.14	0.40	0.58	0.66	0.85	0.85	0.85	0.86
1 yr T-bond	0.10	0.38	0.57	0.67	0.88	0.89	0.89	0.90
5 yr T-bond	0.13	0.21	0.42	0.51	0.83	0.86	0.86	0.87
10 yr T-bond	0.19	0.12	0.36	0.44	0.75	0.80	0.81	0.81
Aaa bond	0.24	0.06	0.39	0.47	0.70	0.74	0.76	0.76
Baa bond	0.29	0.02	0.36	0.46	0.63	0.67	0.71	0.71
CP-FF spread	0.71	0.11	0.14	0.15	0.18	0.28	0.28	0.29
3 mo-FF spread	0.57	0.24	0.26	0.27	0.32	0.42	0.42	0.43
6 mo-FF spread	0.58	0.24	0.25	0.26	0.31	0.41	0.41	0.42
1 yr-FF spread	0.63	0.18	0.19	0.19	0.26	0.36	0.37	0.37
5 yr-FF spread	0.51	0.34	0.36	0.38	0.39	0.47	0.49	0.49
10 yr-FF spread	0.46	0.40	0.43	0.45	0.46	0.53	0.54	0.54
Aaa-FF spread	0.40	0.46	0.49	0.52	0.52	0.58	0.60	0.60
Baa-FF spread	0.35	0.51	0.54	0.56	0.58	0.63	0.65	0.65
Ex rate: avg	0.27	0.00	0.05	0.16	0.16	0.27	0.45	0.73
Ex rate: Switz	0.40	0.00	0.02	0.07	0.09	0.20	0.40	0.60
Ex rate: Japan	0.55	0.02	0.04	0.13	0.13	0.18	0.30	0.45
Ex rate: UK	0.53	0.00	0.01	0.08	0.08	0.14	0.26	0.47
EX rate: Canada	0.77	0.00	0.07	0.11	0.11	0.18	0.18	0.23
PPI: fin gds	0.56	0.05	0.17	0.40	0.42	0.43	0.43	0.44
PPI: cons gds	0.56	0.03	0.14	0.40	0.42	0.43	0.43	0.44
PPI: int mat'ls	0.54	0.18	0.26	0.44	0.45	0.45	0.46	0.46
PPI: crude mat'ls	0.77	0.02	0.06	0.21	0.22	0.22	0.22	0.23
Spot market price	0.78	0.10	0.12	0.13	0.18	0.18	0.18	0.22
Sens mat'ls price	0.75	0.11	0.14	0.16	0.21	0.23	0.24	0.25
NAPM com price	0.57	0.32	0.37	0.41	0.43	0.43	0.43	0.43
CPI-U: all	0.22	0.09	0.38	0.75	0.76	0.77	0.77	0.78
CPI-U: apparel	0.88	0.04	0.07	0.11	0.11	0.12	0.12	0.12
CPI-U: transp	0.43	0.02	0.18	0.55	0.56	0.56	0.56	0.57
CPI-U: medical	0.96	0.02	0.03	0.03	0.04	0.04	0.04	0.04
CPI-U: comm.	0.21	0.05	0.30	0.75	0.77	0.77	0.78	0.79
CPI-U: dbles	0.90	0.01	0.08	0.08	0.09	0.10	0.10	0.10
CPI-U: services	0.81	0.11	0.16	0.17	0.17	0.19	0.19	0.19
CPI-U: ex food	0.39	0.09	0.33	0.58	0.59	0.59	0.60	0.61
CPI-U: ex shelter	0.23	0.05	0.31	0.74	0.76	0.76	0.77	0.77

CPI-U: ex med	0.24	0.09	0.35	0.73	0.75	0.75	0.75	0.76
PCE defl	0.34	0.05	0.24	0.62	0.65	0.65	0.66	0.66
PCE defl: dlbes	0.91	0.03	0.06	0.07	0.09	0.09	0.09	0.09
PCE defl: nondble	0.24	0.05	0.27	0.73	0.75	0.75	0.75	0.76
PCE defl: service	0.95	0.00	0.01	0.03	0.04	0.04	0.04	0.05
AHE: goods	0.82	0.04	0.06	0.06	0.06	0.07	0.07	0.18
AHE: const	0.94	0.01	0.02	0.02	0.02	0.03	0.04	0.06
AHE: mfg	0.73	0.07	0.08	0.08	0.09	0.12	0.12	0.27
Consumer expect	0.67	0.03	0.14	0.15	0.21	0.25	0.31	0.33
Average by horizon								
6 month	**0.49**	**0.28**	**0.36**	**0.40**	**0.44**	**0.47**	**0.49**	**0.51**
12 month	**0.45**	**0.33**	**0.40**	**0.44**	**0.47**	**0.51**	**0.52**	**0.55**
24 month	**0.44**	**0.35**	**0.42**	**0.46**	**0.49**	**0.52**	**0.54**	**0.56**
48 month	**0.43**	**0.36**	**0.43**	**0.47**	**0.50**	**0.53**	**0.55**	**0.57**
Bus cycle freqs	**0.42**	**0.37**	**0.44**	**0.49**	**0.51**	**0.54**	**0.56**	**0.58**

Notes: The entry in the first numeric column is the fraction of the variance of the 24-month ahead forecast error explained by the idiosyncratic disturbance ν_{it}. The entries in the remaining columns are the cumulative fraction of the variance explained by the dynamic innovations, up to and including the dynamic innovation in the column heading. The seven dynamic factors were computed as described in Section 2.4.

Table 3

Economic Significance of Restriction #4:

Marginal R^2s (increases in the R^2) resulting from adding $X_{jt-1},\ldots, X_{jt-6}$ to the k^{th} equation in the 9-equation system, $F_t = \Phi(L)F_{t-1} + \Psi_j(L)X_{jt-1} + \varepsilon_{Ft}$.

Added regressor:	**Increase in the R^2 in the equation for static factor number:**								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
PI	0.005	0.003	0.016	0.005	0.009	0.010	0.022	0.041	0.010
PI less transfers	0.002	0.003	0.016	0.008	0.009	0.015	0.017	0.036	0.010
Consumption	0.003	0.023	0.045	0.024	0.004	0.017	0.016	0.034	0.013
M&T sales	0.016	0.026	0.043	0.010	0.015	0.009	0.025	0.024	0.010
Retail sales	0.007	0.016	0.029	0.018	0.008	0.028	0.015	0.048	0.011
IP: total	0.006	0.005	0.018	0.040	0.010	0.007	0.010	0.029	0.022
IP: products	0.010	0.016	0.019	0.034	0.010	0.014	0.010	0.024	0.016
IP: final prod	0.009	0.016	0.014	0.038	0.010	0.016	0.008	0.020	0.012
IP: cons gds	0.009	0.020	0.015	0.018	0.004	0.016	0.007	0.029	0.013
IP: cons dble	0.010	0.008	0.018	0.015	0.011	0.008	0.014	0.028	0.008
IP: cons nondble	0.007	0.018	0.010	0.015	0.012	0.017	0.009	0.010	0.017
IP: bus eqpt	0.003	0.009	0.006	0.021	0.018	0.007	0.021	0.013	0.011
IP: matls	0.011	0.003	0.017	0.030	0.015	0.005	0.005	0.017	0.021
IP: dble matls	0.019	0.003	0.013	0.028	0.016	0.007	0.010	0.020	0.016
IP: nondble matls	0.012	0.008	0.017	0.022	0.017	0.002	0.004	0.010	0.007
IP: mfg	0.013	0.006	0.020	0.032	0.007	0.012	0.011	0.026	0.037
IP: res util	0.006	0.010	0.019	0.017	0.008	0.019	0.009	0.006	0.022
IP: fuels	0.008	0.004	0.011	0.003	0.010	0.008	0.007	0.022	0.005
NAPM prodn	0.014	0.009	0.016	0.040	0.012	0.018	0.016	0.020	0.035
Cap util	0.014	0.004	0.020	0.031	0.007	0.007	0.028	0.023	0.020
Help wanted indx	0.034	0.010	0.018	0.015	0.004	0.007	0.020	0.021	0.033
Help wanted/emp	0.009	0.031	0.024	0.011	0.009	0.006	0.004	0.022	0.024
Emp CPS total	0.005	0.004	0.003	0.026	0.023	0.005	0.009	0.005	0.022
Emp CPS nonag	0.005	0.002	0.003	0.025	0.013	0.003	0.009	0.004	0.017
U: all	0.005	0.033	0.030	0.027	0.010	0.012	0.010	0.042	0.015
U: mean duration	0.003	0.009	0.005	0.015	0.015	0.003	0.006	0.014	0.012
U < 5 wks	0.004	0.021	0.025	0.001	0.013	0.003	0.012	0.014	0.026
U 5-14 wks	0.006	0.012	0.014	0.044	0.004	0.017	0.039	0.023	0.012
U 15+ wks	0.002	0.005	0.010	0.033	0.012	0.005	0.011	0.009	0.016
U 15-26 wks	0.001	0.005	0.010	0.033	0.010	0.004	0.013	0.017	0.004
U 27+ wks	0.003	0.005	0.009	0.012	0.009	0.018	0.001	0.014	0.013
UI claims	0.010	0.014	0.016	0.032	0.009	0.002	0.016	0.024	0.015
Emp: total	0.007	0.005	0.016	0.054	0.018	0.003	0.005	0.014	0.015
Emp: gds prod	0.008	0.007	0.007	0.051	0.012	0.012	0.014	0.015	0.015
Emp: mining	0.018	0.017	0.010	0.018	0.004	0.015	0.009	0.004	0.014
Emp: const	0.003	0.010	0.004	0.010	0.006	0.007	0.008	0.012	0.011
Emp: mfg	0.014	0.010	0.009	0.044	0.012	0.021	0.024	0.014	0.022
Emp: dble gds	0.016	0.012	0.008	0.044	0.016	0.022	0.023	0.021	0.024
Emp: nondbles	0.019	0.014	0.011	0.031	0.002	0.021	0.011	0.013	0.010
Emp: services	0.009	0.004	0.017	0.020	0.019	0.005	0.006	0.010	0.014
Emp: TTU	0.009	0.004	0.009	0.029	0.023	0.004	0.007	0.007	0.011
Emp: wholesale	0.007	0.013	0.005	0.036	0.021	0.009	0.014	0.014	0.020
Emp: retail	0.007	0.002	0.008	0.018	0.021	0.006	0.007	0.005	0.006
Emp: FIRE	0.008	0.005	0.020	0.011	0.014	0.013	0.016	0.008	0.032
Emp: Govt	0.007	0.006	0.007	0.006	0.010	0.005	0.003	0.011	0.002
Emp-hrs nonag	0.009	0.012	0.014	0.032	0.018	0.005	0.004	0.030	0.019
Avg hrs	0.011	0.015	0.007	0.015	0.008	0.008	0.011	0.039	0.030
Overtime: mfg	0.004	0.008	0.012	0.009	0.005	0.011	0.029	0.007	0.004
Avg hrs: mfg	0.012	0.013	0.014	0.016	0.007	0.011	0.012	0.031	0.022
NAPM empl	0.009	0.021	0.011	0.028	0.013	0.010	0.031	0.010	0.036
Starts: nonfarm	0.012	0.040	0.011	0.008	0.013	0.022	0.015	0.017	0.043
Starts: NE	0.009	0.010	0.021	0.008	0.012	0.005	0.007	0.011	0.018
Starts: MW	0.006	0.010	0.008	0.004	0.007	0.028	0.007	0.018	0.021
Starts: South	0.008	0.044	0.017	0.012	0.018	0.016	0.012	0.006	0.038
Starts: West	0.013	0.016	0.009	0.007	0.008	0.034	0.014	0.006	0.034
BP: total	0.019	0.027	0.010	0.012	0.015	0.036	0.020	0.020	0.032
BP: NE	0.005	0.015	0.008	0.008	0.010	0.006	0.023	0.036	0.016

BP: MW	0.008	0.008	0.004	0.005	0.006	0.030	0.003	0.015	0.034
BP: South	0.022	0.036	0.015	0.012	0.009	0.012	0.018	0.015	0.015
BP: West	0.019	0.016	0.009	0.011	0.006	0.037	0.025	0.006	0.026
PMI	0.016	0.011	0.021	0.033	0.015	0.018	0.020	0.009	0.040
NAPM new ordrs	0.022	0.006	0.025	0.026	0.017	0.013	0.011	0.014	0.042
NAPM vendor del	0.023	0.032	0.012	0.011	0.005	0.021	0.012	0.002	0.007
NAPM Invent	0.006	0.020	0.003	0.016	0.004	0.011	0.039	0.008	0.023
Orders: cons gds	0.007	0.037	0.046	0.008	0.005	0.013	0.013	0.024	0.014
Orders: dble gds	0.007	0.029	0.044	0.004	0.012	0.010	0.014	0.030	0.004
Orders: cap gds	0.008	0.007	0.004	0.007	0.012	0.003	0.009	0.012	0.013
Unf orders: dble	0.005	0.025	0.015	0.013	0.013	0.009	0.017	0.024	0.019
M&T invent	0.006	0.014	0.013	0.020	0.029	0.009	0.021	0.022	0.005
M&T invent/sales	0.008	0.014	0.029	0.021	0.005	0.017	0.029	0.015	0.003
M1	0.002	0.011	0.012	0.004	0.008	0.006	0.007	0.005	0.021
M2	0.004	0.015	0.015	0.020	0.010	0.008	0.009	0.004	0.005
M3	0.002	0.014	0.011	0.009	0.015	0.002	0.008	0.007	0.007
M2 (real)	0.012	0.016	0.017	0.023	0.008	0.021	0.021	0.019	0.005
MB	0.002	0.012	0.005	0.007	0.012	0.004	0.024	0.012	0.016
Reserves tot	0.002	0.006	0.019	0.016	0.006	0.027	0.041	0.002	0.023
Reserves nonbor	0.000	0.006	0.025	0.007	0.005	0.016	0.030	0.005	0.012
C&I loans	0.004	0.010	0.001	0.005	0.010	0.019	0.009	0.003	0.009
ΔC&I loans	0.005	0.008	0.002	0.005	0.023	0.030	0.011	0.008	0.011
Cons credit	0.006	0.005	0.017	0.010	0.001	0.008	0.003	0.005	0.006
Inst cred/PI	0.006	0.004	0.009	0.011	0.007	0.010	0.025	0.005	0.015
S&P 500	0.026	0.012	0.014	0.012	0.021	0.012	0.027	0.008	0.008
S&P: indust	0.025	0.010	0.010	0.011	0.022	0.014	0.024	0.007	0.008
S&P div yield	0.018	0.023	0.021	0.013	0.012	0.012	0.025	0.013	0.003
S&P PE ratio	0.016	0.008	0.006	0.016	0.016	0.053	0.007	0.010	0.003
Fed Funds	0.010	0.048	0.027	0.014	0.008	0.017	0.010	0.015	0.017
Comm paper	0.018	0.050	0.037	0.012	0.010	0.010	0.013	0.014	0.015
3 mo T-bill	0.014	0.050	0.034	0.008	0.012	0.015	0.015	0.004	0.014
6 mo T-bill	0.018	0.043	0.031	0.013	0.013	0.011	0.016	0.003	0.012
1 yr T-bond	0.020	0.047	0.024	0.012	0.011	0.012	0.016	0.006	0.011
5 yr T-bond	0.012	0.049	0.016	0.023	0.014	0.011	0.004	0.008	0.007
10 yr T-bond	0.005	0.028	0.013	0.024	0.016	0.007	0.004	0.008	0.004
Aaa bond	0.008	0.032	0.013	0.029	0.020	0.011	0.012	0.008	0.009
Baa bond	0.016	0.026	0.012	0.027	0.013	0.011	0.016	0.011	0.012
CP-FF spread	0.016	0.092	0.022	0.016	0.011	0.012	0.001	0.019	0.019
3 mo-FF spread	0.026	0.077	0.015	0.013	0.015	0.023	0.006	0.027	0.024
6 mo-FF spread	0.024	0.079	0.014	0.013	0.010	0.019	0.009	0.025	0.019
1 yr-FF spread	0.020	0.085	0.018	0.014	0.004	0.017	0.010	0.021	0.015
5 yr-FF spread	0.017	0.072	0.028	0.014	0.007	0.011	0.028	0.025	0.013
10 yr-FF spread	0.016	0.068	0.031	0.013	0.006	0.011	0.035	0.025	0.014
Aaa-FF spread	0.015	0.072	0.032	0.014	0.004	0.011	0.037	0.025	0.014
Baa-FF spread	0.011	0.072	0.030	0.013	0.006	0.011	0.044	0.024	0.016
Ex rate: avg	0.005	0.033	0.030	0.016	0.015	0.003	0.016	0.010	0.008
Ex rate: Switz	0.010	0.017	0.025	0.016	0.021	0.006	0.014	0.011	0.006
Ex rate: Japan	0.004	0.017	0.026	0.011	0.008	0.006	0.006	0.010	0.007
Ex rate: UK	0.002	0.020	0.030	0.004	0.009	0.013	0.011	0.009	0.012
EX rate: Canada	0.006	0.009	0.009	0.003	0.008	0.001	0.010	0.017	0.011
PPI: fin gds	0.002	0.002	0.009	0.009	0.005	0.016	0.013	0.014	0.008
PPI: cons gds	0.002	0.003	0.009	0.009	0.007	0.015	0.014	0.010	0.007
PPI: int mat'ls	0.004	0.008	0.006	0.015	0.020	0.017	0.012	0.011	0.011
PPI: crude mat'ls	0.003	0.003	0.007	0.005	0.008	0.018	0.017	0.024	0.008
Spot market price	0.005	0.007	0.008	0.011	0.007	0.012	0.006	0.024	0.015
Sens mat'ls price	0.009	0.010	0.017	0.023	0.010	0.034	0.004	0.020	0.025
NAPM com price	0.002	0.039	0.013	0.021	0.008	0.015	0.012	0.010	0.018
CPI-U: all	0.005	0.007	0.040	0.020	0.011	0.019	0.006	0.018	0.004
CPI-U: apparel	0.003	0.006	0.007	0.002	0.010	0.014	0.011	0.012	0.014
CPI-U: transp	0.007	0.008	0.028	0.010	0.012	0.024	0.019	0.008	0.006
CPI-U: medical	0.009	0.027	0.009	0.013	0.010	0.037	0.022	0.006	0.008
CPI-U: comm.	0.004	0.010	0.020	0.017	0.006	0.029	0.025	0.011	0.001
CPI-U: dbles	0.011	0.018	0.024	0.017	0.002	0.039	0.009	0.018	0.013
CPI-U: services	0.007	0.014	0.030	0.008	0.013	0.019	0.010	0.034	0.012
CPI-U: ex food	0.008	0.005	0.039	0.010	0.016	0.023	0.013	0.016	0.005
CPI-U: ex shelter	0.005	0.036	0.023	0.025	0.011	0.024	0.008	0.016	0.004

CPI-U: ex med	0.009	0.009	0.044	0.012	0.004	0.023	0.017	0.018	0.013
PCE defl	0.003	0.006	0.023	0.010	0.006	0.025	0.028	0.007	0.002
PCE defl: dlbes	0.002	0.010	0.009	0.006	0.016	0.017	0.012	0.002	0.003
PCE defl: nondble	0.002	0.013	0.016	0.016	0.003	0.022	0.019	0.008	0.004
PCE defl: service	0.002	0.003	0.017	0.018	0.002	0.012	0.042	0.000	0.006
AHE: goods	0.009	0.008	0.005	0.010	0.008	0.001	0.009	0.014	0.007
AHE: const	0.017	0.009	0.006	0.007	0.013	0.008	0.015	0.015	0.009
AHE: mfg	0.003	0.006	0.009	0.009	0.004	0.005	0.008	0.008	0.016
Consumer expect	0.014	0.013	0.008	0.005	0.009	0.014	0.008	0.005	0.019
Average marginal R^2	0.009	0.019	0.017	0.017	0.011	0.014	0.015	0.015	0.015
Total restricted R^2	0.569	0.228	0.199	0.325	0.217	0.085	0.077	0.154	0.064

Notes: Entries are the marginal R^2 from adding six lags of the row variable to the regression of $\hat{F}_{kt}$ (where k varies over the nine columns) on two lags of $\hat{F}_t$.

Table 4
Economic Significance of Restriction #5:
Marginal R^2s from adding $X_{jt-1},\ldots, X_{jt-6}$ to the regression of X_{it} on (*i*) six lags of X_{it} (first entry in each cell) and (*ii*) two lags of $\hat{F}_t$ and six lags of X_{it} (second entry)

Added regressor:	**IP: total**	**Emp: total**	**U: all**	**CPI-U: all**	**PCE defl**	**3 mo T-bill**	**10 yr T-bond**	**Average, all 131**
PI	0.02 0.01	0.01 0.00	0.04 0.01	0.02 0.00	0.02 0.00	0.03 0.01	0.02 0.01	0.007
PI less transfers	0.01 0.00	0.01 0.00	0.03 0.01	0.03 0.00	0.02 0.00	0.03 0.01	0.02 0.01	0.006
Consumption	0.05 0.00	0.04 0.01	0.08 0.00	0.05 0.04	0.04 0.02	0.04 0.02	0.05 0.03	0.009
M&T sales	0.04 0.02	0.02 0.02	0.10 0.01	0.06 0.02	0.04 0.02	0.04 0.01	0.04 0.02	0.012
Retail sales	0.04 0.01	0.02 0.01	0.06 0.00	0.05 0.02	0.04 0.02	0.02 0.01	0.03 0.02	0.009
IP: total	. .	0.05 0.01	0.11 0.02	0.03 0.01	0.02 0.01	0.03 0.01	0.02 0.01	0.008
IP: products	0.03 0.02	0.04 0.01	0.08 0.01	0.03 0.01	0.02 0.01	0.02 0.01	0.02 0.01	0.010
IP: final prod	0.03 0.02	0.03 0.01	0.07 0.01	0.03 0.01	0.02 0.01	0.02 0.00	0.02 0.01	0.009
IP: cons gds	0.02 0.01	0.03 0.01	0.06 0.01	0.02 0.02	0.01 0.01	0.00 0.01	0.02 0.02	0.009
IP: cons dble	0.01 0.02	0.03 0.01	0.07 0.01	0.03 0.01	0.02 0.01	0.01 0.01	0.01 0.02	0.009
IP: cons nondble	0.02 0.01	0.02 0.01	0.01 0.01	0.01 0.02	0.01 0.00	0.00 0.01	0.01 0.01	0.008
IP: bus eqpt	0.01 0.00	0.02 0.00	0.06 0.01	0.03 0.01	0.02 0.00	0.05 0.01	0.02 0.01	0.007
IP: matls	0.02 0.01	0.04 0.01	0.11 0.02	0.02 0.01	0.01 0.01	0.04 0.01	0.02 0.01	0.008
IP: dble matls	0.03 0.02	0.03 0.02	0.08 0.01	0.03 0.01	0.02 0.01	0.03 0.00	0.01 0.00	0.010
IP: nondble matls	0.04 0.02	0.04 0.02	0.07 0.01	0.03 0.02	0.02 0.01	0.03 0.02	0.01 0.01	0.009
IP: mfg	0.01 0.01	0.04 0.02	0.11 0.01	0.03 0.02	0.02 0.01	0.03 0.01	0.02 0.01	0.010
IP: res util	0.01 0.00	0.02 0.01	0.01 0.01	0.02 0.01	0.01 0.01	0.01 0.00	0.01 0.01	0.009
IP: fuels	0.01 0.01	0.00 0.01	0.02 0.02	0.00 0.00	0.00 0.01	0.01 0.01	0.02 0.01	0.008
NAPM prodn	0.11 0.04	0.05 0.00	0.11 0.01	0.05 0.03	0.02 0.01	0.05 0.00	0.00 0.01	0.011
Cap util	0.00 0.02	0.04 0.01	0.11 0.01	0.03 0.02	0.02 0.01	0.03 0.01	0.02 0.01	0.010
Help wanted indx	0.11 0.02	0.11 0.03	0.14 0.03	0.04 0.01	0.02 0.00	0.08 0.01	0.04 0.01	0.013
Help wanted/emp	0.07 0.01	0.07 0.01	0.05 0.01	0.04 0.01	0.02 0.00	0.06 0.02	0.03 0.02	0.010
Emp CPS total	0.03 0.01	0.01 0.00	0.01 0.02	0.03 0.00	0.02 0.00	0.04 0.01	0.01 0.00	0.008
Emp CPS nonag	0.02 0.01	0.01 0.00	0.01 0.01	0.03 0.01	0.02 0.01	0.04 0.00	0.01 0.00	0.007
U: all	0.04 0.01	0.04 0.01	. .	0.04 0.01	0.02 0.01	0.05 0.03	0.02 0.02	0.010
U: mean duration	0.01 0.00	0.01 0.00	0.02 0.01	0.01 0.00	0.01 0.00	0.01 0.00	0.00 0.01	0.007
U < 5 wks	0.02 0.01	0.04 0.01	0.02 0.01	0.03 0.01	0.03 0.02	0.02 0.01	0.01 0.01	0.009
U 5-14 wks	0.04 0.01	0.02 0.00	0.03 0.01	0.03 0.02	0.02 0.02	0.02 0.01	0.01 0.01	0.010
U 15+ wks	0.01 0.00	0.01 0.01	0.01 0.01	0.02 0.01	0.01 0.00	0.04 0.00	0.01 0.01	0.007
U 15-26 wks	0.01 0.00	0.00 0.01	0.01 0.01	0.01 0.01	0.01 0.01	0.03 0.00	0.01 0.01	0.007
U 27+ wks	0.01 0.00	0.01 0.01	0.02 0.01	0.02 0.00	0.01 0.00	0.03 0.01	0.01 0.01	0.007
UI claims	0.08 0.02	0.07 0.01	0.14 0.02	0.02 0.01	0.01 0.01	0.04 0.01	0.02 0.01	0.010
Emp: total	0.03 0.01	. .	0.12 0.02	0.04 0.02	0.02 0.01	0.06 0.00	0.02 0.01	0.009
Emp: gds prod	0.03 0.01	0.02 0.01	0.10 0.01	0.03 0.01	0.02 0.00	0.06 0.00	0.02 0.01	0.009
Emp: mining	0.03 0.03	0.02 0.01	0.02 0.02	0.01 0.01	0.01 0.01	0.02 0.01	0.03 0.02	0.009
Emp: const	0.02 0.00	0.02 0.00	0.03 0.01	0.01 0.01	0.01 0.01	0.03 0.00	0.01 0.00	0.007
Emp: mfg	0.03 0.01	0.03 0.01	0.09 0.02	0.03 0.01	0.02 0.01	0.06 0.00	0.02 0.01	0.010
Emp: dble gds	0.02 0.01	0.02 0.01	0.07 0.02	0.03 0.01	0.02 0.00	0.06 0.01	0.02 0.01	0.011
Emp: nondbles	0.05 0.02	0.04 0.04	0.06 0.01	0.03 0.01	0.03 0.01	0.03 0.00	0.01 0.01	0.011
Emp: services	0.01 0.01	0.01 0.01	0.04 0.01	0.03 0.01	0.02 0.01	0.04 0.01	0.01 0.01	0.009
Emp: TTU	0.04 0.02	0.01 0.01	0.08 0.02	0.03 0.01	0.02 0.01	0.05 0.01	0.01 0.00	0.009
Emp: wholesale	0.04 0.01	0.02 0.01	0.03 0.02	0.04 0.01	0.02 0.01	0.08 0.01	0.03 0.01	0.010
Emp: retail	0.03 0.02	0.01 0.01	0.05 0.02	0.02 0.01	0.01 0.01	0.03 0.01	0.01 0.01	0.008
Emp: FIRE	0.01 0.01	0.02 0.02	0.02 0.01	0.02 0.01	0.01 0.01	0.02 0.01	0.01 0.01	0.009
Emp: Govt	0.01 0.01	0.01 0.00	0.02 0.01	0.01 0.01	0.01 0.00	0.01 0.00	0.02 0.01	0.007
Emp-hrs nonag	0.00 0.01	0.00 0.01	0.04 0.01	0.03 0.01	0.02 0.01	0.05 0.02	0.02 0.01	0.009
Avg hrs	0.01 0.01	0.00 0.01	0.02 0.02	0.02 0.01	0.01 0.01	0.02 0.02	0.01 0.01	0.009
Overtime: mfg	0.02 0.00	0.03 0.00	0.04 0.00	0.02 0.00	0.01 0.00	0.02 0.01	0.01 0.01	0.007
Avg hrs: mfg	0.02 0.02	0.00 0.01	0.03 0.01	0.02 0.01	0.02 0.01	0.02 0.02	0.01 0.01	0.009
NAPM empl	0.05 0.01	0.03 0.00	0.07 0.01	0.05 0.01	0.03 0.01	0.09 0.02	0.03 0.02	0.011
Starts: nonfarm	0.06 0.01	0.04 0.01	0.08 0.01	0.03 0.01	0.02 0.01	0.04 0.02	0.03 0.02	0.012
Starts: NE	0.02 0.01	0.01 0.01	0.02 0.00	0.02 0.01	0.02 0.01	0.02 0.01	0.01 0.01	0.008
Starts: MW	0.02 0.01	0.01 0.01	0.03 0.00	0.03 0.01	0.02 0.01	0.03 0.01	0.01 0.01	0.009
Starts: South	0.05 0.01	0.04 0.01	0.08 0.01	0.03 0.02	0.01 0.01	0.04 0.02	0.02 0.02	0.011
Starts: West	0.05 0.01	0.04 0.01	0.06 0.01	0.02 0.01	0.02 0.01	0.04 0.01	0.01 0.01	0.010

BP: total	0.08	0.02	0.05	0.01	0.09	0.01	0.03	0.01	0.02	0.01	0.03	0.01	0.03	0.01	0.012
BP: NE	0.06	0.01	0.06	0.00	0.07	0.00	0.03	0.01	0.02	0.00	0.02	0.01	0.01	0.01	0.009
BP: MW	0.08	0.01	0.07	0.01	0.09	0.00	0.03	0.00	0.02	0.01	0.05	0.01	0.03	0.01	0.008
BP: South	0.11	0.02	0.11	0.02	0.14	0.02	0.04	0.01	0.02	0.01	0.03	0.01	0.03	0.01	0.012
BP: West	0.10	0.02	0.09	0.01	0.11	0.01	0.04	0.02	0.02	0.00	0.03	0.01	0.02	0.01	0.011
PMI	0.13	0.04	0.06	0.00	0.12	0.01	0.05	0.02	0.03	0.02	0.07	0.01	0.02	0.01	0.012
NAPM new ordrs	0.14	0.04	0.06	0.00	0.13	0.01	0.04	0.02	0.02	0.01	0.06	0.01	0.02	0.01	0.012
NAPM vendor del	0.08	0.03	0.06	0.02	0.06	0.01	0.03	0.01	0.03	0.02	0.04	0.01	0.02	0.02	0.013
NAPM Invent	0.02	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.02	0.01	0.03	0.01	0.01	0.01	0.009
Orders: cons gds	0.05	0.01	0.04	0.01	0.10	0.01	0.05	0.02	0.03	0.01	0.04	0.02	0.03	0.04	0.009
Orders: dble gds	0.04	0.01	0.04	0.01	0.09	0.02	0.05	0.02	0.03	0.01	0.04	0.01	0.04	0.03	0.009
Orders: cap gds	0.03	0.01	0.03	0.02	0.03	0.01	0.02	0.01	0.01	0.00	0.04	0.01	0.02	0.00	0.007
Unf orders: dble	0.05	0.01	0.03	0.00	0.04	0.02	0.02	0.01	0.02	0.01	0.04	0.01	0.02	0.02	0.008
M&T invent	0.04	0.01	0.02	0.01	0.02	0.00	0.02	0.02	0.02	0.01	0.02	0.01	0.00	0.00	0.010
M&T invent/sales	0.06	0.01	0.04	0.01	0.10	0.01	0.05	0.03	0.03	0.01	0.03	0.01	0.04	0.02	0.010
M1	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.03	0.01	0.02	0.01	0.007
M2	0.00	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.02	0.02	0.008
M3	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.02	0.01	0.007
M2 (real)	0.05	0.02	0.03	0.00	0.03	0.00	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.011
MB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.007
Reserves tot	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.04	0.01	0.00	0.01	0.01	0.01	0.010
Reserves nonbor	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.03	0.01	0.00	0.02	0.02	0.02	0.008
C&I loans	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.006
∆C&I loans	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.01	0.01	0.007
Cons credit	0.01	0.01	0.00	0.00	0.03	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.01	0.006
Inst cred/PI	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.02	0.01	0.007
S&P 500	0.06	0.03	0.04	0.02	0.05	0.01	0.01	0.01	0.02	0.01	0.03	0.01	0.03	0.01	0.012
S&P: indust	0.06	0.03	0.04	0.02	0.05	0.01	0.01	0.00	0.02	0.01	0.03	0.01	0.03	0.01	0.011
S&P div yield	0.07	0.02	0.05	0.01	0.06	0.02	0.02	0.01	0.02	0.02	0.04	0.03	0.03	0.01	0.012
S&P PE ratio	0.05	0.03	0.02	0.01	0.04	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.009
Fed Funds	0.02	0.01	0.01	0.01	0.01	0.01	0.06	0.04	0.02	0.02	0.02	0.03	0.03	0.02	0.013
Comm paper	0.03	0.02	0.02	0.01	0.01	0.01	0.05	0.04	0.01	0.01	0.01	0.01	0.07	0.06	0.014
3 mo T-bill	0.03	0.02	0.02	0.01	0.01	0.02	0.05	0.04	0.01	0.01	.	.	0.06	0.06	0.013
6 mo T-bill	0.04	0.02	0.02	0.01	0.02	0.02	0.06	0.03	0.01	0.01	0.04	0.02	0.05	0.05	0.013
1 yr T-bond	0.04	0.02	0.02	0.01	0.02	0.01	0.06	0.03	0.01	0.01	0.07	0.03	0.06	0.05	0.014
5 yr T-bond	0.03	0.02	0.02	0.01	0.02	0.01	0.06	0.03	0.02	0.02	0.06	0.03	0.02	0.02	0.011
10 yr T-bond	0.03	0.01	0.02	0.01	0.03	0.01	0.05	0.03	0.02	0.01	0.05	0.02	.	.	0.009
Aaa bond	0.05	0.01	0.03	0.00	0.04	0.01	0.05	0.03	0.02	0.01	0.04	0.02	0.01	0.01	0.010
Baa bond	0.05	0.01	0.03	0.01	0.04	0.01	0.04	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.011
CP-FF spread	0.03	0.03	0.01	0.00	0.03	0.02	0.02	0.03	0.02	0.02	0.04	0.05	0.06	0.06	0.014
3 mo-FF spread	0.06	0.04	0.03	0.01	0.07	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.02	0.03	0.017
6 mo-FF spread	0.06	0.04	0.03	0.01	0.07	0.03	0.03	0.03	0.02	0.02	0.01	0.03	0.03	0.04	0.017
1 yr-FF spread	0.05	0.02	0.03	0.01	0.07	0.03	0.02	0.04	0.01	0.02	0.01	0.03	0.04	0.07	0.016
5 yr-FF spread	0.04	0.02	0.02	0.00	0.06	0.02	0.03	0.04	0.01	0.02	0.01	0.03	0.04	0.06	0.016
10 yr-FF spread	0.04	0.02	0.03	0.01	0.06	0.02	0.04	0.04	0.01	0.02	0.01	0.03	0.03	0.05	0.016
Aaa-FF spread	0.03	0.02	0.02	0.01	0.05	0.02	0.05	0.04	0.02	0.02	0.01	0.03	0.03	0.04	0.015
Baa-FF spread	0.03	0.01	0.02	0.00	0.05	0.03	0.05	0.04	0.02	0.02	0.01	0.04	0.03	0.04	0.015
Ex rate: avg	0.01	0.01	0.01	0.01	0.02	0.01	0.03	0.03	0.01	0.02	0.03	0.01	0.03	0.01	0.009
Ex rate: Switz	0.01	0.02	0.01	0.01	0.02	0.02	0.03	0.02	0.01	0.02	0.01	0.01	0.02	0.02	0.009
Ex rate: Japan	0.01	0.00	0.01	0.00	0.02	0.01	0.03	0.03	0.01	0.02	0.02	0.01	0.01	0.00	0.008
Ex rate: UK	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.007
EX rate: Canada	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.006
PPI: fin gds	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.01	0.05	0.01	0.01	0.00	0.00	0.01	0.006
PPI: cons gds	0.00	0.00	0.00	0.00	0.02	0.01	0.02	0.01	0.05	0.01	0.02	0.01	0.00	0.01	0.007
PPI: int mat'ls	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.03	0.01	0.03	0.01	0.01	0.01	0.008
PPI: crude mat'ls	0.00	0.00	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.007
Spot market price	0.02	0.01	0.01	0.00	0.02	0.01	0.02	0.01	0.01	0.01	0.03	0.01	0.01	0.00	0.007
Sens mat'ls price	0.04	0.01	0.03	0.01	0.04	0.00	0.03	0.01	0.02	0.01	0.03	0.00	0.02	0.01	0.009
NAPM com price	0.02	0.01	0.01	0.00	0.02	0.00	0.02	0.01	0.02	0.01	0.05	0.03	0.04	0.03	0.009
CPI-U: all	0.01	0.00	0.01	0.00	0.02	0.01	.	.	0.03	0.01	0.05	0.04	0.02	0.02	0.009
CPI-U: apparel	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.006
CPI-U: transp	0.01	0.01	0.01	0.01	0.01	0.00	0.03	0.01	0.03	0.01	0.01	0.01	0.03	0.02	0.008
CPI-U: medical	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.00	0.01	0.01	0.009
CPI-U: comm.	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.04	0.01	0.02	0.02	0.02	0.01	0.008
CPI-U: dbles	0.02	0.01	0.02	0.01	0.03	0.01	0.05	0.04	0.03	0.02	0.02	0.01	0.04	0.04	0.010
CPI-U: services	0.02	0.01	0.01	0.00	0.03	0.01	0.01	0.02	0.01	0.01	0.03	0.02	0.01	0.01	0.010

CPI-U: ex food	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.03	0.02	0.009
CPI-U: ex shelter	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.04	0.02	0.02	0.02	0.02	0.02	0.009
CPI-U: ex med	0.01	0.01	0.02	0.01	0.03	0.02	0.03	0.03	0.03	0.01	0.04	0.04	0.02	0.02	0.010
PCE defl	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.00	.	.	0.02	0.01	0.03	0.02	0.009
PCE defl: dlbes	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.006
PCE defl: nondble	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.04	0.01	0.01	0.01	0.01	0.01	0.007
PCE defl: service	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.04	0.01	0.00	0.01	0.02	0.02	0.008
AHE: goods	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.02	0.01	0.02	0.01	0.007
AHE: const	0.02	0.03	0.03	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.009
AHE: mfg	0.01	0.00	0.01	0.00	0.02	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.006
Consumer expect	0.05	0.01	0.03	0.01	0.03	0.01	0.01	0.00	0.01	0.00	0.02	0.01	0.01	0.00	0.008

Notes: The entries are marginal R^2s from adding six lags of the row variable to a regression of the column variable on six of its lags (first entry in a cell) or, additionally, two lags of $\hat{F}_t$ (second entry). The final column is the average marginal R^2 from adding the row variable X_j to the other 131 regressions of X_{jt} on six of its lags and two lags of $\hat{F}_t$.

Table 5
Estimation of the Number of Dynamic Factors q^S Among the Slow-Moving Variables

# dynamic factors (*q*)	1	2	3	4	5	6	7	8	9	10
1	**-0.542**	-0.553	-0.558	-0.566	-0.577	-0.583	-0.587	-0.594	-0.598	-0.606
2	.	**-0.621**	-0.627	-0.636	-0.648	-0.654	-0.658	-0.664	-0.668	-0.674
3	.	.	**-0.636**	-0.645	-0.662	-0.668	-0.672	-0.678	-0.681	-0.687
4	.	.	.	**-0.645**	**-0.663**	**-0.670**	**-0.674**	**-0.680**	**-0.685**	**-0.691**
5	.	.	.	.	-0.659	-0.667	-0.672	-0.678	-0.683	-0.689
6	.	.	.	.	.	-0.661	-0.666	-0.672	-0.677	-0.683
7	.	.	.	.	.	.	-0.660	-0.666	-0.671	-0.678
8	.	.	.	.	.	.	.	-0.654	-0.659	-0.666
9	.	.	.	.	.	.	.	.	-0.650	-0.657
10	.	.	.	.	.	.	.	.	.	-0.644

Notes: Entries are the Bai-Ng (2002) IC_{p2} information criterion, computed using the slow-moving variables (listed in the Appendix). See the notes to Table 1.

Table 6. Effect of the monetary policy shock:
Impulse responses and forecast error variance decompositions for all variables

Variable	Impulse response at horizon:					Percent of forecast error variance explained at horizon:				
	0	6	12	24	36	0	6	12	24	36
Fed Funds	**1.0**	**0.8**	**0.8**	**0.8**	**0.8**	**22.9%**	**21.7%**	**14.9%**	**10.9%**	**9.6%**
PI	0.2	0.1	0.0	0.0	0.0	0.5	0.4	0.2	0.1	0.1
PI less transfers	0.2	0.0	-0.1	-0.1	-0.1	0.5	0.4	0.2	0.1	0.1
Consumption	-0.4	-0.8	-0.8	-0.8	-0.8	4.1	12.9	15.3	16.7	17.2
M&T sales	-0.7	-1.5	-1.7	-1.6	-1.6	3.0	7.1	8.8	9.8	10.1
Retail sales	-1.3	-1.9	-1.8	-1.8	-1.8	6.8	17.3	20.2	22.1	22.8
IP: total	0.1	-0.4	-0.7	-0.8	-0.8	0.0	0.3	0.8	1.2	1.3
IP: products	0.0	-0.4	-0.7	-0.7	-0.7	0.0	0.4	0.9	1.3	1.4
IP: final prod	0.0	-0.4	-0.6	-0.6	-0.6	0.0	0.3	0.8	1.2	1.3
IP: cons gds	-0.3	-0.7	-0.7	-0.7	-0.7	0.7	1.2	2.1	2.6	2.7
IP: cons dble	-0.6	-1.6	-1.7	-1.6	-1.6	0.4	1.0	1.9	2.3	2.4
IP: cons nondble	-0.2	-0.3	-0.3	-0.3	-0.3	0.3	0.5	1.0	1.3	1.4
IP: bus eqpt	0.1	-0.1	-0.7	-0.9	-1.0	0.1	0.2	0.2	0.5	0.6
IP: matls	0.1	-0.5	-0.9	-0.9	-0.9	0.1	0.3	0.7	1.1	1.1
IP: dble matls	0.1	-0.7	-1.2	-1.3	-1.3	0.0	0.2	0.6	0.9	1.0
IP: nondble matls	0.1	-0.6	-0.8	-0.8	-0.8	0.0	0.4	1.0	1.4	1.5
IP: mfg	0.0	-0.6	-0.9	-0.9	-0.9	0.0	0.4	1.0	1.5	1.6
IP: res util	0.6	0.4	0.5	0.5	0.5	0.3	0.6	0.6	0.6	0.6
IP: fuels	-0.8	-1.0	-1.0	-0.9	-0.9	1.2	2.6	3.2	3.4	3.6
NAPM prodn	1.2	-1.8	-0.7	-0.1	0.0	0.8	1.8	2.6	2.6	2.6
Cap util	0.0	-0.5	-0.8	-0.8	-0.8	0.0	0.5	1.3	1.7	1.9
Help wanted indx	0.1	-2.5	-3.5	-3.7	-3.7	0.0	2.4	3.9	4.8	5.0
Help wanted/emp	0.0	-0.1	-0.1	-0.1	-0.1	0.0	2.3	3.6	4.4	4.6
Emp CPS total	0.1	-0.1	-0.2	-0.2	-0.2	1.3	0.4	0.5	0.8	0.9
Emp CPS nonag	0.1	0.0	-0.1	-0.2	-0.2	1.6	0.5	0.5	0.6	0.7
U: all	-0.1	0.1	0.2	0.2	0.2	1.4	0.3	0.9	1.4	1.5
U: mean duration	0.1	0.1	0.3	0.3	0.3	0.2	0.2	0.5	1.1	1.3
U < 5 wks	-1.8	0.8	1.0	1.0	1.0	1.1	0.6	0.7	0.7	0.7
U 5-14 wks	-0.7	2.2	3.1	3.2	3.2	0.1	0.5	1.2	1.7	1.8
U 15+ wks	0.5	3.1	6.1	6.6	6.6	0.1	0.5	1.3	2.0	2.2
U 15-26 wks	1.1	3.3	5.5	5.7	5.7	0.1	0.5	1.4	2.0	2.2
U 27+ wks	-0.3	2.5	6.3	7.3	7.2	0.0	0.2	0.8	1.4	1.6
UI claims	0.6	5.1	5.4	5.2	5.2	0.1	2.9	4.2	4.9	5.1
Emp: total	0.0	-0.2	-0.4	-0.4	-0.5	0.0	0.3	1.0	1.6	1.8
Emp: gds prod	0.1	-0.1	-0.5	-0.6	-0.6	0.2	0.2	0.5	1.0	1.1
Emp: mining	0.3	0.7	0.6	0.6	0.6	0.1	0.8	0.7	0.6	0.5
Emp: const	-0.2	-0.7	-1.1	-1.2	-1.2	0.3	1.1	2.0	2.8	3.0
Emp: mfg	0.1	0.0	-0.3	-0.4	-0.4	0.8	0.4	0.3	0.5	0.6
Emp: dble gds	0.2	0.1	-0.3	-0.5	-0.5	1.0	0.5	0.2	0.3	0.4
Emp: nondbles	0.0	-0.1	-0.3	-0.4	-0.4	0.0	0.1	0.7	1.2	1.3
Emp: services	0.0	-0.1	-0.2	-0.3	-0.3	0.1	0.3	0.9	1.6	1.8
Emp: TTU	0.0	-0.2	-0.4	-0.5	-0.5	0.0	0.7	1.6	2.3	2.6
Emp: wholesale	0.1	0.0	-0.1	-0.3	-0.3	1.0	0.3	0.2	0.4	0.6
Emp: retail	0.0	-0.3	-0.4	-0.5	-0.5	0.0	1.1	2.1	2.9	3.2
Emp: FIRE	0.0	-0.1	-0.2	-0.3	-0.3	0.0	0.2	0.4	0.7	0.9
Emp: Govt	0.0	0.3	0.3	0.4	0.4	0.1	1.7	2.0	2.1	2.0
Emp-hrs nonag	0.0	-0.1	-0.3	-0.3	-0.3	0.0	0.3	0.5	0.8	0.9
Avg hrs	0.0	-0.1	-0.1	0.0	0.0	0.1	0.5	0.8	1.1	1.1
Overtime: mfg	0.0	0.0	0.0	0.0	0.0	0.7	0.5	0.4	0.4	0.4
Avg hrs: mfg	0.0	-0.1	-0.1	0.0	0.0	0.0	0.4	0.6	0.8	0.8
NAPM empl	1.8	-0.7	-0.6	-0.1	0.0	3.0	1.2	1.4	1.5	1.5
Starts: nonfarm	-4.9	-6.9	-5.0	-2.8	-1.6	2.6	9.6	11.4	12.2	12.4
Starts: NE	-7.7	-5.3	-4.3	-3.2	-2.5	1.4	2.9	3.5	3.8	4.0
Starts: MW	-5.5	-6.0	-4.5	-2.5	-1.5	0.9	3.7	4.7	5.2	5.3
Starts: South	-3.5	-6.0	-4.5	-2.8	-1.8	0.9	5.7	7.1	7.6	7.8
Starts: West	-5.0	-7.5	-5.8	-3.6	-2.3	1.2	5.9	7.1	7.6	7.7
BP: total	-5.1	-8.7	-6.5	-4.0	-2.6	4.3	14.8	16.8	17.4	17.5

BP: NE	-5.3	-6.0	-5.1	-3.9	-3.0	1.4	4.8	5.9	6.6	6.9
BP: MW	-9.5	-10.2	-7.8	-5.0	-3.3	5.1	14.1	16.0	16.9	17.1
BP: South	-3.3	-7.5	-6.1	-4.5	-3.6	1.2	7.6	8.8	8.9	8.9
BP: West	-5.2	-8.8	-6.8	-4.5	-3.2	2.2	9.4	10.6	10.9	10.9
PMI	1.0	-1.7	-1.0	-0.2	-0.1	1.1	1.7	2.6	2.8	2.8
NAPM new ordrs	1.0	-2.0	-0.9	-0.2	0.0	0.4	2.5	3.3	3.4	3.4
NAPM vendor del	0.3	-2.0	-1.7	-0.4	-0.1	0.1	1.0	1.9	2.3	2.3
NAPM Invent	1.1	-0.2	-0.5	-0.1	0.0	0.8	0.7	0.7	0.8	0.8
Orders: cons gds	-0.6	-2.3	-2.3	-2.2	-2.2	0.7	4.1	5.5	6.3	6.6
Orders: dble gds	-1.0	-3.0	-3.1	-3.1	-3.1	0.7	3.9	5.3	6.1	6.3
Orders: cap gds	-0.5	-2.1	-2.5	-2.5	-2.5	0.0	0.9	1.7	2.3	2.5
Unf orders: dble	-0.2	-1.8	-3.0	-4.1	-4.4	0.6	3.1	4.4	5.5	5.8
M&T invent	0.1	0.5	0.4	0.3	0.3	0.3	3.4	2.2	1.1	0.8
M&T invent/sales	0.0	0.0	0.0	0.0	0.0	3.4	10.6	13.1	14.5	15.0
M1	-3.2	-2.1	-2.2	-2.3	-2.3	1.8	8.6	9.1	9.2	9.2
M2	-2.7	-1.7	-1.7	-1.8	-1.8	5.2	14.2	13.2	12.1	11.7
M3	-1.9	-1.4	-1.3	-1.3	-1.3	2.1	7.2	7.1	6.9	6.8
M2 (real)	-0.2	-1.1	-1.5	-1.8	-2.0	3.9	10.7	9.2	7.6	6.9
MB	-0.8	-0.7	-0.7	-0.7	-0.7	0.2	1.7	1.7	1.6	1.6
Reserves tot	-0.6	-1.1	-0.9	-0.8	-0.8	0.0	0.3	0.3	0.2	0.2
Reserves nonbor	-24.5	-6.8	-7.3	-7.5	-7.5	3.5	4.8	4.6	4.4	4.3
C&I loans	1.8	-0.7	-1.0	-1.0	-1.0	0.1	0.1	0.1	0.2	0.2
∆C&I loans	14.3	1.2	-0.8	-0.4	-0.1	0.3	0.3	0.3	0.3	0.3
Cons credit	-1.4	-1.7	-1.8	-1.8	-1.8	0.3	1.8	2.6	3.3	3.6
Inst cred/PI	0.0	-0.2	-0.2	-0.3	-0.3	1.5	5.2	6.4	7.4	7.8
S&P 500	-1.9	-5.6	-5.3	-5.1	-5.1	2.0	7.5	8.1	8.1	8.1
S&P: indust	-1.6	-5.5	-5.2	-5.1	-5.1	1.4	6.8	7.5	7.6	7.6
S&P div yield	0.1	0.2	0.2	0.2	0.2	3.8	10.2	10.4	10.0	9.8
S&P PE ratio	-2.4	-7.0	-6.5	-6.1	-6.1	1.6	6.2	6.1	5.5	5.2
Comm paper	1.3	1.1	1.1	1.0	1.0	45.4	36.3	27.4	22.1	20.2
3 mo T-bill	1.1	1.0	0.9	0.9	0.9	47.1	32.3	24.7	20.2	18.7
6 mo T-bill	1.1	1.0	0.9	0.9	0.9	56.0	35.0	26.8	22.1	20.5
1 yr T-bond	1.2	1.1	1.0	1.0	1.0	60.7	36.4	28.5	23.9	22.3
5 yr T-bond	0.9	0.9	0.8	0.8	0.8	50.1	31.0	26.6	24.2	23.3
10 yr T-bond	0.7	0.7	0.7	0.7	0.7	41.5	26.8	23.7	22.2	21.7
Aaa bond	0.5	0.6	0.6	0.6	0.6	38.1	29.0	26.7	25.3	24.8
Baa bond	0.4	0.7	0.7	0.7	0.7	33.7	29.7	28.4	27.6	27.3
CP-FF spread	0.2	0.1	0.1	0.1	0.0	4.5	4.2	4.3	4.6	4.7
3 mo-FF spread	0.1	0.0	0.0	0.0	0.0	0.4	1.3	0.8	0.5	0.4
6 mo-FF spread	0.1	0.0	0.0	0.0	0.0	0.4	1.5	0.9	0.6	0.5
1 yr-FF spread	0.2	0.0	0.0	0.0	0.0	1.2	1.3	0.9	0.6	0.6
5 yr-FF spread	-0.2	-0.2	-0.1	-0.1	-0.1	0.8	5.3	3.6	2.6	2.3
10 yr-FF spread	-0.4	-0.3	-0.2	-0.2	-0.1	2.9	8.2	5.6	3.9	3.5
Aaa-FF spread	-0.5	-0.4	-0.3	-0.2	-0.1	6.4	10.5	6.9	5.0	4.4
Baa-FF spread	-0.6	-0.4	-0.3	-0.2	-0.1	8.5	10.6	6.7	4.8	4.3
Ex rate: avg	1.7	2.7	2.8	2.8	2.8	7.8	7.5	7.8	8.1	8.2
Ex rate: Switz	2.7	3.6	3.8	3.8	3.8	7.2	5.5	5.4	5.5	5.5
Ex rate: Japan	1.9	3.0	3.1	3.0	3.0	4.1	3.7	4.2	4.5	4.6
Ex rate: UK	-1.5	-1.9	-2.0	-1.9	-1.9	3.2	2.3	2.3	2.3	2.3
EX rate: Canada	0.6	1.3	1.4	1.4	1.4	2.7	5.2	5.4	5.5	5.6
PPI: fin gds	-1.7	-1.7	-1.8	-1.8	-1.8	0.6	2.7	4.1	5.4	6.1
PPI: cons gds	-2.8	-2.3	-2.4	-2.4	-2.4	1.0	3.6	5.2	6.8	7.6
PPI: int mat'ls	-1.7	-2.8	-2.9	-2.9	-2.9	0.5	3.9	5.7	7.3	7.9
PPI: crude mat'ls	-15.4	-10.2	-10.0	-10.1	-10.1	1.1	3.2	4.3	5.4	6.0
Spot market price	0.6	-4.9	-5.6	-5.9	-6.0	0.0	1.9	2.5	2.9	3.2
Sens mat'ls price	-0.9	-6.5	-6.5	-6.5	-6.5	0.0	4.5	5.6	6.4	6.8
NAPM com price	0.9	-1.3	-1.5	-0.7	-0.3	0.3	0.3	0.7	0.9	1.0
CPI-U: all	0.3	-0.2	-0.2	-0.2	-0.2	0.1	0.3	0.3	0.4	0.4
CPI-U: apparel	0.8	0.2	0.1	0.0	0.0	0.2	0.2	0.2	0.1	0.1
CPI-U: transp	-1.6	-1.7	-1.7	-1.7	-1.7	0.3	1.0	1.5	2.0	2.3
CPI-U: medical	0.2	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.1
CPI-U: comm.	-0.3	-0.7	-0.8	-0.8	-0.8	0.0	0.7	1.1	1.6	1.9
CPI-U: dbles	1.7	0.4	0.6	0.6	0.6	1.7	2.5	2.4	2.3	2.3
CPI-U: services	0.6	0.2	0.2	0.2	0.2	0.3	1.1	0.9	0.7	0.6
CPI-U: ex food	0.3	-0.1	-0.2	-0.2	-0.2	0.1	0.2	0.2	0.3	0.3
CPI-U: ex shelter	-0.1	-0.5	-0.5	-0.5	-0.5	0.0	0.4	0.8	1.1	1.3

CPI-U: ex med	0.1	-0.3	-0.3	-0.3	-0.3	0.0	0.2	0.4	0.5	0.6
PCE defl	0.0	-0.2	-0.3	-0.3	-0.3	0.0	0.4	0.7	1.0	1.2
PCE defl: dlbes	1.5	0.5	0.4	0.4	0.4	1.4	1.6	1.5	1.4	1.3
PCE defl: nondble	-0.9	-1.0	-1.0	-1.0	-1.0	0.3	1.3	2.1	2.9	3.2
PCE defl: service	0.3	0.1	0.1	0.1	0.1	0.2	0.3	0.3	0.3	0.3
AHE: goods	1.2	0.3	0.3	0.3	0.3	0.8	0.8	0.7	0.7	0.7
AHE: const	1.7	0.4	0.3	0.3	0.3	0.4	0.5	0.5	0.5	0.5
AHE: mfg	1.8	0.3	0.3	0.3	0.3	1.1	1.0	0.9	0.9	0.9
Consumer expect	1.6	-0.3	0.3	0.3	0.3	1.1	0.3	0.2	0.1	0.1

Notes: Estimated using the structural FAVAR with Bernanke-Boivin-Eliasz (2005) identification of the monetary policy shock. The model has 9 static factors, 4 slow-moving dynamic factors, a VAR(2) specification for F_t, and 6 lags in D(L).

Table 7
Sensitivity of Structural FAVAR Results to Including an Observed Factor:
Impulse responses and forecast error variance decompositions at the 24-month horizon
when an observable variable is added to the X_t and F_t equations.

Additional Predictor Variable	Impulse response, and percent of forecast error explained, for the variable:							
	FedFunds	IP: total	Emp: total	U: all	CPI-U: all	PCE defl	3 mo T-bill	10 yr T-bond
None	**0.7 10.5**	**-0.8 1.3**	**-0.5 1.7**	**0.2 1.5**	**-0.2 0.4**	**-0.3 1.0**	**0.9 19.9**	**0.7 22.4**
S&P 500	0.8 10.4	-0.8 1.2	-0.5 1.9	0.2 1.7	-0.2 0.4	-0.2 0.7	0.9 20.6	0.7 22.7
Ex rate: avg	0.7 9.4	-0.8 1.2	-0.4 1.5	0.2 1.4	-0.3 0.6	-0.3 1.2	0.8 19.0	0.7 24.0
M2 (real)	0.8 10.5	-0.8 1.2	-0.4 1.4	0.2 1.7	-0.3 0.7	-0.4 1.5	0.9 19.1	0.7 22.8
Spot market price	0.7 9.9	-0.8 1.2	-0.5 1.8	0.2 1.8	-0.3 0.5	-0.3 0.9	0.9 20.1	0.7 22.9
10 yr-FF spread	1.0 13.5	-0.9 1.2	-0.5 1.4	0.2 2.3	-0.3 0.4	-0.3 0.7	0.9 22.2	0.8 23.2
Consumption	0.8 11.0	-0.8 1.2	-0.4 1.4	0.2 1.8	-0.3 0.8	-0.3 1.5	0.8 18.5	0.7 22.2
IP: total	0.8 11.6	. .	-0.5 1.7	0.2 1.5	-0.2 0.4	-0.3 1.2	0.9 20.2	0.7 21.7
Emp: total	0.8 11.8	-0.8 1.3	. .	0.1 1.2	-0.3 0.6	-0.4 1.5	0.8 19.5	0.6 19.4
U: all	0.8 10.9	-0.8 1.3	-0.5 1.7	. .	-0.3 0.5	-0.3 1.2	0.8 19.4	0.7 20.4
CPI-U: all	0.8 10.8	-0.8 1.3	-0.5 1.7	0.2 1.6	. .	-0.3 0.9	0.9 21.0	0.7 21.6
PCE defl	0.7 10.4	-0.8 1.3	-0.5 1.8	0.2 1.5	-0.2 0.4	. .	0.9 20.6	0.7 22.6
3 mo T-bill	1.0 13.8	-0.9 1.4	-0.5 1.6	0.2 1.7	0.0 0.4	-0.3 0.6	. .	0.8 24.8
10 yr T-bond	0.9 11.9	-0.9 1.2	-0.5 1.7	0.2 1.9	-0.3 0.5	-0.4 1.2	1.0 20.1	. .

Notes: Entries in each cell are (first) the 24-month impulse response to, and (second) the fraction of the forecast error variance explained by, the monetary policy shock, when the row variable is treated as an observable factor (so the number of static factors increases from 9 to 10). All other aspects of the model are the same as for Table 6. Results for the benchmark model with the DFM restrictions imposed are shown for comparison purposes in the first line.

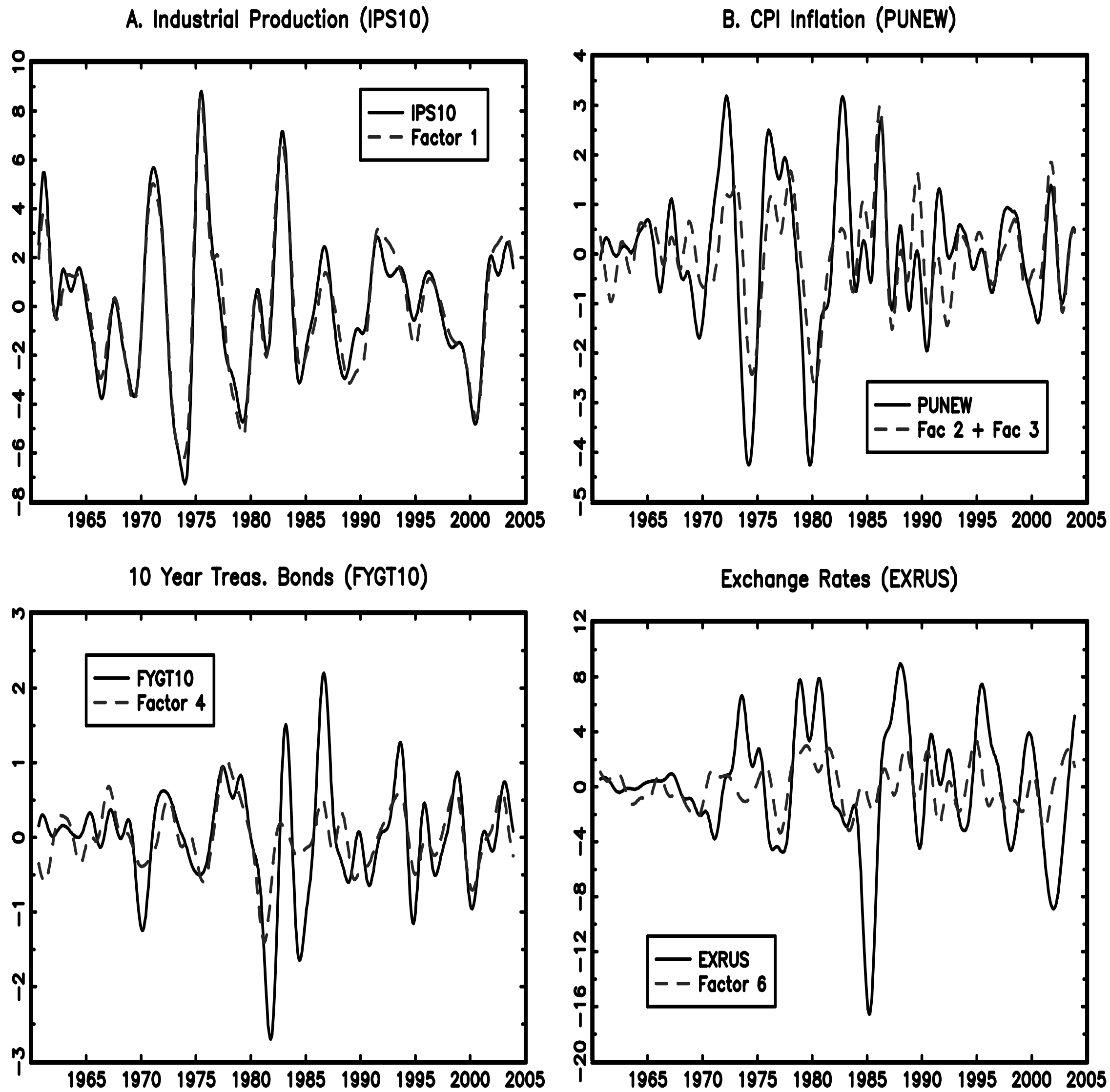

Figure 1. Business cycle components, and the part explained by the indicated factors, of (a) industrial production; (b) total CPI inflation; (c) the 10-year Treasury bond rate; and (d) the trade-weighted US v. world exchange rate.

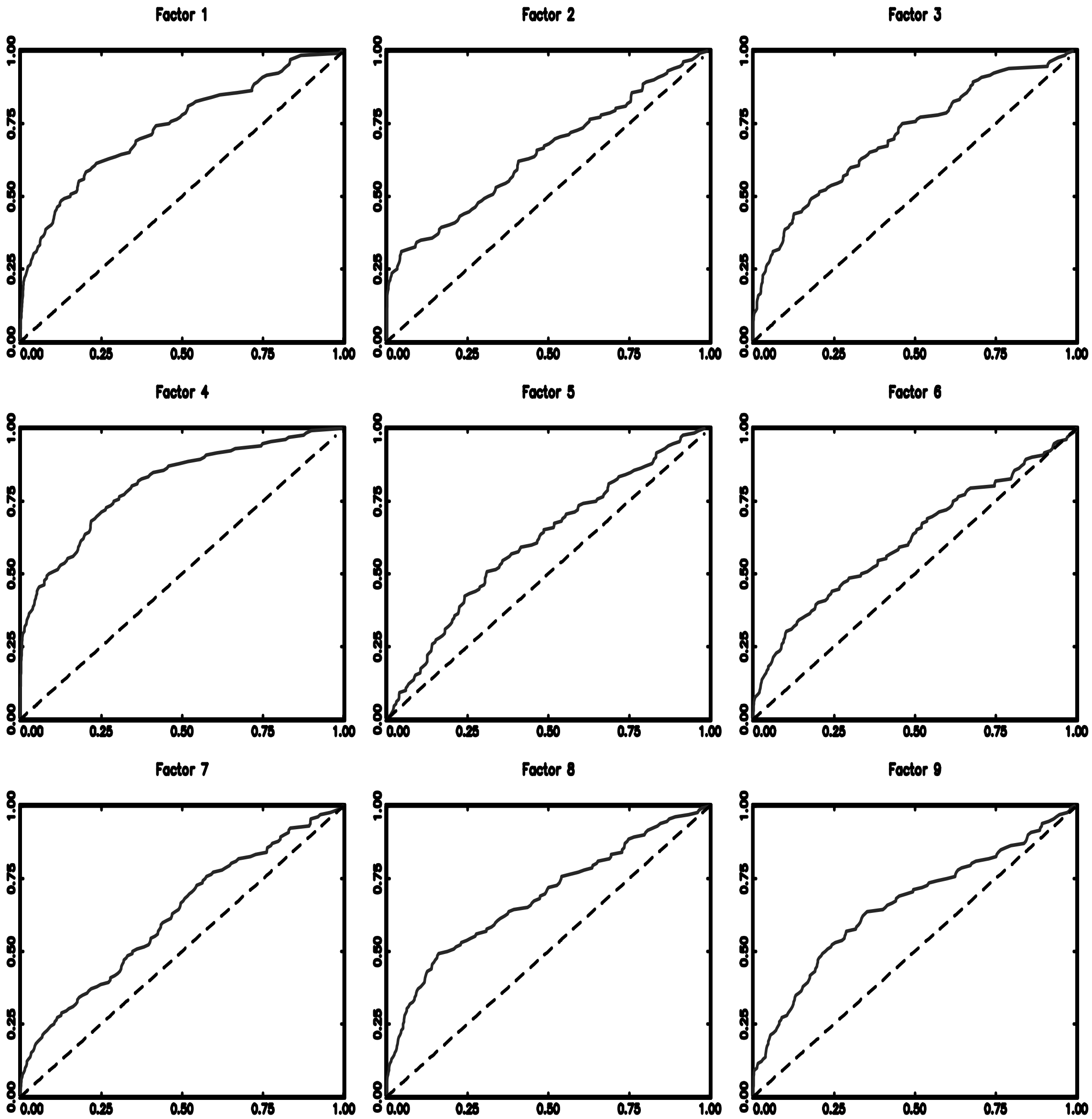

Figure 2. Statistical significance of restriction #4:
Empirical cdfs of p-values (fraction of p-values less than the value on the horizontal axis) of tests of whether $X_{jt-1},\ldots, X_{jt-6}$ appears in the k^{th} equation in the 9-equation system, $F_t = \Phi(L)F_{t-1} + \Psi_j(L)X_{jt-1} + \varepsilon_{Ft}$.

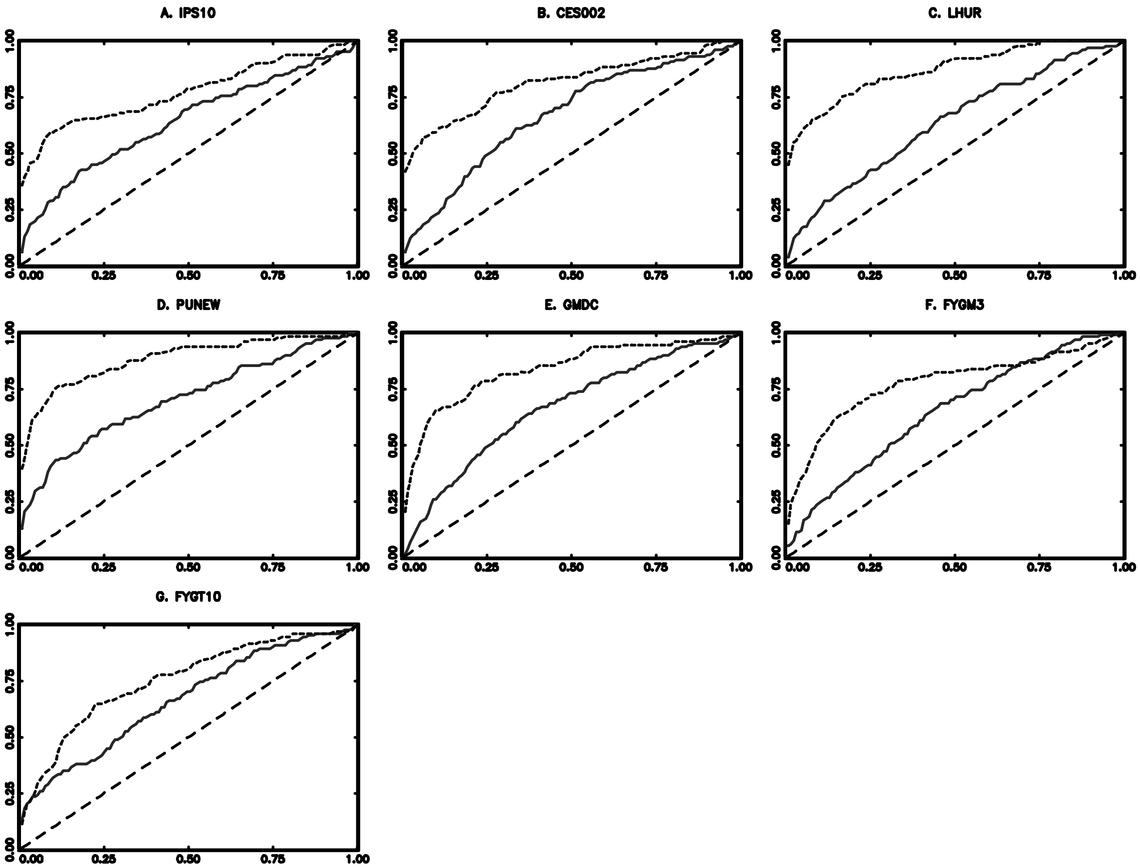

Figure 3. Statistical significance of restriction #5:
Empirical cdfs of p-values of tests of whether X_{jt} predicts X_{it} (*i*) given lags of X_{it} (dashed line) and (*ii*) given lags of X_{it} and lags of F_t (solid line) for seven different dependent variables: (a) industrial production, (b) nonfarm private employment, (c) the unemploy*ment rate, (d) CPI inflation, (e) PCE deflator inflation, (f) the 90-day T-bill rate, and (g) the 10-year T-bond rate.

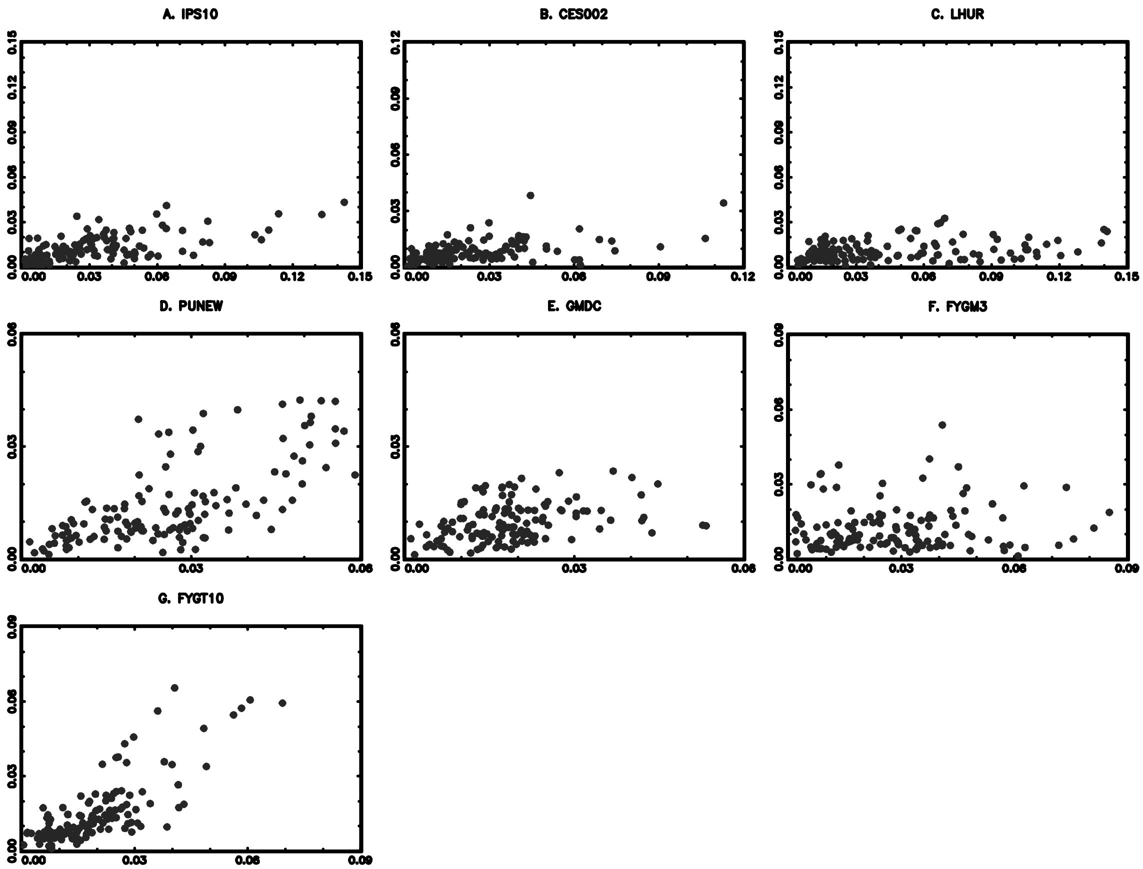

Figure 4. Economic significance of restriction #5:
Scatterplots of the marginal R^2s from adding six lags X_{jt-1} as a predictor in a regression of X_{it} on (*i*) $X_{it-1},\ldots, X_{it-6}$ (horizontal axis) and on (*ii*) $X_{it-1},\ldots, X_{it-6}$ and F_{t-1} and F_{t-2} (vertical axis) for seven different dependent variables: (a) industrial production, (b) nonfarm private employment, (c) the unemployment rate, (d) CPI inflation, (e) PCE deflator inflation, (f) the 90-day T-bill rate, and (g) the 10-year T-bond rate.

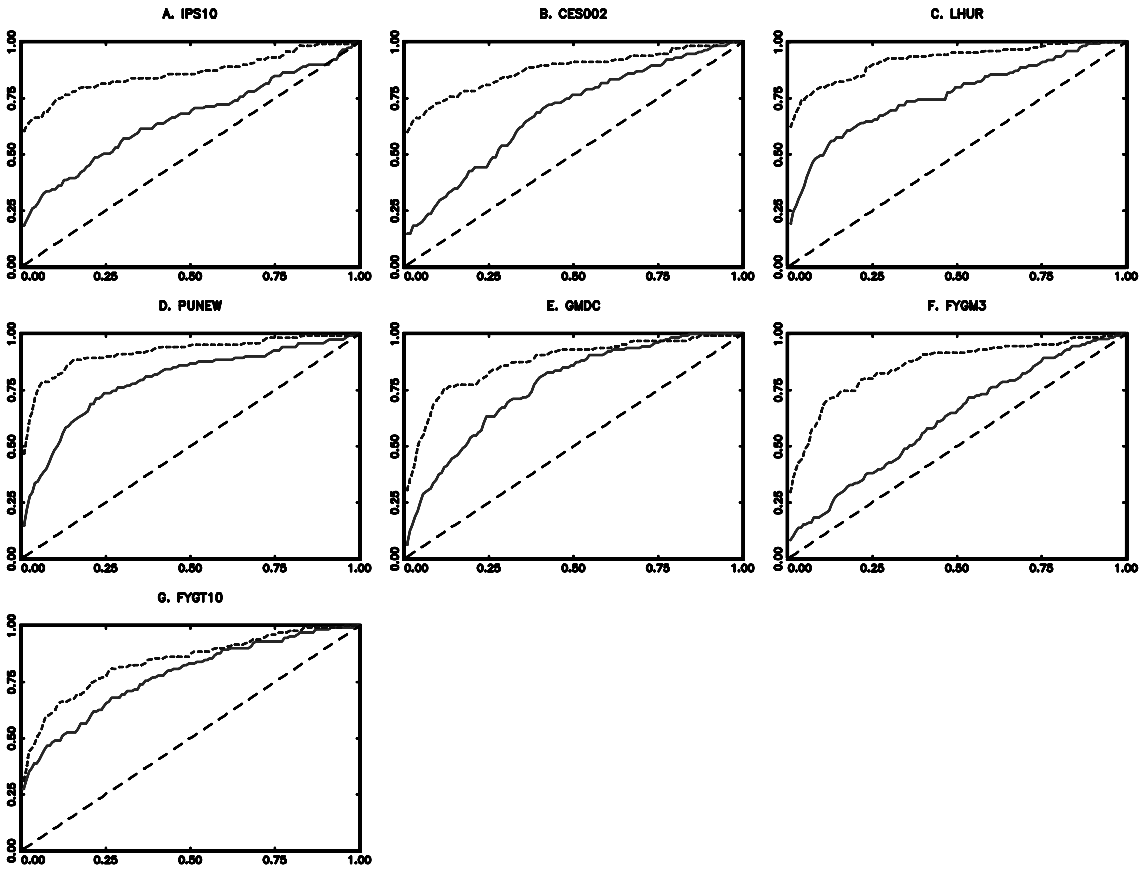

Figure 5. Statistical significance of restriction #6:
Empirical cdfs of *p*-values of tests of whether X_{jt} explains X_{it} (*i*) given lags of X_{it} (dashed line) and (*ii*) given F_t and lags of X_{it} (solid line): (a) industrial production, (b) nonfarm private employment, (c) the unemploy*ment rate, (d) CPI inflation, (e) PCE deflator inflation, (f) the 90-day T-bill rate, and (g) the 10-year T-bond rate.

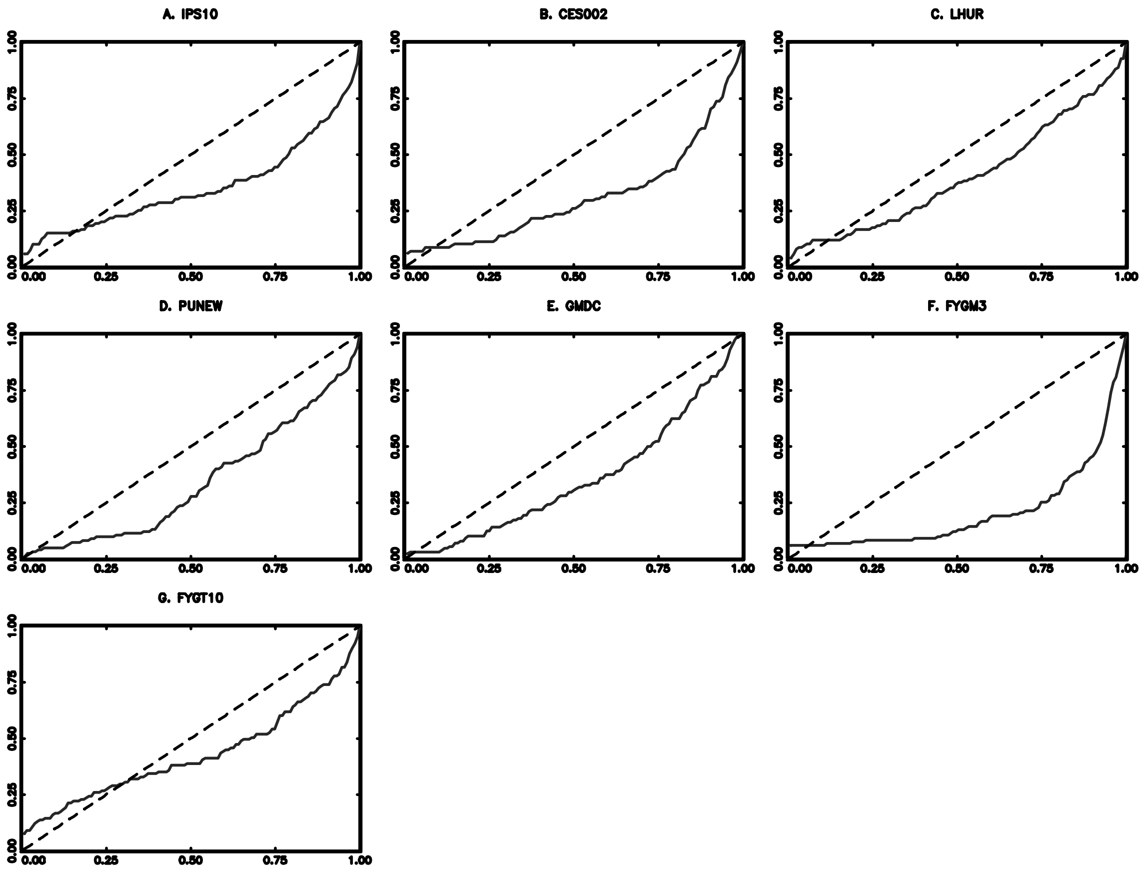

Figure 6. Economic significance of restriction #6:
Empirical cdfs of p-values of Hausman tests on the coefficient of F_t when X_{jt} is included v. excluded from the regression of X_{it} on F_t and six lags of X_{it}: (a) industrial production, (b) nonfarm private employment, (c) the unemploy*ment rate, (d) CPI inflation, (e) PCE deflator inflation, (f) the 90-day T-bill rate, and (g) the 10-year T-bond rate.

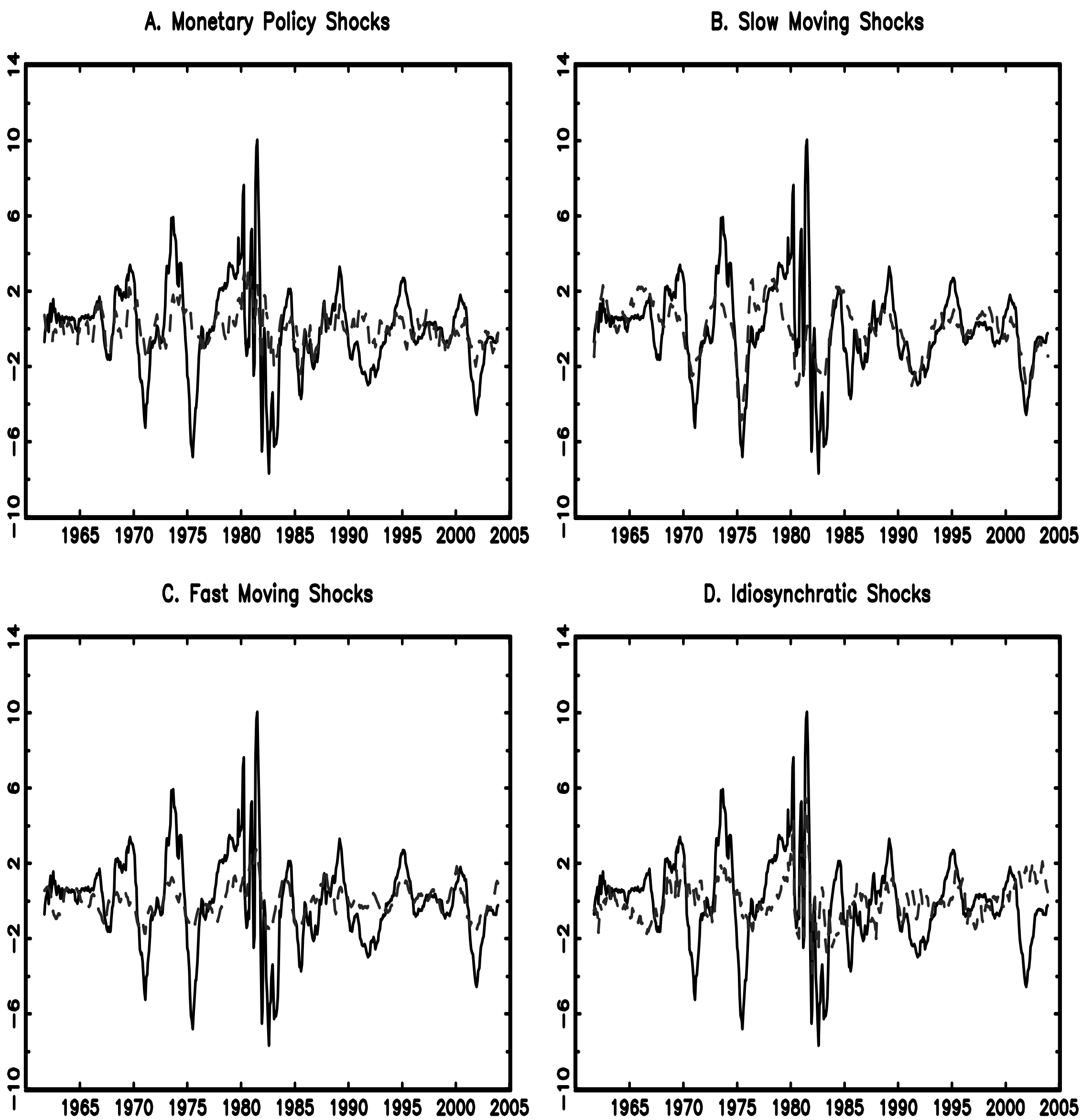

Figure 7. Movements in the 12-month difference of the Federal Funds rate ($FF_t - FF_{t-12}$) arising from: (a) the monetary policy shock; (b) the slow-moving shocks; (c) the fast-moving shocks; and (d) the idiosyncratic shock

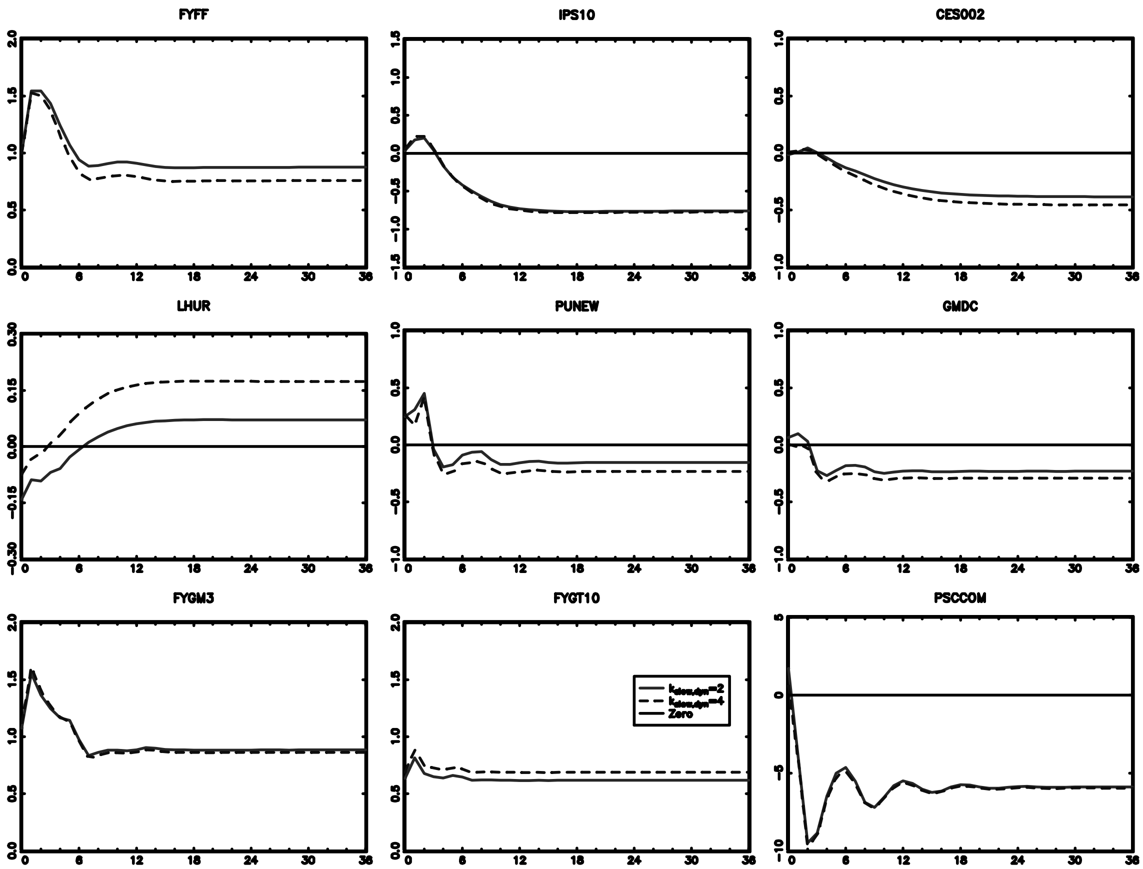

Figure 8. Impulse response functions with respect to the monetary policy shock for 4 slow-moving factors (dashed line) and 2 slow-moving factors (solid line): (a) federal funds rate; (b) industrial production; (c) total employment; (d) the unemployment rate; (d) CPI-U inflation (all); (e) PCE deflator inflation; (f) 3-month T-bill rate; (g) 10-year T-bond rate; (h) Spot market price index

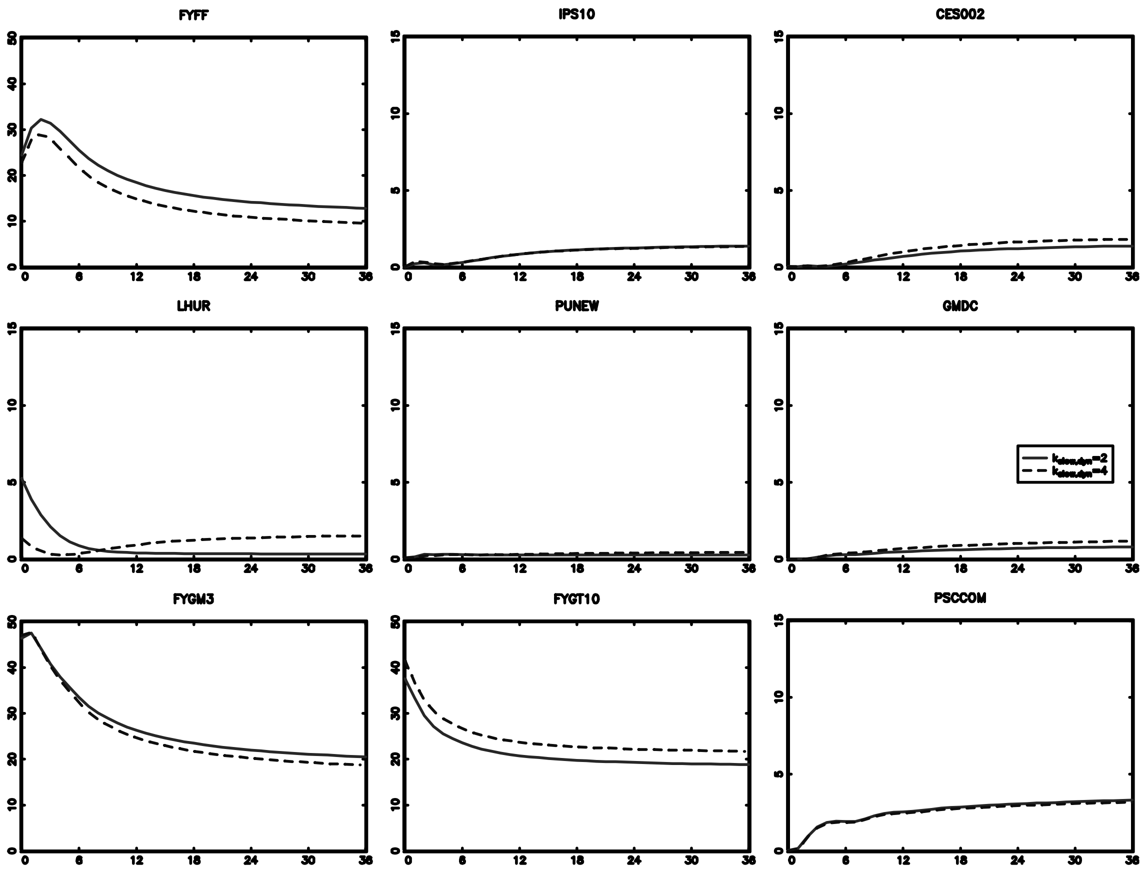

Figure 9. Forecast error variance decompositions with respect to the monetary policy shock for 4 slow-moving factors (dashed line) and 2 slow-moving factors (solid line): (a) federal funds rate; (b) industrial production; (c) total employment; (d) the unemployment rate; (d) CPI-U inflation (all); (e) PCE deflator inflation; (f) 3-month T-bill rate; (g) 10-year T-bond rate; (h) Spot market price index