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Data-Rich DSGE and Dynamic Factor Models

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Abstract

Dynamic factor models and dynamic stochastic general equilibrium (DSGE) models are widely used for empirical research in macroeconomics. The empirical factor literature argues that the co-movement of large panels of macroeconomic and financial data can be captured by relatively few common unobserved factors. Similarly, the dynamics in DSGE models are often governed by a handful of state variables and exogenous processes such as preference and/or technology shocks. Boivin and Giannoni (2006) combine a DSGE and a factor model into a data-rich DSGE model, in which DSGE states are factors and factor dynamics are subject to DSGE model implied restrictions. We compare a data-rich DSGE model with a standard New Keynesian core to an empirical dynamic factor model by estimating both on a rich panel of U.S. macroeconomic and financial data compiled by Stock and Watson (2008). We find that the spaces spanned by the empirical factors and by the data-rich DSGE model states are very close. This proximity allows us to propagate monetary policy and technology innovations in an otherwise non-structural dynamic factor model to obtain predictions for many more series than just a handful of traditional macro variables, including measures of real activity, price indices, labor market indicators, interest rate spreads, money and credit stocks, and exchange rates.

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I. Introduction

Dynamic factor models (DFM) and dynamic stochastic general equilibrium (DSGE) models are widely used for empirical research in macroeconomics. The traditional areas of DFM application are the construction of coincident and leading indicators (e.g., Stock and Watson 1989, Altissimo et al. 2001, Matheson 2011) and the forecasting of macro time series (Stock and Watson 1999, 2002a, b; Forni, Hallin, Lippi and Reichlin 2003; Boivin and Ng 2005). DFMs are also used for real-time monitoring (Giannone, Reichlin, Small 2008; Aruoba, Diebold, and Scotti 2009; Aruoba, Diebold 2010), in monetary policy applications (e.g., the Factor Augmented VAR approach of Bernanke, Boivin, and Eliasz 2005, Stock and Watson 2005) and in the study of international business cycles (Kose, Otrok, Whiteman 2003, 2008; Del Negro and Otrok 2008; Aruoba, Diebold, Kose, Terrones 2011). The micro-founded optimization-based DSGE models primarily focus on understanding the sources of business cycle fluctuations and on assessing the importance of nominal rigidities and various types of frictions in the economy. Recently, they appear to have been able to replicate well many salient features of the data (e.g., Christiano, Eichenbaum, and Evans 2005; Smets and Wouters 2003, 2007). As a result, the versions of DSGE models extended to open economy and multisector contexts are increasingly used as tools for projections and policy analysis at major central banks (Adolfson et al. 2007, 2008; Edge, Kiley and Laforte 2009; Coenen, McAdam and Straub 2008).

The empirical factor literature argues that the co-movement of large panels of macroeconomic and financial data can be captured by relatively few common unobserved factors. Early work by Sargent and Sims (1977) found that the dynamic index model with two indices fits well the real variables in their panel. Giannone, Reichlin and Sala (2004) claim that the number of common shocks, or, in their terminology, the stochastic dimension of the U.S. economy, is two. Based on recent theoretical work developing more formal number-of-factors criteria, several authors (e.g., Bai and Ng 2007; Hallin and Liška 2007; Stock and Watson 2005) have argued for a higher number of dynamic factors that drive large U.S. macroeconomic panels – ranging from four to seven.

The dynamics in DSGE models are also often governed by a handful of state variables and exogenous processes such as preference and/or technology shocks. Boivin and Giannoni

(2006) combine a DSGE and a factor model into a data-rich DSGE model, in which DSGE states are factors and factor dynamics are subject to DSGE model implied restrictions. They argue that the richer information coming from large macroeconomic and financial panels can provide better estimates of the DSGE states and of the structural shocks driving the economy. In addition, Boivin and Giannoni (2006) showed – and we confirm their conclusions in a related work in Kryshko (2011) – that the data-rich DSGE model delivers different estimates of deep structural parameters of the model compared to standard non-data-rich estimation.

In this paper, we take both a data-rich DSGE model and an empirical dynamic factor model to the same rich data set, and ask: How similar or different would be the latent empirical factors extracted by a factor model versus the estimated data-rich DSGE model states? Do they span a common factor space? Or – in other words – can we predict the true estimated DFM latent factors from the DSGE model states with a fair amount of accuracy? We ask this question for three reasons. First, the factor spaces comparison may serve as a useful tool for evaluating a DSGE model. Recent research has shown that misspecification remains a concern for valid inference in DSGE models (Del Negro, Schorfheide, Smets and Wouters 2007 – DSSW hereafter). If a DSGE model is taken to a particular small set of observables, misspecification often manifests itself through the inferior fit. Dynamic factor models usually fit well and perform well in forecasting. So if it turns out that the spaces spanned by two models are close, that is good news for a DSGE model. This means that a DSGE model overall captures the sources of co-movement in the large panel of data as a sort of a core, and that the differences in fit between a data-rich DSGE model and a DFM are potentially due to restricted factor loadings in the former. Second, a well known weakness of dynamic factor models is that the latent common components extracted by DFMs from the large panels of data do not mean much in general. If factor spaces in two models are closely aligned, this facilitates the economic interpretation of a dynamic factor model, since the empirical factors become isomorphic to the DSGE model state variables that have clear economic meaning. Third, if factor spaces are close, we are able to propagate the structural shocks in an otherwise completely non-structural dynamic factor model to obtain predictions for a broad range of macro series of interest.[2] This way of doing policy analysis is more reliable, because, in addition to the impulse responses derived in the data-rich DSGE model, which might be misspecified, we are able to generate a second set of responses to the same shocks in the context of a factor model that is primarily data-driven and fits better.

We compare a data-rich DSGE model with a standard New Keynesian core to an empirical dynamic factor model by estimating both on a rich panel of U.S. macroeconomic and financial data compiled by Stock and Watson (2008). The specific version of the data-rich DSGE model is taken from Kryshko (2011). The estimation involves Bayesian Markov Chain Monte Carlo (MCMC) methods.

We find that the spaces spanned by the empirical factors and by the data-rich DSGE model states are very close meaning that, using a collection of linear regressions, we are able to predict the true estimated factors from the DSGE states fairly accurately. Given the accuracy, we can use this predictive link to map in every period the impact of any structural DSGE shock on the data-rich DSGE states into the empirical factors. We then multiply the responses of empirical factors by the DFM factor loadings to generate the impulse responses of data indicators to structural shocks. Applying this procedure, we propagate monetary policy and technology innovations in an otherwise non-structural dynamic factor model to obtain predictions for many more series than just a handful of traditional macro variables, including measures of real activity, price indices, labor market indicators, interest rate spreads, money and credit stocks, and exchange rates. For instance, contractionary monetary policy realistically leads to a decline in housing starts and in residential investment, to a hump-shaped positive response of the unemployment rate peaking in the 5th quarter after the shock before returning to normal, to the negative rates of commodity price inflation, to a widening of interest rate spreads, to a contraction of consumer credit and to an appreciation of the dollar – despite the fact that our DSGE model does not model these features explicitly.

[2] This is similar in spirit to the Factor Augmented VAR approach (FAVAR, originally implemented by Bernanke, Boivin and Eliasz (2005) and also by Stock and Watson (2005) to study the impact of monetary policy shocks on a large panel of macro data) and similar to the structural factor model of Forni, Giannone, Lippi and Reichlin (2009). The paper by Bäurle (2008) is the closest work related to the analysis in this paper. It offers a method to incorporate the prior information from a DSGE model in estimation of a dynamic factor model and analyzes the impact of the monetary policy shocks on both the factors and selected data series.

The paper is organized as follows. In Section II we present the variant of a dynamic factor model and a quick snapshot of the data-rich DSGE model to be used in the empirical analysis. Our econometric methodology to estimate two models is discussed in Section III. Section IV describes our data set and transformations. In Section V we proceed by conducting the empirical analysis. We begin by discussing the choice of the prior distributions of dynamic factor model's parameters. Second, we analyze the estimated empirical factors and the posterior estimates of the DSGE model state variables and explore how well they are able to capture the co-movements in the data. Third, we compare the spaces spanned by the latent empirical factors and by the data-rich DSGE model state variables. Finally, we use the proximity of the factor spaces to propagate the monetary policy and technology innovations in an otherwise non-structural dynamic factor model to obtain the predictions for the macro series of interest. Section VI concludes.

II. Two Models

In this section, we begin by describing the variant of a dynamic factor model. Then, we present a quick snapshot of the data-rich DSGE model with a New Keynesian core to be estimated on the same large panel of macro and financial series.

A. Dynamic Factor Model

We choose to work with the version of the dynamic factor model as originally developed by Geweke (1977) and Sargent and Sims (1977) and recently used by Stock and Watson (2005). If the forecasting performance is a correct guide to choose the appropriate factor model specification, the literature remains rather inconclusive in that respect. For example, Forni, Hallin, Lippi and Reichlin (2003) found supportive results for the generalized dynamic factor specification over the static factor specification, while Boivin and Ng (2005) documented little differences for the competing factor specifications.

Let F_t denote the $N \times 1$ vector of common unobserved factors that are related to a $J \times 1$ large[3] ($J \gg N$) panel of macroeconomic and financial data X_t according to the following factor model:

$$X_t = \mathbf{\Lambda} F_t + e_t \tag{1}$$
$$F_t = \mathbf{G} F_{t-1} + \eta_t, \qquad \eta_t \sim iid\ N(\mathbf{0}, \mathbf{Q}) \tag{2}$$
$$e_t = \mathbf{\Psi} e_{t-1} + v_t, \qquad v_t \sim iid\ N(\mathbf{0}, \mathbf{R}), \tag{3}$$

where $\mathbf{\Lambda}$ is the $J \times N$ matrix of factor loadings, e_t is the idiosyncratic errors allowed to be serially correlated, $\mathbf{G}$ is the $N \times N$ matrix that governs common factor dynamics and η_t is the vector of stochastic innovations. The factors and idiosyncratic errors are assumed to be uncorrelated at all leads and lags: $E(F_t e_{i,s}) = 0$, all i, t and s. As in Stock and Watson (2005), we assume that matrices $\mathbf{Q}$, $\mathbf{R}$ and $\mathbf{\Psi}$ are diagonal, which implies we have an *exact* dynamic factor model: $E(e_{i,t} e_{j,s}) = 0$, $i \neq j$, all t and s. This is in contrast to the *approximate* DFM of Chamberlain and Rothschild (1983) that relaxes this assumption and allows for some correlation across idiosyncratic errors $e_{i,t}$ and $e_{j,t}$, $i \neq j$. As written, the model is already in static form, since data series X_t load only on contemporaneous factors and not on their lags.[4]

B. Data-Rich DSGE Model

The specific version of the data-rich DSGE model that we work with in this paper is taken from Kryshko (2011), Section II.

Its New Keynesian business cycle core features capital as the factor of production, nominal rigidities in price setting, and investment adjustment costs. The real money stock enters households' utility in additively separable fashion. The economy is populated by households, final and intermediate goods-producing firms and a central bank (monetary authority). A

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[3] A typical panel includes from one to two hundred series: e.g. Stock and Watson's (2005) database has $J = 132$, while in Giannone, Reichlin and Sala (2004) $J = 190$. The number of common factors is usually in single digits.

[4] In general, a measurement equation is often written as $X_t = \lambda(L) f_t + e_t$, with data loading on current and lagged dynamic factors f_t. However, assuming $\lambda(L)$ has at most p lags, and defining $F_t = (f_t', ..., f_{t-p}')'$, we can rewrite it as (1). Here F_t is the vector of static factors as opposed to dynamic factors f_t. To make things simpler, in the model (1)-(3), however, the static and dynamic factors coincide.

representative household works, consumes, saves, holds money balances and accumulates capital. It consumes the final output manufactured by perfectly competitive final good firms. The final good producers produce by combining a continuum of differentiated intermediate goods supplied by monopolistically competitive intermediate goods firms. To manufacture their output, intermediate goods producers hire labor and capital services from households. Also, when optimizing their prices, intermediate goods firms face the nominal price rigidity a la Calvo (1983), and those firms that are unable to re-optimize may index their price to lagged inflation. Monetary policy is conducted by the central bank setting the one-period nominal interest rate on public debt via a Taylor-type interest rate feedback rule. Given the interest rate, the central bank supplies enough nominal money balances to meet equilibrium demand from households.

In Kryshko (2011), Section II we have shown that if $\boldsymbol{\theta}$ is the vector of deep structural parameters characterizing preferences and technology in our DSGE model and ε_t is the vector of exogenous shocks, then the equilibrium dynamics of the data-rich DSGE model can be summarized by the transition equation of the non-redundant DSGE model state variables S_t:

$$S_t = \mathbf{G}(\boldsymbol{\theta}) S_{t-1} + \mathbf{H}(\boldsymbol{\theta}) \varepsilon_t, \qquad \text{where } \varepsilon_t \sim iid\ N(0, \mathbf{Q}(\boldsymbol{\theta})) \tag{4}$$

and the collection of measurement equations connecting the core macro series X_t^F and the non-core informational macro series X_t^S to the DSGE model states:

$$\underbrace{\begin{bmatrix} X_t^F \\ \hline X_t^S \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} \boldsymbol{\Lambda}_{\mathbf{F}}(\boldsymbol{\theta}) \\ \hline \boldsymbol{\Lambda}_{\mathbf{S}} \end{bmatrix}}_{\boldsymbol{\Lambda}(\boldsymbol{\theta})} S_t + \underbrace{\begin{bmatrix} e_t^F \\ \hline e_t^S \end{bmatrix}}_{e_t}, \tag{5}$$

where the measurement errors e_t may be serially correlated, but uncorrelated across different data indicators ($\boldsymbol{\Psi}$, $\mathbf{R}$ are diagonal):

$$e_t = \boldsymbol{\Psi} e_{t-1} + v_t, \qquad v_t \sim iid\ N(\mathbf{0}, \mathbf{R}). \tag{6}$$

Notice that the state-space representation of the data-rich DSGE model (4)-(6) is very much like the dynamic factor model (1)-(3) in which transition of the unobserved factors is governed by a DSGE model solution and where some factor loadings are restricted by the economic meaning of the DSGE model concepts.

III. ECONOMETRIC METHODOLOGY

This section discusses the estimation techniques for the two models considered in this paper. First, we refer the reader to Kryshko (2011) on the details about a Markov Chain Monte Carlo algorithm to estimate the data-rich DSGE model, including the choice of the prior for factor loadings. Second, we describe the Gibbs sampler to estimate a dynamic factor model.

A. Estimation of the Data-Rich DSGE Model

We refer the reader to Kryshko (2011), Section III.A and that paper's appendices regarding the implementation details of the MCMC algorithm to estimate our data-rich DSGE model.

B. Estimation of the Dynamic Factor Model

Consider the original dynamic factor model described in Section II.A:

$$X_t = \mathbf{\Lambda} F_t + e_t \tag{7}$$

$$F_t = \mathbf{G} F_{t-1} + \eta_t, \qquad \eta_t \sim iid\ N(\mathbf{0}, \mathbf{Q}) \tag{8}$$

$$e_t = \mathbf{\Psi} e_{t-1} + v_t, \qquad v_t \sim iid\ N(\mathbf{0}, \mathbf{R}). \tag{9}$$

Let us collect the state-space matrices into $\Gamma = \{\mathbf{\Lambda}, \mathbf{\Psi}, \mathbf{R}, \mathbf{G}\}$ and the latent empirical factors into $F^T = \{F_1, F_2, \ldots, F_T\}$. Similar to the data-rich DSGE model (4)-(6), (7)-(9) is a linear Gaussian state-space model, and we are interested in joint inference about model parameters Γ and latent factors F^T. Unlike in the data-rich DSGE model, though, we no longer have deep structural parameters determining the behavior of matrices in transition equation (8).

We sidestep the problem of a proper dimension of factor space by assuming that $\dim(F_t) = N = 6$, the number of non-redundant model states in the data-rich DSGE model. In contrast, the dynamic factor literature has devoted considerable attention to developing the objective criteria that would determine the proper number of static factors by trading the fit against complexity (Bai and Ng, 2002) and of dynamic factors (e.g., Bai and Ng 2007, Hallin and Liska 2007, Amengual and Watson 2007, Stock and Watson 2005) in DFMs similar to the one above. However, our choice is indirectly supported by the work of Stock and Watson

(2005) and Jungbacker and Koopman (2008), who, roughly based on these criteria, find seven dynamic and seven static factors driving a similar panel of macro and financial data.

A principal components analysis of the data set X^T reveals that our choice for the number of factors is not an unreasonable one. As Table C1 demonstrates, the first 6 principal components account for about 75 percent of the variation in the data. The scree plot in Figure C1 shows a very flat slope of the ordered eigenvalues curve when going from the 6[th] to 7[th] eigenvalue. Putting in the 7[th] principal component would add 4.4 percent to the total variance of the data explained, a fairly marginal improvement over the already high cumulative proportion of 75 percent.

Another problem associated with the dynamic factor model (7)-(9) is that the scales and signs of factors F_t and of factor loadings $\mathbf{\Lambda}$ are not separately identified. Regarding scales, take any invertible $N \times N$ matrix $\mathbf{P}$ and notice that the transformed model is observationally equivalent to the original one:

$$X_t = \underbrace{\mathbf{\Lambda P^{-1}}}_{\tilde{\mathbf{\Lambda}}} \underbrace{\mathbf{P} F_t}_{\tilde{F}_t} + e_t \tag{10}$$

$$\underbrace{\mathbf{P} F_t}_{\tilde{F}_t} = \underbrace{\mathbf{PGP^{-1}}}_{\tilde{\mathbf{G}}} \underbrace{\mathbf{P} F_{t-1}}_{\tilde{F}_{t-1}} + \tilde{\eta}_t, \qquad \tilde{\eta}_t \sim iid\, N(\mathbf{0}, \underbrace{\mathbf{PQP}'}_{\tilde{\mathbf{Q}}}) \tag{11}$$

Regarding signs, for the moment think of (7)-(9) as a model with only one factor. Then multiply by -1 the transition equation (8), as well as the factor loading and the factor itself in measurement equation (7). We obtain the new model, yet it is observationally equivalent to the original.

We follow the factor literature (e.g. Geweke and Zhu 1996; Jungbacker and Koopman 2008) and make the following normalization assumptions to tell factors apart from factor loadings: (i) set $\mathbf{Q} = \mathbf{I}_N$ to fix the scale of factors; (ii) require one loading in $\mathbf{\Lambda}$ to be positive for each factor (sign restrictions); and (iii) normalize some factor loadings in $\mathbf{\Lambda}$ to pin down specific factor rotation.

Denote by $\mathbf{\Lambda_1}$ the upper $N \times N$ block of $\mathbf{\Lambda}$ so that $\mathbf{\Lambda} = \left[\mathbf{\Lambda}_1'; \mathbf{\Lambda}_2'\right]'$. One way to implement (ii) and (iii) would be to assume that $\mathbf{\Lambda_1}$ is lower triangular (i.e., $\lambda_{ij} = 0$ for $j > i$, $i = 1, 2, ..., N-1$)

with strictly positive diagonal $\lambda_{ii} > 0,\ i = \overline{1, N}$ (see Harvey 1989, p.451). However, our data set in estimation, to be described later in the Section IV, will consist of *core* and *non-core* macro and financial series. Furthermore, within the core series we will have four blocks of variables: real output, inflation, the nominal interest rate and the inverse velocity of money, respectively; each block contains several measures of the same concept. For example, the output block comprises real GDP, total industrial production and industrial production in the manufacturing sector; the inflation block includes GDP deflator inflation, CPI inflation and personal consumption expenditures inflation. For this reason, we choose another alternative to implement normalizations (ii) and (iii) – the block-diagonal scheme that to some degree exploits the group structure of the core series in data X_t:

	F_1	F_2	F_3	F_4	F_5	F_6
Real output #1	1	1	+1	0	0	0
Real output #2	1	+1	1	0	0	0
Real output #3	1	1	1	0	0	0
Inflation #1	1	1	0	1	0	0
Inflation #2	+1	1	0	1	0	0
Inflation #3	1	1	0	1	0	0
Interest rate #1	1	1	0	0	+1	0
Interest rate #2	1	1	0	0	1	0
Interest rate #3	1	1	0	0	1	0
IVM #1	1	1	0	0	0	1
IVM #2	1	1	0	0	0	+1
IVM #3	1	1	0	0	0	1
$X^{non-core}$	1	1	1	1	1	1

(12)

where 1s stand for non-zero elements in $\mathbf{\Lambda}$.

We acknowledge that our block-diagonal scheme imposes some overidentifying restrictions on factor loadings beyond those minimally necessary. However, scheme (12) can also be interpreted as a special case of the appealing dynamic hierarchical factor model of Moench, Ng, and Potter (2008), which – on top of aggregate common factors – introduces intermediate block factors and makes use of the block structure of the data.

Now, to estimate the model (7)-(9) under normalizing assumptions (i)-(iii), we again apply the Bayesian MCMC methods as in the estimation of the data-rich DSGE model (Kryshko 2011, Section III.A). We construct a Gibbs sampler that iterates on a complete set of known conditional posterior densities to generate draws from the joint posterior distribution $p(\Gamma, F^T \mid X^T)$ of model parameters $\Gamma = \{\mathbf{\Lambda}, \mathbf{\Psi}, \mathbf{R}, \mathbf{G}\}$ and latent factors F^T:

$$p(F^T \mid \Gamma; X^T) \propto p(F^T \mid \Gamma) p(X^T \mid \Gamma, F^T) \tag{13}$$

$$p(\Gamma \mid F^T; X^T) \propto p(\Gamma) p(F^T \mid \Gamma) p(X^T \mid \Gamma, F^T) \tag{14}$$

The main steps of the Gibbs sampler are:

1. Specify initial values $\Gamma^{(0)}$ and $F^{T,(0)}$.
2. Repeat for $g = 1, 2, ..., n_{sim}$

   2.1. Generate latent factors $F^{T,(g)}$ from $p(F^T \mid \Gamma^{(g-1)}; X^T)$ using the Carter-Kohn (1994) forward-backward algorithm;

   2.2. Generate state-space parameters $\Gamma^{(g)}$ from $p(\Gamma \mid F^{T,(g)}; X^T)$ by drawing from a complete set of known conditional densities.

3. Return $\left\{\Gamma^{(g)}, F^{T,(g)}\right\}_{g=1}^{n_{sim}}$

Compared to the MCMC algorithm for the data-rich DSGE model, this Gibbs sampler is easier and it differs in two key respects: (i) we no longer have the complicated Metropolis step, since there are no deep structural parameters $\boldsymbol{\theta}$ coming from the economic model; and (ii) inside Γ, we have to draw matrix $\mathbf{G}$ from the transition equation of factors (in the data-rich DSGE model it was pinned down by numerical solution of a DSGE model given structural parameters $\boldsymbol{\theta}$).

To draw the latent factors F^T from $p(F^T \mid \Gamma; X^T)$, we use the familiar Carter-Kohn (1994) machinery. First, we apply the Kalman filter to the linear Gaussian state-space system (7)-(9) to generate filtered latent factors $\hat{F}_{t|t}$, $t = \overline{1,T}$. Then, starting from $\hat{F}_{T|T}$, we roll back in time along the Kalman smoother recursions and generate $F^T = \{F_1, F_2, \ldots, F_T\}$ by recursively sampling from a sequence of conditional Gaussian distributions.

To sample from the conditional posterior $p(\Gamma \mid F^T; X^T)$, we notice the following: with diagonality of matrices $\mathbf{\Psi}$ and $\mathbf{R}$ and conditional on factors F^T, (7) and (9) are a set of standard multivariate linear regressions with AR(1) errors and Gaussian innovations $(k = \overline{1, J})$:

$$X_{k,t} = \mathbf{\Lambda}_k' F_t + e_{k,t}, \qquad e_{k,t} = \psi_{kk} e_{k,t-1} + v_{k,t}, \quad v_{k,t} \sim iid\ N(0, R_{kk}). \tag{15}$$

Hence, under the conjugate prior $p(\mathbf{\Lambda}, \mathbf{\Psi}, \mathbf{R})$, we can apply the insight of Chib and Greenberg (1994) to derive the conditional posteriors $\left[\mathbf{R} \mid (\mathbf{\Lambda}, \mathbf{\Psi}); \mathbf{G}, F^T, X^T\right]$, $\left[\mathbf{\Lambda} \mid (\mathbf{R}, \mathbf{\Psi}); \mathbf{G}, F^T, X^T\right]$, $\left[\mathbf{\Psi} \mid (\mathbf{\Lambda}, \mathbf{R}); \mathbf{G}, F^T, X^T\right]$ and to sample accordingly.

What remains to be drawn is the transition matrix $\mathbf{G}$. Given factors F^T, the conditional posterior $p(\mathbf{G} \mid (\mathbf{\Lambda}, \mathbf{R}, \mathbf{\Psi}); F^T, X^T)$ can be derived from a VAR(1) in (8):

$$F_t = \mathbf{G} F_{t-1} + \eta_t, \qquad \eta_t \sim iid\ N(\mathbf{0}, \mathbf{I}_N). \tag{16}$$

We assume the so-called Minnesota prior (Doan, Litterman and Sims, 1984; the specific version comes from Lubik and Schorfheide, 2005) on transition matrix $\mathbf{G}$ and truncate it to the region consistent with the stationarity of (16). We implement our prior by a set of dummy observations that tilt the VAR to a collection of univariate random walks (details are in Appendix A).

To estimate the empirical DFM, in the actual implementation of the Gibbs sampler we have applied the Jungbacker-Koopman (2008) computational speed-up presented in Kryshko (2011), Section III.B (and already utilized to improve the speed of computations in the data-rich DSGE model's estimation). We find that the "improved" estimation of the empirical DFM runs 10.5 times faster than the no-speedup estimation, a magnitude consistent with the CPU gains reported by Jungbacker and Koopman (2008) for a DFM of a similar size in their study.

IV. DATA

To estimate the dynamic factor model and the data-rich DSGE model, we employ the large panel of U.S. quarterly macroeconomic and financial time series compiled by Stock and Watson (2008). The panel covers 1959:Q1 – 2006:Q4, however, our sample in this paper is restricted only to 1984:Q1 – 2005:Q4 so as to avoid dealing with the issue of the Great Moderation[5] and to concentrate on a period with a relatively stable monetary policy regime.

Our data set is identical to the one employed in Kryshko (2011) and consists of 12 *core series* that either measure specific DSGE model concepts or are used in the DFM normalization scheme (12), and 77 *non-core* informational series that load on all DSGE states (DFM factors) and may contain useful information about the aggregate state of the economy. The core series include three measures of real output (real GDP, the index of total industrial production and the index of industrial production: manufacturing), three measures of price inflation (GDP deflator inflation, personal consumption expenditure (PCE) deflator inflation, and CPI inflation), three indicators of the nominal interest rates (the federal funds rate, the 3-month T-bill rate and the yield on AAA-rated corporate bonds), and three series measuring the inverse velocity of money (IVM based on the M1 aggregate and the M2 aggregate and IVM based on the adjusted monetary base). The 77 non-core series include the measures of real activity, labor market variables, housing indicators, prices and wages, financial variables (interest rate spreads, exchange rate depreciations, credit stocks, stock returns) and, together with appropriate transformations to eliminate trends, are described in Appendix B. To save space, we refer the reader to Kryshko (2011), Section IV that describes in detail the construction of all data indicators included in our data set.

Because measurement equations (5) and (7) are modeled without intercepts, we estimate a dynamic factor model and a data-rich DSGE model on a demeaned data set. Also, in line with standard practice in the factor literature, we standardize each time series so that its sample variance is equal to unity (however, we do not scale the core series when estimating the data-rich DSGE model).

V. EMPIRICAL ANALYSIS

The next step in our analysis is to take a dynamic factor model and a data-rich DSGE model to the data using the MCMC algorithms described above and to present the empirical results.

[5] The "Great Moderation" refers to a decline in the volatility of output and inflation observed in the U.S. since the mid-1980s until the recent financial crisis. The papers by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) argue that a break in the volatility of U.S. GDP growth occurred in 1984:Q1.

We begin by discussing the choice of the prior distributions of dynamic factor model's parameters. Second, we analyze the estimated empirical factors and the estimates of the DSGE model state variables and explore how well they are able to capture the co-movements in the data. Third, we compare the spaces spanned by the latent empirical factors and by the data-rich DSGE model state variables. Finally, we use the proximity of the factor spaces to propagate the monetary policy and technology innovations in an otherwise non-structural dynamic factor model and obtain the predictions from both models for the core and non-core macro and financial series of interest.

A. Priors and Posteriors

Since we estimate the DFM (7)-(9) and the data-rich DSGE model (4)-(6) using Bayesian techniques, we have to provide prior distributions for both models' parameters.

Let us first turn to a dynamic factor model. Let $\mathbf{\Lambda}_k$ and R_{kk} be the factor loadings and a variance of the measurement error innovation for the k^{th} measurement equation, $k = 1..J$. Similarly to Boivin and Giannoni (2006) and Kose, Otrok and Whiteman (2008), we assume a joint Normal-InverseGamma prior distribution for $\left(\mathbf{\Lambda}_k, R_{kk}\right)$ so that $R_{kk} \sim IG_2(s_0, \nu_0)$ with location parameter $s_0 = 0.001$ and degrees of freedom $\nu_0 = 3$, and the prior mean of factor loadings is centered around the vector of zeros $\mathbf{\Lambda}_k \mid R_{kk} \sim \; N(\mathbf{\Lambda}_{k,0}, R_{kk}\mathbf{M}_0^{-1})$ with $\mathbf{\Lambda}_{k,0} = \mathbf{0}$ and $\mathbf{M}_0 = \mathbf{I}_N$. The prior for the k^{th} measurement equation's autocorrelation Ψ_{kk}, all k, is $N(0,1)$. We are making it perfectly tight, however, because there could be data series with stochastic trends we seek to capture with potentially highly persistent dynamic factors and not with highly persistent measurement errors. This implies that all measurement errors are *iid* mean-zero normal random variables. Finally, as explained in Section III.B, for the factor transition matrix $\mathbf{G}$, we implement a version of a Minnesota prior (Lubik and Schorfheide, 2005) and tilt the transition equation (8) to a collection of univariate random walks.[6]

[6] The hyperparameters in the actual implementation of the Minnesota prior were set as follows: $\tau = 5$, $d = 0.5$, $\iota = 1$, $w = 1$, $\lambda = 0$, $\mu = 0$. We have also truncated the prior to the region consistent with the stationarity of the factor transition equation.

In our data-rich DSGE model, we have two groups of parameters: state-space model parameters comprising matrices $\mathbf{\Lambda}$, $\mathbf{\Psi}$ and $\mathbf{R}$, and deep structural parameters $\boldsymbol{\theta}$ of an underlying DSGE model. The prior for the state-space matrices is elicited differently for the core and the non-core data indicators contained in X_t. Regarding the non-core measurement equations, the prior for $\left(\mathbf{\Lambda}_k, R_{kk}\right)$ and for Ψ_{kk} is identical to the one assumed in DFM above. The prior distribution for the factor loadings in the core measurement equations follows the same scheme as elaborated in Kryshko (2011), Section V.A. Our choice of prior distribution for the deep structural parameters of a DSGE model is exactly identical to the one presented in Section V.A of Kryshko (2011).

We use the Gibbs sampler presented above in Section III.B and the Gibbs sampler with Metropolis step outlined in Kryshko (2011), Section III.A to estimate our empirical dynamic factor model and the data-rich DSGE model, respectively. The only parameters of direct interest are the deep structural parameters $\boldsymbol{\theta}$ of an underlying DSGE model, and we have already discussed them extensively in Kryshko (2011). We do not discuss the posterior estimates of DFM parameters here either, since we are more interested in comparing factor spaces spanned by the estimated latent factors and by the DSGE model states. However, all the parameter estimates are collected in the technical appendix to this paper, which is available upon request.

B. Empirical Factors and Estimated DSGE Model States

Our empirical analysis proceeds by plotting the estimated empirical factors extracted by a dynamic factor model and the estimated DSGE state variables from our data-rich DSGE model.

Figure C2 depicts the posterior means and 90 percent credible intervals of the estimated data-rich DSGE model states. These include three endogenous variables (model inflation $\hat{\pi}_t$, the nominal interest rate $\hat{R}_t$ and real household consumption $\hat{X}_t$) and three structural AR(1) shocks (government spending g_t, money demand χ_t and neutral technology Z_t). In Kryshko (2011) we have noted four observations. First, all three structural disturbances exhibit large swings and prolonged deviations from zero capturing the persistent low-frequency movements in the data. Second, the estimated data-rich DSGE model states are much *smoother* than their counterparts in the regular DSGE model, because in the data-rich context, the model states are the common components of a large panel of data, and they have to capture well not only a few core macro series (as is the case in the regular DSGE model), but also very many non-core informational series. The third observation is that the money demand shock χ_t appeared to be very different in the data-rich versus the regular DSGE model estimation, owing primarily to the fact that in the data-rich DSGE model it helped explain housing variables, consumer credit and non-GDP measures of output at the cost of the poorer fit for the IVM_M2S. The fourth observation was a counterfactual behavior of government spending shock and real consumption during recessions: the former tended to fall and the latter to rise when times are bad.

We proceed by discussing the latent empirical factors extracted by our DFM from the same rich data set. Figure C3 plots the posterior means and 90 percent credible intervals of the estimated factors. First, note that unlike the DSGE model states, these factors have in general *no economic interpretation*. This is less true of factors F3-F6, because of the assumed normalization scheme (12). Second, while factors 3 and 5 indeed look much like the data on real output and nominal interest rate, factors 4 and 6 – despite the normalization – do not. This shows that the exclusion normalizations favoring a certain ex-ante meaning of a particular factor are not a sufficient condition to guarantee this meaning ex-post after estimation. The third observation is that the credible intervals for F1 and F2 – the latent factors common to all macro and financial series in the panel – are not uniformly wide or narrow, as is more or less the case for factors F3-F6. During several years prior to 1990-91 recession, the 90 percent credible bands for factor F1 expand, and then quickly shrink after recession is over. The same pattern is observed for factor F2 for several years preceding the 2001 recession. One interpretation of this finding could be that the volatility of these two factors is not constant over time and follows a regime-switching dynamics over the business cycle. Clearly, to have a stronger case, one might like to estimate a DFM on the full postwar sample of available U.S. data.

C. How Well Factors Trace Data

Let us now turn to the question of how well the factors and the DSGE states are able to trace the actual data. *A priori* we should expect that the unrestricted dynamic factor model will do a better job on that dimension than the data-rich DSGE model whose cross-equation restrictions might be misspecified and the factor loadings in which might be unduly restricted. And that's indeed what we find and what can be concluded from inspecting Table C2 and Table C3 which present the (posterior mean of) fraction of the unconditional variance of the data series captured by the empirical factors and by the DSGE model states. On average, the data-rich DSGE model states "explain" about 75 percent of variance for the core macro series and 72 percent of variance for the non-core. The latent empirical factors extracted by a DFM are able to account for 95 and 94 percent of the variance for the core and non-core series, respectively. So overall, the empirical factors capture more than the DSGE states.

More specifically, within the core series it is the measures of inflation and of inverse money velocities that are traced relatively more poorly than the real output and nominal interest rates in both models. The same picture is observed in the non-core block of series: price and wage inflation measures and the financial variables in both models tend to have a higher fraction of unconditional variance due to measurement errors. In the data-rich DSGE model, the state variables capture about 15 to 25 percent of the variance in exchange rate depreciations and stock returns, but about 65 to 85 percent of the variance of interest rate spreads and credit stocks. This is not surprising given that our theoretical model does not have New Open-Economy Macroeconomics mechanisms (e.g., Lubik and Schorfheide, 2005 or Adolfson, Laseén, Linde, Villani, 2005, 2008) and does not feature financial intermediation (e.g., Bernanke, Gertler, Gilchrist, 1999). In the dynamic factor model, these percentages are much higher: the latent factors explain about 97-98 percent of the variance of the interest spreads and credit stocks, about 65-82 percent of the variability in exchange rate depreciations and 80-82 percent of stock returns (Table C4). This suggests that our DSGE model is potentially misspecified along this "financial" dimension.

D. Comparing Factor Spaces

Up to this point, we have done two things: (i) we have estimated the empirical latent factors in a dynamic factor model and the DSGE states in a data-rich DSGE model; and (ii) we have established that both factors and DSGE states are able to explain a significant portion of the co-movement in the rich panel of U.S. macro and financial series. From Figure C2 and Figure C3 we have learned that the states and the factors look quite different; therefore now we come to our central question: can the empirical factors and the estimated DSGE model state variables span the same factor space? Or, in other words, can we predict the true estimated DFM latent factors from the DSGE model states with a fair amount of accuracy?

Let $F_t^{(pm)}$ and $S_t^{(pm)}$ denote the posterior means of the empirical factors and of the data-rich DSGE model state variables. For each latent factor $F_{i,t}^{(pm)}$, we estimate, by Ordinary Least Squares, the following simple linear regression:

$$F_{i,t}^{(pm)} = \beta_{0,i} + \boldsymbol{\beta}'_{1,i} S_t^{(pm)} + u_{i,t} \tag{17}$$

with mean zero and homoscedastic error term $u_{i,t}$. We report the R^2s for the collection of linear predictive regressions (17) in Table C7. Denoting the OLS estimates by $\hat{\boldsymbol{\beta}}_0 = [\beta_{0,1},..., \beta_{0,N}]'$ and by $\hat{\boldsymbol{\beta}}_1 = [\boldsymbol{\beta}_{1,1},..., \boldsymbol{\beta}_{1,N}]'$, we then construct the predicted empirical factors $\hat{F}_t^{(pm)}$:

$$\hat{F}_t^{(pm)} = \boldsymbol{\beta}_0 + \hat{\boldsymbol{\beta}}_1 S_t^{(pm)} \tag{18}$$

The Figure C4 overlays true estimated DFM factors $F_t^{(pm)}$ versus those predicted by the DSGE states $\hat{F}_t^{(pm)}$.

From both Table C7 and Figure C4 we can clearly conclude that the DSGE states predict empirical factors really well and therefore the factor spaces spanned by the DSGE model state variables and by the DFM latent factors are very closely aligned. What are the implications of this important finding? First, this implies that a DSGE model indeed captures the essential sources of co-movement in the large panel of data as a sort of a core and that the differences in fit between a data-rich DSGE model and a DFM are potentially due to restricted factor loadings in the former. Second, this also implies a greater degree of comfort about propagation of structural shocks to a wide array of macro and financial series – which is the essence of many policy experiments. Third, the proximity of factor spaces facilitates economic interpretation of a dynamic factor model, as the empirical factors are now isomorphic – through the link (18) – to the DSGE model state variables with clear economic meaning.

E. Propagation of Monetary Policy and Technology Innovations

The final – and the most appealing – implication of the factor spaces proximity in the two models is that it allows us to map the DSGE model state variables into DFM empirical factors every period and therefore propagate any structural shocks from the DSGE model in an *otherwise completely non-structural* dynamic factor model to obtain predictions for a broad range of macro series of interest. Suppose $\mathbf{\Lambda}^{dfm-dsge}$ and $\mathbf{\Lambda}^{dfm}$ denote the posterior means of factor loadings in the data-rich DSGE model (4)-(6) and in the empirical DFM (7)-(9), respectively. Then, for any structural shock $\varepsilon_{i,t}$, we can generate two sets of impulse responses of a large panel of data X_t:

$$\left(\frac{\partial X_{t+h}}{\partial \varepsilon_{i,t}}\right)_{dfm-dsge} = \mathbf{\Lambda}^{dfm-dsge} \times \frac{\partial S_{t+h}}{\partial \varepsilon_{i,t}} \tag{19}$$

$$\left(\frac{\partial X_{t+h}}{\partial \varepsilon_{i,t}}\right)_{dfm} = \mathbf{\Lambda}^{dfm} \times \frac{\partial F_{t+h}}{\partial \varepsilon_{i,t}} = \mathbf{\Lambda}^{dfm}\left[\hat{\boldsymbol{\beta}}_1 \frac{\partial S_{t+h}}{\partial \varepsilon_{i,t}}\right], \tag{20}$$

where $\partial S_{t+h} / \partial \varepsilon_{i,t}$ is computed from the transition equation of the data-rich DSGE model for every horizon $h = 0,1,2,...$ and where we have used the link between S_t and F_t determined by (18).

In what follows we focus on propagating monetary policy ($\varepsilon_{R,t}$) and technology ($\varepsilon_{Z,t}$) innovations in both the data-rich DSGE and the dynamic factor model to generate predictions for the core and non-core macro series. The corresponding impulse response functions (IRFs) are presented in Figure C5, Figure C6, Figure C7 and Figure C8. It is natural to compare our results to findings in two strands of the literature: Factor Augmented Vector Autoregression (FAVAR) literature (e.g. Bernanke, Boivin, Eliasz, 2005; Stock and Watson, 2005) and the regular DSGE literature (e.g. Christiano, Eichenbaum, Evans, 2005; Smets and Wouters, 2003, 2007; DSSW 2007; Aruoba and Schorfheide, 2009; Adolfson, Laseén, Linde, and Villani, 2008). In FAVAR studies, we are able to obtain predictions for a rich panel of U.S. data similar to ours, but only of the monetary policy innovations. In the regular DSGE literature, one can propagate any structural shocks including monetary policy and technology innovations, but to a limited number of core macro variables (e.g., real GDP, consumption, investment, inflation, the interest rate, the wage rate and hours worked in Smets and Wouters, 2007). The framework that we propose in this paper delivers on both fronts: we are able to compute the responses of the core and non-core variables to both monetary policy and technology shocks. Moreover, we will have two sets of responses: from the data-rich DSGE model, which might be misspecified, and from the dynamic factor model that is primarily data-driven and fits better.

At least from the perspective of monetary policy innovations, we tend to favor the predictions obtained from the empirical dynamic factor model (20). It turns out (we provide evidence below) that the two models' predictions for the non-core variables are fairly close. The responses of the core series, though, seem more plausible in the empirical DFM case, since, for example, channeling the shock through the DFM helps eliminate the puzzling behavior of price inflation observed in the data-rich DSGE model context that we have documented in Kryshko (2011), Section V.E.

One general observation from comparing IRFs should be emphasized from the very beginning. The responses of core variables like real GDP, real consumption and investment, and inflation in regular DGSE studies are often hump-shaped, matching well the empirical findings from identified VARs. Our IRFs do not have many humps, because the underlying theoretical DSGE model, as presented in Kryshko (2011), Section II.B, abstracts from, say, habit in consumption or variable capital utilization – mechanisms that help get the humps in those often more elaborate models. This, however, can be fixed by replacing the present DSGE model with a more elaborate one.

Let us turn first to the *effects of monetary policy innovation,* which are summarized in Figure C5 and Figure C6. A contractionary monetary policy shock corresponds to 0.75 percent (or 75 basis points) increase in the federal funds rate. As the nominal policy rate rises and the opportunity costs of holding money for households increase, we observe a strong liquidity effect associated with falling real money balances. Also, high interest rates make the saving motive and buying more bonds temporarily a more attractive option. This raises households' marginal utility of consumption and discourages current spending in favor of the future consumption. Because the household faces investment adjustment costs and cannot adjust investment quickly, and government spending in the model is exogenous, the lower consumption leads to a fall in aggregate demand. The firms respond to lower demand in part by contracting real output and in part by reducing the optimal price. Hence, the aggregate price level falls, but not as much given nominal rigidities in the intermediate goods-producing sector.

Why do the monopolistically competitive firms respond to falling demand in part by charging a lower price? The short answer is that because they are able to cut their marginal costs. On the one hand, higher interest rates inhibit investment and the return on capital is falling. On the other hand, firms may now economize on real wages. The market for labor is perfectly competitive, since we assume no wage rigidities. This implies that the real wage is equal to the marginal product of labor, but also that it is equal to the household's marginal rate of substitution between consumption and leisure, as in Kryshko (2011), Equation (78). Since the disutility of labor in our model is fixed, and the marginal utility of consumption is higher, the household accepts lower real wage and the firms are able to pass on their losses in revenues to households by reducing their own wage bills.

Now given lower marginal costs, the New Keynesian Phillips curve suggests we should observe falling aggregate prices and negative rates of inflation (in terms of a deviation from the steady-state inflation). That's what we see in the second column of Figure C5. Notice that channeling the monetary policy shock through the pure dynamic factor model helps correct the so-called "*price puzzle*"[7] for the data-rich-DSGE-model-implied responses of PCE deflator inflation and CPI inflation. Interestingly, a positive response of CPI inflation to a monetary policy contraction is also documented in Stock and Watson (2005), despite the fact

[7] "Price puzzle" (Sims, 1992) refers to the counterfactual finding in the VAR literature that a measure of prices or inflation responds positively to a contractionary monetary policy shock associated with an unexpected increase in the policy interest rate.

that they use a data-rich Factor Augmented VAR. It has been argued (e.g., Bernanke, Boivin and Eliasz, 2005) that the rich information set helps eliminate this sort of anomaly.

As can be seen from the first column of Figure C5, the response of industrial production (IP) to the monetary policy tightening seems counterfactual compared to FAVAR findings (we have documented this finding in Kryshko, 2011 too). First, this may have something to do with the inherent inertia of IP in responding to monetary policy. It continues to be driven by excessive optimism from the previous phase of the business cycle and it takes time to adjust to new conditions. But once IP falls below the trend, it remains subdued for a long time. Second, this may have something to do with the way the monetary policy shock is identified in the FAVAR literature. By construction, in a FAVAR the industrial production is contained in the list of "slow moving" variables, and the identification of the monetary policy shock is achieved by postulating that it does not affect slow variables contemporaneously. Regarding the responses of real GDP, we document that the data-rich DSGE and DFM models disagree about the magnitude of the contraction. The DFM-implied response is almost negligible implying that the costs of disinflation are very small (which is hard to believe), whereas the data-rich-DSGE-model-implied response is about minus 0.5 percent – hump shape aside, a value in the ballpark of findings in the regular DSGE literature.

If we look at the effects of the monetary policy tightening on non-core macro and financial variables (Figure C6), they complete the picture for the core series with details. Real activity measures, such as real consumption of durables, real residential investment and housing starts, broadly decline. Prices go down as well; in particular, we observe negative rates of commodity price inflation and investment deflator inflation. The measures of employment fall (e.g., employment in the services sector) indicating tensions in the labor market, while unemployment gains momentum with a lag before eventually returning to normal. The interest rate spreads (for instance, the 6-month over the 3-month Treasury bill rate) widen considerably, reflecting tighter money market conditions and increased liquidity risks and credit risks. Consumer credit contracts, in part due to lower demand from borrowers facing higher interest rates and in part owing to the reduced availability of funds. The dollar appreciates, reflecting intensified capital inflows lured by higher returns in the domestic financial market. As a result, both export and import price indices fall, thereby translating – according to the magnitudes in Figure C6 – into a deterioration of the U.S. terms of trade.

Broadly speaking, the reported results are qualitatively very similar to the FAVAR findings of Bernanke, Boivin and Eliasz (2005) and Stock and Watson (2005). Except for the humps, they also accord well with the monetary policy effects on the core variables documented in the regular DSGE literature. On top of that, the responses of the non-core variables seem to provide a reasonable and consistent picture of monetary tightening as well.

We plot the *effects of a positive technology innovation* in Figure C7 (core series) and Figure C8 (non-core series). Following the positive TFP shock, real output broadly increases (although there is a disagreement between the DFM and the data-rich DSGE model as to the response of real GDP), as our economy becomes more productive and the firms find it optimal to produce more. New demand comes primarily from higher capital investment, reflecting much better future return on capital, and also from additional household consumption fueled by greater income. The higher output on the supply side plus improved efficiency implies a downward pressure on prices. Through the lenses of the New Keynesian Phillips curve, the current period inflation is positively related to expected future inflation and to current marginal costs. A positive technology shock has raised production efficiency and reduced the current marginal costs (the elevated real wage resulting from increased labor demand was not enough to prevent that). However, because technology innovation is very persistent, the firms expect future marginal costs and thus future inflation to be lower as well. This anticipation effect, coupled with currently low marginal costs, leads to prices falling now, as is evident from column 2 of the Figure C7.

The increase in real output above steady state and the fall of inflation below target level, under the estimated Taylor (1993) rule, requires the Fed to move the policy rate in opposite directions. The fact that the Fed actually lowers the policy rate means that the falling prices effect dominates, with other interest rates following the course of the federal funds rate (column 3, Figure C7). Declining interest rates boost real output even more, which in turn raises further the return on capital. As the positive impact of technological innovation dissipates, this higher return, through the future marginal costs channel, fuels inflationary expectations that ultimately translate into contemporaneous upward price pressures. The Fed reacts by increasing the policy rate, which explains the observed hump in the interest rate IRF. Given temporarily lower interest rates, households choose to hold, with some lag, relatively higher real money balances (from column 4, Figure C7, this applies more to M1S and the monetary base, and less to the M2S aggregate that comprises a hefty portion of interest-bearing time deposits). A part of the growing money demand comes endogenously from the elevated level of economic activity.

These results – both in terms of the magnitudes and shapes of responses – align fairly closely with findings in the regular DSGE literature (e.g., Smets and Wouters, 2007; Aruoba, Schorfheide, 2009; and DSSW 2007).

The responses of the non-core macroeconomic series (Figure C8) appear to enrich the story for core variables with additional insights. Following a positive technology innovation, the subcomponents of real GDP (real consumption of durables, real residential investment) or the components of industrial production (e.g., production of business equipment) generally expand (although there is weaker agreement between the predictions of the DFM and the data-rich DSGE model). Measures of employment (e.g., employment in the services sector) increase. However, this stands in contrast to the results in Smets and Wouters (2003) and Adolfson, Laseén, Linde, Villani (2005), who find in European data that employment actually falls after a positive stationary TFP shock. As marginal costs fall, commodity price inflation (P_COM) and investment deflator inflation (PInv_GDP) follow the overall downward price pressures trend. The interest rate spreads (SFYGM6) shrink, in part reflecting the lower level of perceived risks, while credit conditions ease, leading to growth in business loans. Despite the interest rates being below average for a prolonged period of time, the dollar appreciates, but by less than after the monetary tightening. Finally, the real wage (RComp_Hour) increases, while average hours worked (Hours_AVG) decline. The rise in the real wage and the initial fall in hours worked are in line with evidence documented by Smets and Wouters (2007). However, the subsequent dynamics of hours are quite different: in Smets and Wouters the hours turn significantly positive after about two years. Here they stay below steady state for much longer. This may have something to do with a greater amount of persistence in the technology process in our model.

VI. Conclusions

In this paper, we have compared a data-rich DSGE model with a standard New Keynesian core to an empirical dynamic factor model by estimating both on a rich panel of U.S. macroeconomic and financial indicators compiled by Stock and Watson (2008). We have established that the spaces spanned by the empirical factors and by the data-rich DSGE model states are very closely aligned.

This key finding has several important implications. First, it implies that a DSGE model indeed captures the essential sources of co-movement in the data and that the differences in fit between a data-rich DSGE model and a DFM are potentially due to restricted factor loadings in the former. Second, it also implies a greater degree of comfort about the propagation of structural shocks to a wide array of macro and financial series. Third, the proximity of factor spaces facilitated economic interpretation of a dynamic factor model, since the empirical factors have become isomorphic to the DSGE model state variables with clear economic meaning.

Most important, the proximity of factor spaces in the two models has allowed us to propagate the monetary policy and technology innovations in an otherwise completely non-structural dynamic factor model to obtain predictions for many more series than just a handful of traditional macro variables, including measures of real activity, price indices, labor market indicators, interest rate spreads, money and credit stocks, and exchange rates. The responses of these non-core variables therefore provide a more complete and comprehensive picture of the effects of monetary policy and technology shocks and may serve as a check on the empirical plausibility of a DSGE model.

APPENDIX A. DFM: GIBBS SAMPLER: DRAWING TRANSITION EQUATION MATRIX

We need to generate $\mathbf{G}$ from the conditional density $p(\mathbf{G} \mid \mathbf{Q}, \mathbf{\Lambda}, \mathbf{\Psi}, \mathbf{R}, F^T; X^T)$. Note, however, that the dependence of $\mathbf{G}$ on the other state-space matrices – except for $\mathbf{Q}$ – is exclusively through the factors. This is because given factors F_t, the transition equation (8) is a VAR(1):

$$F_t = \mathbf{G}F_{t-1} + \eta_t, \qquad \eta_t \sim iid\ N(\mathbf{0}, \mathbf{Q}), \qquad t = 1, ..., T. \tag{21}$$

Therefore, $p(\mathbf{G} \mid \mathbf{Q}, \mathbf{\Lambda}, \mathbf{\Psi}, \mathbf{R}, F^T; X^T) = p(\mathbf{G} \mid \mathbf{Q}, F^T)$.

Rewrite the VAR in matrix notation

$$Y = X\mathbf{G} + \eta \tag{22}$$

where Y, X and η are the $(T-1) \times N$ matrices with rows F_t', F_{t-1}' and η_t', respectively. To specify a prior distribution for the VAR parameters, we follow Lubik and Schorfheide (2005) and use a version of Minnesota Prior (Doan, Litterman, Sims 1984) implemented with T^* dummy observations Y^* and X^*. The likelihood function of dummy observations $p(Y^* \mid \mathbf{G}, \mathbf{Q})$ combined with the improper prior distribution $\left|\mathbf{Q}\right|^{-(N+1)/2} \times \mathbf{1}_{\mathbf{G}}$ induces the proper prior for the VAR parameters:

$$p(\mathbf{G}, \mathbf{Q}) \propto p(Y^* \mid \mathbf{G}, \mathbf{Q}) \left|\mathbf{Q}\right|^{-(N+1)/2} \times \mathbf{1}_{\mathbf{G}}, \tag{23}$$

where $\mathbf{1}_{\mathbf{G}}$ denotes an indicator function equal to 1 if all eigenvalues of $\mathbf{G}$ lie inside unit circle. In actual implementation of Minnesota Prior, we set the hyperparameters as follows $\tau = 5,\ d = 0.5,\ \iota = 1,\ \ w = 1,\ \lambda = 0,\ \mu = 0$ to generate Y^* and X^*. Essentially, our prior is tilting the transition equation (21) to a collection of the univariate random walks.

Combining this prior with the likelihood function $p(Y \mid \mathbf{G}, \mathbf{Q})$, we obtain the posterior density of the VAR parameters:

$$p(\mathbf{G}, \mathbf{Q} \mid Y) \propto p(Y \mid \mathbf{G}, \mathbf{Q}) p(\mathbf{G}, \mathbf{Q}) = p(Y \mid \mathbf{G}, \mathbf{Q}) p(Y^* \mid \mathbf{G}, \mathbf{Q}) \left|\mathbf{Q}\right|^{-(N+1)/2} \times \mathbf{1}_{\mathbf{G}}. \tag{24}$$

It can be shown (e.g. Del Negro, Schorfheide 2004) that our posterior density $p(\mathbf{G}, \mathbf{Q} \mid Y) = p(\mathbf{G}, \mathbf{Q} \mid F^T)$ is truncated Normal-Inverse-Wishart:

$$\mathbf{Q} \mid Y \quad \sim IW(\tilde{\mathbf{Q}}, (T + T^* - N)) \tag{25}$$

$$\mathbf{G} \mid \mathbf{Q}, Y \sim N(\tilde{\mathbf{G}}, \mathbf{\Sigma}_G) \times \mathbf{1}_{\mathbf{G}} \tag{26}$$

where

$$\tilde{\mathbf{G}} = \left(X^{*\prime} X^{*} + X'X \right)^{-1} \left(X^{*\prime} Y^{*} + X'Y \right)$$

$$\tilde{\mathbf{Q}} = \left(Y^{*\prime} Y^{*} + Y'Y \right) - \left(X^{*\prime} Y^{*} + X'Y \right)' \left(X^{*\prime} X^{*} + X'X \right)^{-1} \left(X^{*\prime} Y^{*} + X'Y \right)$$

$$\mathbf{\Sigma}_G = \mathbf{Q} \otimes \left(X^{*\prime} X^{*} + X'X \right)^{-1}.$$

As discussed in Section III.B, to fix the scale of factors F_t in estimation, we do not estimate $\mathbf{Q}$ and instead set $\mathbf{Q} = \mathbf{I}_N$. Given $\mathbf{Q}$, we then only draw $\mathbf{G}$ using the posterior distribution (26). Finally, we enforce the stationarity of factors by discarding those draws of matrix $\mathbf{G}$ that have at least one eigenvalue greater than or equal to one in absolute value (explosive eigenvalues).

APPENDIX B. DATA: DESCRIPTION AND TRANSFORMATIONS

#	Short Name	SW Mnemonic	Trans Code	Description
Core Series				
	Real Output			
1.	RGDP		4	Real Per-capita Gross Domestic Product
2.	IP_TOTAL		4	Per-capita Industrial Production Index: Total
3.	IP_MFG		4	Per-capita Industrial Production Index: Manufacturing
	Inflation			
4.	PGDP		4	GDP Deflator Inflation
5.	PCED		4	Personal Consumption Expenditure Deflator Inflation
6.	CPI_ALL		4	Consumer Price Index (All Items) Inflation
	Nominal Interest Rate			
7.	FedFunds		4	Interest Rate: Federal Funds (effective), % per annum
8.	TBill_3m		4	Interest Rate: U.S. Treasury bills, secondary market, 3 month, % per annum
9.	AAABond		4	Bond Yield: Moody's AAA Corporate, % per annum
	Inverse Velocity of Money (M/Y)			
10.	IVM_M1S_det		4	Inverse Velocity of Money based on M1S aggregate
11.	IVM_M2S		4	Inverse Velocity of Money based on M2S aggregate
12.	IVM_MBase_bar		4	Inverse Velocity of Money based on adjusted Monetary Base
Non-Core Series				
	Output and Components			
1.	IP_CONS_DBLE	IPS13	3*	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS
2.	IP_CONS_NONDBLE	IPS18	3*	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS
3.	IP_BUS_EQPT	IPS25	3*	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT
4.	IP_DBLE_MATS	IPS34	3*	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS
5.	IP_NONDBLE_MATS	IPS38	3*	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS
6.	IP_FUELS	IPS306	3*	INDUSTRIAL PRODUCTION INDEX - FUELS
7.	PMP	PMP	0	NAPM PRODUCTION INDEX (PERCENT)
8.	RCONS	GDP252	3*	Real Personal Consumption Expenditures, Quantity Index (2000=100) , SAAR
9.	RCONS_DUR	GDP253	3*	Real Personal Consumption Expenditures - Durable Goods , Quantity Index (2000=100), SAAR
10.	RCONS_SERV	GDP255	3*	Real Personal Consumption Expenditures - Services, Quantity Index (2000=100) , SAAR
11.	REXPORTS	GDP263	3*	Real Exports, Quantity Index (2000=100) , SAAR
12.	RIMPORTS	GDP264	3*	Real Imports, Quantity Index (2000=100) , SAAR
13.	RGOV	GDP265	3*	Real Government Consumption Expenditures & Gross Investment, Quantity Index (2000=100), SAAR
	Labor Market			
14.	EMP_MINING	CES006	3*	EMPLOYEES, NONFARM - MINING
15.	EMP_CONST	CES011	3*	EMPLOYEES, NONFARM - CONSTRUCTION
16.	EMP_DBLE_GDS	CES017	3*	EMPLOYEES, NONFARM - DURABLE GOODS
17.	EMP_NONDBLES	CES033	3*	EMPLOYEES, NONFARM - NONDURABLE GOODS
18.	EMP_SERVICES	CES046	3*	EMPLOYEES, NONFARM - SERVICE-PROVIDING
19.	EMP_TTU	CES048	3*	EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES
20.	EMP_WHOLESALE	CES049	3*	EMPLOYEES, NONFARM - WHOLESALE TRADE
21.	EMP_RETAIL	CES053	3*	EMPLOYEES, NONFARM - RETAIL TRADE
22.	EMP_FIRE	CES088	3	EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES
23.	EMP_GOVT	CES140	3	EMPLOYEES, NONFARM - GOVERNMENT
24.	URATE_ALL	LHUR	0	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)
25.	U_DURATION	LHU680	0	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)
26.	U_L5WKS	LHU5	3	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)
27.	U_5_14WKS	LHU14	3	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)
28.	U_M15WKS	LHU15	3	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)
29.	U_15_26WKS	LHU26	3	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)
30.	U_M27WKS	LHU27	3	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)
31.	HOURS_AVG	CES151	0	AVG WKLY HOURS, PROD WRKRS, NONFARM - GOODS-PRODUCING
	Housing			
32.	HSTARTS_NE	HSNE	1	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.
33.	HSTARTS_MW	HSMW	1	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.
34.	HSTARTS_SOU	HSSOU	1	HOUSING STARTS:SOUTH (THOUS.U.)S.A.
35.	HSTARTS_WST	HSWST	1	HOUSING STARTS:WEST (THOUS.U.)S.A.

35.	HSTARTS_WST	HSWST	1	HOUSING STARTS:WEST (THOUS.U.)S.A.
36.	RRESINV	GDP261	3*	Real Gross Private Domestic Investment - Residential, Quantity Index (2000=100), SAAR
	Financial Variables			
37.	SFYGM6	Sfygm6	0	fygm6-fygm3 fygm6: INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA) fygm3: INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)
38.	SFYGT1	Sfygt1	0	fygt1-fygm3 fygt1: INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
39.	SFYGT10	Sfygt10	0	fygt10-fygm3 fygt10: INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
40.	SFYBAAC	sFYBAAC	0	FYBAAC-Fygt10 FYBAAC: BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)
41.	BUS_LOANS	BUSLOANS	3	Commercial and Industrial Loans at All Commercial Banks (FRED) Billions $ (SA)
42.	CONS_CREDIT	CCINRV	3*	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)
43.	DLOG_EXR_US	EXRUS	2	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)
44.	DLOG_EXR_CHF	EXRSW	2	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)
45.	DLOG_EXR_YEN	EXRJAN	2	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)
46.	DLOG_EXR_GBP	EXRUK	2	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)
47.	DLOG_EXR_CAN	EXRCAN	2	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)
48.	DLOG_SP500	FSPCOM	2	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)
49.	DLOG_SP_IND	FSPIN	2	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)
50.	DLOG_DJIA	FSDJ	2	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE
	Investment, Inventories, Orders			
51.	NAPMI	PMI	0	PURCHASING MANAGERS' INDEX (SA)
52.	NAPM_NEW_ORDRS	PMNO	0	NAPM NEW ORDERS INDEX (PERCENT)
53.	NAPM_VENDOR_DEL	PMDEL	0	NAPM VENDOR DELIVERIES INDEX (PERCENT)
54.	NAPM_INVENTORIES	PMNV	0	NAPM INVENTORIES INDEX (PERCENT)
55.	RINV_GDP	GDP256	3*	Real Gross Private Domestic Investment, Quantity Index (2000=100) , SAAR
56.	RNONRESINV_STRUCT	GDP259	1	Real Gross Private Domestic Investment - Nonresidential - Structures, Quantity Index (2000=100), SAAR
57.	RNONRESINV_BEQUIPT	GDP260	3*	Real Gross Private Domestic Investment - Nonresidential - Equipment & Software
	Prices and Wages			
58.	RAHE_CONST	CES277R	3*	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - CONSTRUCTION (CES277/PI071)
59.	RAHE_MFG	CES278R	3	REAL AVG HRLY EARNINGS, PROD WRKRS, NONFARM - MFG (CES278/PI071)
60.	P_COM	PSCCOMR	2	Real SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES(1967=100) (PSCCOM/PCEPILFE) PSCCOM: SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES(1967=100) PCEPILFE: PCE Price Index Less Food and Energy (SA) Fred
61.	P_OIL	PW561R	2	PPI Crude (Relative to Core PCE) (pw561/PCEPiLFE) pw561: PRODUCER PRICE INDEX: CRUDE PETROLEUM (82=100,NSA)
62.	P_NAPM_COM	PMCP	2	NAPM COMMODITY PRICES INDEX (PERCENT)
63.	RCOMP_HOUR	LBPUR7	1*	REAL COMPENSATION PER HOUR,EMPLOYEES:NONFARM BUSINESS(82=100,SA)
64.	ULC	LBLCPU	1*	UNIT LABOR COST: NONFARM BUSINESS SEC (1982=100,SA)
65.	PCED_DUR	GDP274A	2	Personal Consumption Expenditures: Durable goods Price Index
66.	PCED_NDUR	GDP275A	2	Personal Consumption Expenditures: Nondurable goods Price Index
67.	PCED_SERV	GDP276A	2	Personal Consumption Expenditures: Services Price Index
68.	PINV_GDP	GDP277A	2	Gross private domestic investment Price Index
69.	PINV_NRES_STRUCT	GDP280A	2	GPDI Price Index: Structures
70.	PINV_NRES_EQP	GDP281A	2	GPDI Price Index: Equipment and software Price Index
71.	PINV_RES	GDP282A	2	GPDI Price Index: Residential Price Index
72.	PEXPORTS	GDP284A	2	GDP: Exports Price Index
73.	PIMPORTS	GDP285A	2	GDP: Imports Price Index
74.	PGOV	GDP286A	2	Government consumption expenditures and gross investment Price Index
	Other			
75.	UTL11	UTL11	0	CAPACITY UTILIZATION - MANUFACTURING (SIC)
76.	UMICH_CONS	HHSNTN	1	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)
77.	LABOR_PROD	LBOUT	1*	OUTPUT PER HOUR ALL PERSONS: BUSINESS SEC(1982=100,SA)

Notes: Transformation codes: 0 – nothing; 1 – log(); 2 – dlog(); 3 – log of the ratio of subaggregate to aggregate; 4 – transformation described in Kryshko (2011), Section IV. Asterisk (*) indicates the transformed variable has been further linearly detrended.

Source of data: Stock and Watson (2008), "Forecasting in Dynamic Factor Models Subject to Structural Instability," available online at: http://www.princeton.edu/~mwatson/ddisk/hendryfestschrift_replicationfiles_April28_2008.zip

Full sample available: 1959:Q1-2006:Q4. Sample used in estimation: 1984:Q1-2005:Q4.

All series available at monthly frequency have been converted to quarterly by simple averaging in native units.

APPENDIX C. TABLES AND FIGURES

Figure C1. DFM: Principal Components Analysis
Data set: DFM3.TXT (standardized)

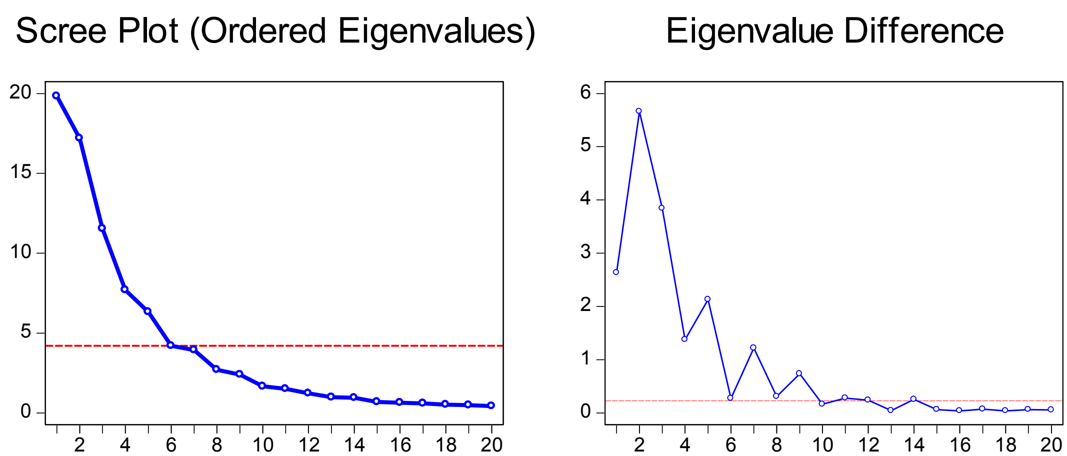


Table C1. DFM: Principal Components Analysis

Sample: 1984Q1 2005Q4
Included observations: 88
Computed using: Ordinary correlations
Extracting 20 of 89 possible components

Eigenvalues: (Sum = 89, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	19.82739	2.631345	0.2228	19.82739	0.2228
2	17.19605	5.659930	0.1932	37.02344	0.4160
3	11.53612	3.839474	0.1296	48.55955	0.5456
4	7.696642	1.375366	0.0865	56.25619	0.6321
5	6.321275	2.126480	0.0710	62.57747	0.7031
6	4.194795	0.270895	0.0471	66.77227	0.7503
7	3.923900	1.220256	0.0441	70.69617	0.7943
8	2.703644	0.305552	0.0304	73.39981	0.8247
9	2.398092	0.736125	0.0269	75.79790	0.8517
10	1.661967	0.160485	0.0187	77.45987	0.8703
11	1.501482	0.280114	0.0169	78.96135	0.8872
12	1.221368	0.238101	0.0137	80.18272	0.9009
13	0.983267	0.040017	0.0110	81.16598	0.9120
14	0.943250	0.252902	0.0106	82.10923	0.9226
15	0.690347	0.063015	0.0078	82.79958	0.9303
16	0.627333	0.038032	0.0070	83.42691	0.9374
17	0.589301	0.069497	0.0066	84.01621	0.9440
18	0.519803	0.038042	0.0058	84.53602	0.9498
19	0.481761	0.062722	0.0054	85.01778	0.9553
20	0.419039	0.054135	0.0047	85.43682	0.9600

Table C2. Pure DFM: Fraction of Unconditional Variance Captured by Factors

iid Measurement Errors; Dataset = DFM3.txt
on average, 100K draws, 20K burn-in

	All Factors	Error term
Core Variables	**0.948**	**0.052**
Real output	0.993	0.007
Inflation	0.896	0.104
Interest rates	0.990	0.010
Money velocities	0.914	0.086
Non-Core Variables	**0.941**	**0.059**
Output and components	0.982	0.018
Labor market	0.981	0.019
Investment, inventories, orders	0.986	0.014
Housing	0.970	0.030
Prices and wages	0.908	0.092
Financial variables	0.854	0.146
Other	0.973	0.027

Table C3. Data-Rich DSGE Model: Fraction of Unconditional Variance Captured by DSGE Model States

iid Measurement Errors; Dataset = DFM3.txt
on average, 20K draws, 4K burn-in

	GOV	CHI	MP	Z	All Shocks	Error term
Core Variables	**0.05**	**0.08**	**0.06**	**0.56**	**0.749**	**0.251**
Real output	0.14	0.21	0.03	0.48	0.852	0.148
Inflation	0.01	0.02	0.01	0.70	0.733	0.267
Interest rates	0.01	0.00	0.15	0.76	0.925	0.075
Money velocities	0.07	0.09	0.04	0.29	0.489	0.512
Non-Core Variables	**0.09**	**0.13**	**0.06**	**0.45**	**0.719**	**0.281**
Output and components	0.07	0.27	0.08	0.45	0.873	0.127
Labor market	0.19	0.14	0.06	0.46	0.848	0.152
Investment, inventories, orders	0.10	0.13	0.02	0.63	0.882	0.118
Housing	0.04	0.26	0.07	0.42	0.794	0.206
Prices and wages	0.03	0.05	0.04	0.45	0.568	0.432
Financial variables	0.06	0.03	0.05	0.32	0.451	0.549
Other	0.02	0.12	0.09	0.64	0.866	0.134

Table C4. Pure DFM: Unconditional Variance Captured by Factors

iid Measurement Errors; Dataset = DFM3.txt
<u>on average</u>, 100K draws, 20K burn-in

Algorithm: Jungbacker-Koopman
Identification: Scheme 2 - Block Diagonal

	F1	F2	F3	F4	F5	F6	All Factors	Measurement Error
Real GDP	0.119	0.142	0.301	0.160	0.115	0.148	0.984	0.016
IP_Total	0.137	0.105	0.343	0.135	0.113	0.164	0.996	0.004
IP_MFG	0.131	0.105	0.350	0.136	0.114	0.162	0.997	0.003
GDP Def inflation	0.147	0.173	0.166	0.169	0.110	0.142	0.907	0.094
PCE Def inflation	0.148	0.177	0.168	0.173	0.110	0.145	0.921	0.079
CPI ALL Inflation	0.130	0.167	0.159	0.166	0.102	0.138	0.862	0.138
FedFunds	0.135	0.169	0.185	0.169	0.186	0.148	0.993	0.008
3m T-Bill rate	0.136	0.166	0.185	0.168	0.189	0.148	0.991	0.009
AAA Bond yield	0.118	0.114	0.192	0.150	0.267	0.147	0.988	0.012
IVM_M1S_det	0.117	0.164	0.149	0.151	0.097	0.130	0.808	0.193
IVM_M2S	0.206	0.141	0.197	0.145	0.114	0.192	0.994	0.006
IVM_MBASE_bar	0.197	0.154	0.175	0.146	0.116	0.152	0.940	0.060
IP_CONS_DBLE	0.134	0.139	0.217	0.159	0.121	0.169	0.938	0.062
IP_CONS_NONDBLE	0.133	0.115	0.253	0.142	0.149	0.201	0.992	0.008
IP_BUS_EQPT	0.161	0.142	0.199	0.191	0.134	0.157	0.984	0.017
IP_DBLE_MATS	0.135	0.110	0.226	0.154	0.137	0.233	0.994	0.006
IP_NONDBLE_MATS	0.147	0.133	0.175	0.185	0.113	0.242	0.996	0.004
IP_FUELS	0.147	0.144	0.212	0.175	0.133	0.149	0.959	0.041
PMP	0.145	0.146	0.216	0.170	0.143	0.170	0.989	0.011
UTL11	0.141	0.181	0.184	0.183	0.143	0.165	0.997	0.003
RAHE_CONST	0.147	0.152	0.192	0.167	0.121	0.180	0.958	0.042
RAHE_MFG	0.166	0.137	0.184	0.149	0.120	0.228	0.983	0.017
EMP_MINING	0.130	0.118	0.211	0.210	0.123	0.169	0.960	0.040
EMP_CONST	0.153	0.141	0.193	0.166	0.112	0.234	0.998	0.002
EMP_DBLE_GDS	0.201	0.140	0.203	0.160	0.133	0.160	0.996	0.004
EMP_NONDBLES	0.158	0.120	0.183	0.183	0.116	0.236	0.995	0.005
EMP_SERVICES	0.164	0.155	0.211	0.141	0.126	0.201	0.997	0.003
EMP_TTU	0.140	0.159	0.184	0.173	0.139	0.176	0.971	0.029
EMP_WHOLESALE	0.144	0.167	0.168	0.142	0.114	0.145	0.879	0.121
EMP_RETAIL	0.162	0.157	0.177	0.163	0.143	0.164	0.967	0.033
EMP_FIRE	0.219	0.142	0.181	0.160	0.121	0.156	0.979	0.021
EMP_GOVT	0.150	0.135	0.266	0.137	0.152	0.155	0.996	0.004
URATE_ALL	0.124	0.175	0.255	0.157	0.141	0.141	0.993	0.007
U_DURATION	0.135	0.143	0.197	0.223	0.116	0.183	0.997	0.003
U_L5WKS	0.128	0.144	0.201	0.211	0.142	0.169	0.995	0.005
U_5_14WKS	0.145	0.143	0.195	0.167	0.154	0.163	0.966	0.034
U_M15WKS	0.132	0.153	0.198	0.218	0.121	0.177	0.998	0.002
U_15_26WKS	0.123	0.153	0.196	0.190	0.160	0.155	0.976	0.024
U_M27WKS	0.136	0.149	0.196	0.218	0.113	0.184	0.997	0.003
HOURS_AVG	0.151	0.147	0.207	0.163	0.145	0.178	0.991	0.009
HSTARTS_NE	0.132	0.135	0.193	0.173	0.154	0.175	0.962	0.038
HSTARTS_MW	0.118	0.121	0.240	0.163	0.155	0.145	0.942	0.058

HSTARTS_MW	0.118	0.121	0.240	0.163	0.155	0.145	0.942	0.058
HSTARTS_SOU	0.133	0.121	0.194	0.240	0.119	0.183	0.990	0.010
HSTARTS_WST	0.128	0.143	0.190	0.223	0.120	0.180	0.982	0.018
SFYGM6	0.138	0.143	0.201	0.167	0.152	0.168	0.970	0.030
SFYGT1	0.133	0.139	0.189	0.164	0.191	0.160	0.976	0.025
SFYGT10	0.150	0.197	0.182	0.160	0.132	0.153	0.974	0.026
SFYBAAC	0.151	0.188	0.178	0.170	0.129	0.171	0.988	0.012
BUS_LOANS	0.140	0.138	0.189	0.199	0.167	0.154	0.986	0.014
CONS_CREDIT	0.140	0.145	0.184	0.176	0.123	0.208	0.976	0.024
P_COM	0.139	0.133	0.189	0.151	0.112	0.150	0.874	0.126
P_OIL	0.117	0.121	0.181	0.139	0.104	0.130	0.792	0.208
P_NAPM_COM	0.138	0.128	0.197	0.147	0.125	0.148	0.882	0.118
DLOG_EXR_US	0.127	0.107	0.141	0.121	0.095	0.118	0.709	0.291
DLOG_EXR_CHF	0.107	0.100	0.135	0.112	0.090	0.111	0.655	0.345
DLOG_EXR_YEN	0.128	0.125	0.168	0.134	0.126	0.134	0.814	0.186
DLOG_EXR_GBP	0.098	0.095	0.129	0.111	0.088	0.105	0.626	0.374
DLOG_EXR_CAN	0.136	0.130	0.160	0.142	0.126	0.132	0.825	0.175
DLOG_SP500	0.133	0.136	0.171	0.138	0.111	0.137	0.827	0.173
DLOG_SP_IND	0.129	0.139	0.167	0.138	0.110	0.136	0.819	0.181
DLOG_DJIA	0.128	0.126	0.174	0.134	0.111	0.133	0.807	0.193
UMICH_CONS	0.142	0.121	0.246	0.142	0.130	0.167	0.949	0.051
NAPMI	0.144	0.149	0.219	0.173	0.140	0.170	0.994	0.006
NAPM_NEW_ORDRS	0.146	0.146	0.214	0.169	0.139	0.170	0.983	0.017
NAPM_VENDOR_DEL	0.142	0.147	0.222	0.170	0.137	0.168	0.985	0.015
NAPM_INVENTORIES	0.137	0.155	0.211	0.176	0.145	0.161	0.985	0.015
RCONS	0.172	0.144	0.187	0.175	0.127	0.177	0.982	0.018
RCONS_DUR	0.141	0.118	0.203	0.175	0.114	0.230	0.980	0.020
RCONS_SERV	0.139	0.134	0.186	0.202	0.115	0.214	0.990	0.010
RINV_GDP	0.153	0.125	0.225	0.155	0.145	0.192	0.995	0.005
RNONRESINV_STRUCT	0.165	0.138	0.187	0.153	0.118	0.224	0.984	0.016
RNONRESINV_BEQUIPT	0.141	0.168	0.185	0.198	0.128	0.156	0.976	0.024
RRESINV	0.176	0.155	0.182	0.186	0.128	0.150	0.977	0.023
REXPORTS	0.152	0.130	0.177	0.226	0.117	0.192	0.993	0.007
RIMPORTS	0.129	0.106	0.236	0.149	0.137	0.222	0.978	0.022
RGOV	0.203	0.133	0.207	0.141	0.138	0.171	0.994	0.006
LABOR_PROD	0.173	0.144	0.175	0.199	0.115	0.166	0.972	0.028
RCOMP_HOUR	0.183	0.161	0.190	0.153	0.123	0.177	0.987	0.014
ULC	0.134	0.151	0.187	0.225	0.122	0.170	0.989	0.011
PCED_DUR	0.135	0.133	0.178	0.174	0.181	0.150	0.950	0.050
PCED_NDUR	0.133	0.152	0.174	0.163	0.108	0.136	0.866	0.134
PCED_SERV	0.131	0.117	0.200	0.139	0.134	0.144	0.865	0.135
PINV_GDP	0.154	0.162	0.174	0.176	0.116	0.142	0.925	0.075
PINV_NRES_STRUCT	0.129	0.165	0.189	0.177	0.137	0.149	0.945	0.055
PINV_NRES_EQP	0.172	0.129	0.182	0.151	0.113	0.149	0.897	0.103
PINV_RES	0.121	0.135	0.191	0.173	0.110	0.140	0.870	0.130
PEXPORTS	0.164	0.147	0.204	0.170	0.123	0.155	0.963	0.037
PIMPORTS	0.149	0.142	0.192	0.162	0.117	0.144	0.906	0.094
PGOV	0.122	0.125	0.156	0.140	0.111	0.124	0.778	0.222

Notes: Please see Appendix B, p.29 for the corresponding mnemonics of data indicators reported here.

Table C5. Data-Rich DSGE Model: Fraction of Unconditional Variance Captured by DSGE Model States

iid Measurement Errors; Dataset = DFM3.txt
on average, 20K draws, 4K burn-in

Algorithm: Jungbacker-Koopman

	GOV	CHI	MP	Z	All Shocks	Measurement Error
Real GDP	0.081	0.000	0.040	0.648	0.770	0.230
IP_Total	0.167	0.308	0.021	0.395	0.891	0.110
IP_MFG	0.166	0.317	0.020	0.392	0.894	0.106
GDP Def inflation	0.011	0.000	0.011	0.789	0.811	0.189
PCE Def inflation	0.004	0.035	0.003	0.703	0.745	0.255
CPI ALL Inflation	0.005	0.031	0.006	0.600	0.642	0.358
FedFunds	0.004	0.000	0.135	0.817	0.956	0.044
3m T-Bill rate	0.007	0.003	0.160	0.788	0.958	0.042
AAA Bond yield	0.013	0.008	0.168	0.672	0.861	0.139
IVM_M1S_det	0.055	0.174	0.016	0.404	0.648	0.352
IVM_M2S	0.042	0.063	0.003	0.071	0.178	0.822
IVM_MBASE_bar	0.099	0.031	0.104	0.406	0.639	0.361
IP_CONS_DBLE	0.051	0.090	0.018	0.650	0.810	0.190
IP_CONS_NONDBLE	0.151	0.551	0.025	0.109	0.836	0.164
IP_BUS_EQPT	0.259	0.103	0.106	0.407	0.874	0.126
IP_DBLE_MATS	0.069	0.677	0.024	0.131	0.901	0.099
IP_NONDBLE_MATS	0.060	0.229	0.028	0.645	0.962	0.038
IP_FUELS	0.081	0.136	0.044	0.457	0.718	0.282
PMP	0.085	0.046	0.014	0.702	0.848	0.153
UTL11	0.010	0.002	0.066	0.913	0.991	0.010
RAHE_CONST	0.131	0.010	0.035	0.566	0.742	0.258
RAHE_MFG	0.116	0.024	0.124	0.651	0.915	0.085
EMP_MINING	0.055	0.030	0.007	0.596	0.688	0.312
EMP_CONST	0.094	0.190	0.134	0.546	0.964	0.037
EMP_DBLE_GDS	0.137	0.272	0.177	0.381	0.967	0.034
EMP_NONDBLES	0.035	0.117	0.186	0.609	0.947	0.053
EMP_SERVICES	0.111	0.400	0.069	0.379	0.958	0.042
EMP_TTU	0.012	0.320	0.011	0.399	0.743	0.258
EMP_WHOLESALE	0.011	0.020	0.056	0.248	0.335	0.665
EMP_RETAIL	0.011	0.237	0.059	0.455	0.761	0.239
EMP_FIRE	0.022	0.150	0.111	0.501	0.784	0.216
EMP_GOVT	0.162	0.237	0.016	0.467	0.882	0.118
URATE_ALL	0.175	0.056	0.014	0.619	0.864	0.136
U_DURATION	0.656	0.149	0.015	0.147	0.967	0.033
U_L5WKS	0.384	0.051	0.031	0.463	0.928	0.072
U_5_14WKS	0.143	0.033	0.011	0.523	0.710	0.290
U_M15WKS	0.575	0.099	0.018	0.284	0.977	0.023
U_15_26WKS	0.096	0.006	0.043	0.715	0.859	0.141
U_M27WKS	0.664	0.160	0.014	0.135	0.973	0.027
HOURS_AVG	0.019	0.032	0.095	0.816	0.961	0.039
HSTARTS_NE	0.009	0.115	0.016	0.679	0.819	0.181

HSTARTS_MW	0.017	0.193	0.115	0.273	0.598	0.402
HSTARTS_SOU	0.058	0.601	0.059	0.152	0.870	0.130
HSTARTS_WST	0.019	0.328	0.075	0.404	0.826	0.174
SFYGM6	0.090	0.041	0.029	0.642	0.802	0.198
SFYGT1	0.067	0.024	0.054	0.698	0.843	0.157
SFYGT10	0.157	0.006	0.025	0.460	0.648	0.352
SFYBAAC	0.034	0.004	0.082	0.811	0.931	0.069
BUS_LOANS	0.279	0.032	0.230	0.251	0.791	0.209
CONS_CREDIT	0.064	0.212	0.065	0.275	0.616	0.384
P_COM	0.038	0.012	0.011	0.335	0.396	0.604
P_OIL	0.008	0.011	0.007	0.263	0.288	0.712
P_NAPM_COM	0.017	0.017	0.010	0.223	0.267	0.733
DLOG_EXR_US	0.008	0.016	0.039	0.118	0.180	0.820
DLOG_EXR_CHF	0.007	0.013	0.030	0.110	0.160	0.840
DLOG_EXR_YEN	0.011	0.010	0.010	0.116	0.147	0.853
DLOG_EXR_GBP	0.007	0.012	0.016	0.117	0.152	0.848
DLOG_EXR_CAN	0.010	0.029	0.058	0.184	0.280	0.720
DLOG_SP500	0.016	0.010	0.026	0.222	0.274	0.726
DLOG_SP_IND	0.016	0.009	0.024	0.259	0.308	0.692
DLOG_DJIA	0.010	0.010	0.017	0.147	0.183	0.817
UMICH_CONS	0.006	0.311	0.046	0.405	0.767	0.233
NAPMI	0.075	0.050	0.016	0.760	0.900	0.100
NAPM_NEW_ORDRS	0.093	0.047	0.010	0.652	0.802	0.198
NAPM_VENDOR_DEL	0.068	0.053	0.015	0.711	0.846	0.154
NAPM_INVENTORIES	0.047	0.046	0.023	0.804	0.919	0.081
RCONS	0.005	0.032	0.196	0.667	0.901	0.099
RCONS_DUR	0.044	0.319	0.144	0.353	0.859	0.141
RCONS_SERV	0.009	0.237	0.099	0.580	0.925	0.075
RINV_GDP	0.005	0.479	0.069	0.415	0.967	0.033
RNONRESINV_STRUCT	0.339	0.184	0.013	0.327	0.863	0.137
RNONRESINV_BEQUIPT	0.095	0.027	0.008	0.750	0.880	0.120
RRESINV	0.092	0.078	0.092	0.596	0.858	0.142
REXPORTS	0.018	0.093	0.196	0.635	0.942	0.058
RIMPORTS	0.055	0.615	0.025	0.119	0.813	0.186
RGOV	0.006	0.339	0.175	0.437	0.957	0.043
LABOR_PROD	0.033	0.044	0.161	0.602	0.839	0.161
RCOMP_HOUR	0.020	0.026	0.176	0.563	0.784	0.216
ULC	0.090	0.215	0.019	0.526	0.850	0.150
PCED_DUR	0.021	0.044	0.023	0.699	0.788	0.212
PCED_NDUR	0.009	0.023	0.006	0.438	0.474	0.526
PCED_SERV	0.007	0.088	0.005	0.457	0.557	0.443
PINV_GDP	0.015	0.036	0.045	0.544	0.639	0.361
PINV_NRES_STRUCT	0.019	0.048	0.023	0.397	0.486	0.514
PINV_NRES_EQP	0.008	0.118	0.023	0.447	0.596	0.404
PINV_RES	0.028	0.080	0.036	0.270	0.414	0.586
PEXPORTS	0.013	0.022	0.015	0.637	0.687	0.313
PIMPORTS	0.012	0.015	0.012	0.499	0.537	0.463
PGOV	0.009	0.019	0.029	0.177	0.233	0.767

Notes: Structural shocks are GOV – government spending, CHI – money demand, MP – monetary policy and Z – neutral technology. Please see Appendix B, p.29 for the corresponding mnemonics of data indicators reported here.

Table C6. Regressing Data-Rich DSGE Model States on DFM Factors

Model Concept		R^2
Inflation	PI_t	0.984
Interest Rate	R_t	0.991
Real Consumption	X_t	0.998
Govt Spending shock	GOV_t	0.999
Money Demand shock	CHI_t	0.999
Technology shock	Z_t	0.990

Notes: Each line reports the R^2 from predictive linear regression:

$$S_{i,t}^{(pm)} = \alpha_{0,i} + \boldsymbol{\alpha}'_{1,i} F_t^{(pm)} + v_{i,t},$$

where $S_{i,t}^{(pm)}$ is the posterior mean of the i^{th} data-rich DSGE model state variable and $F_t^{(pm)}$ is the posterior mean of the empirical factors extracted by DFM.

Table C7. Regressing DFM Factors on Data-Rich DSGE Model States

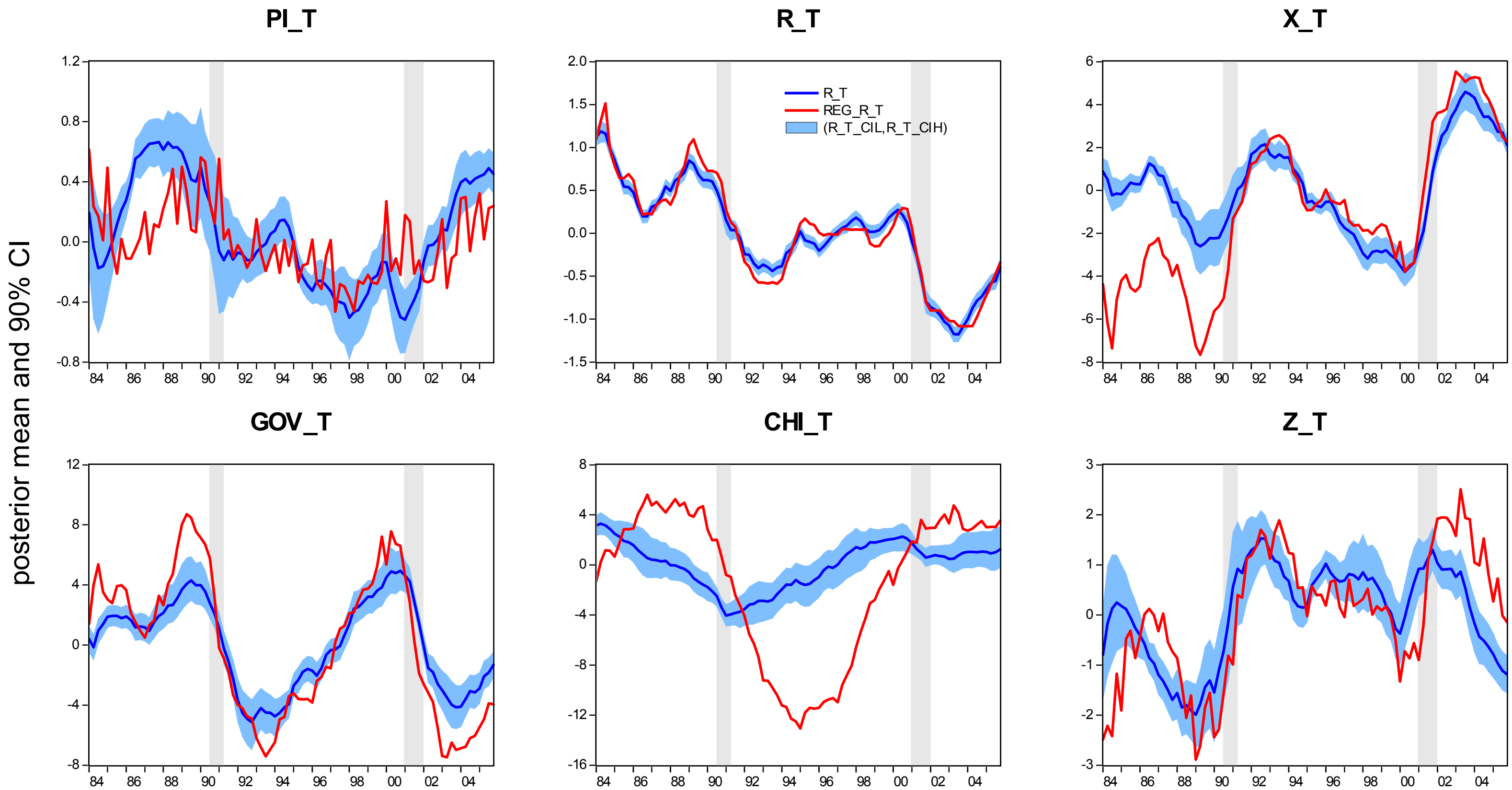
Factors	R^2
Factor 1	0.979
Factor 2	0.924
Factor 3	0.949
Factor 4	0.981
Factor 5	0.989
Factor 6	0.991

Notes: Each line reports the R^2 from predictive linear regression (see (17) in the main text):

$$F_{i,t}^{(pm)} = \beta_{0,i} + \boldsymbol{\beta}'_{1,i} S_t^{(pm)} + u_{i,t},$$

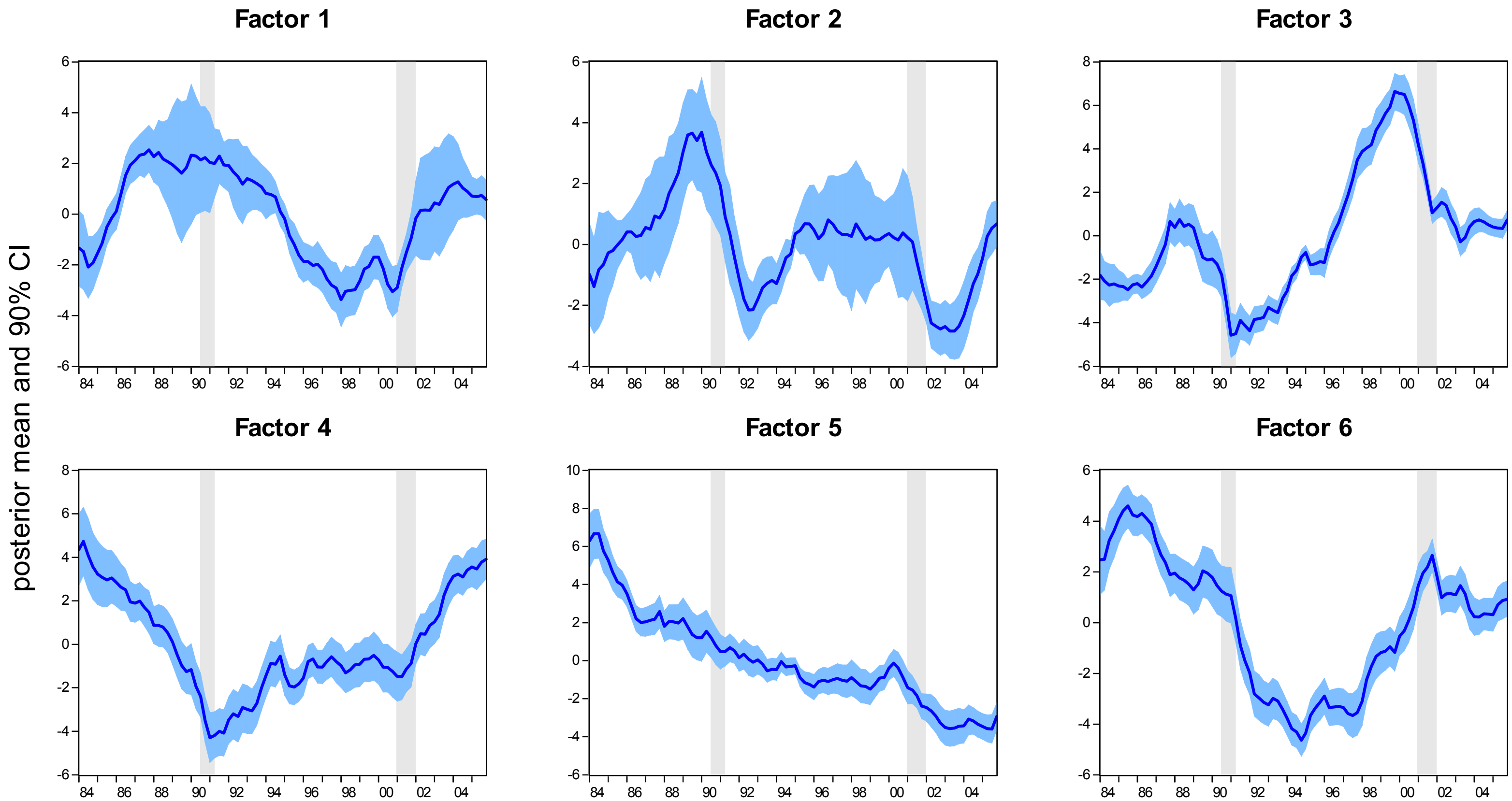
where $F_{i,t}^{(pm)}$ is the posterior mean of the i^{th} empirical factor extracted by DFM and $S_t^{(pm)}$ is the posterior mean of the data-rich DSGE model state variables.

Figure C2. Data-Rich DSGE Model (iid errors): Estimated Model States



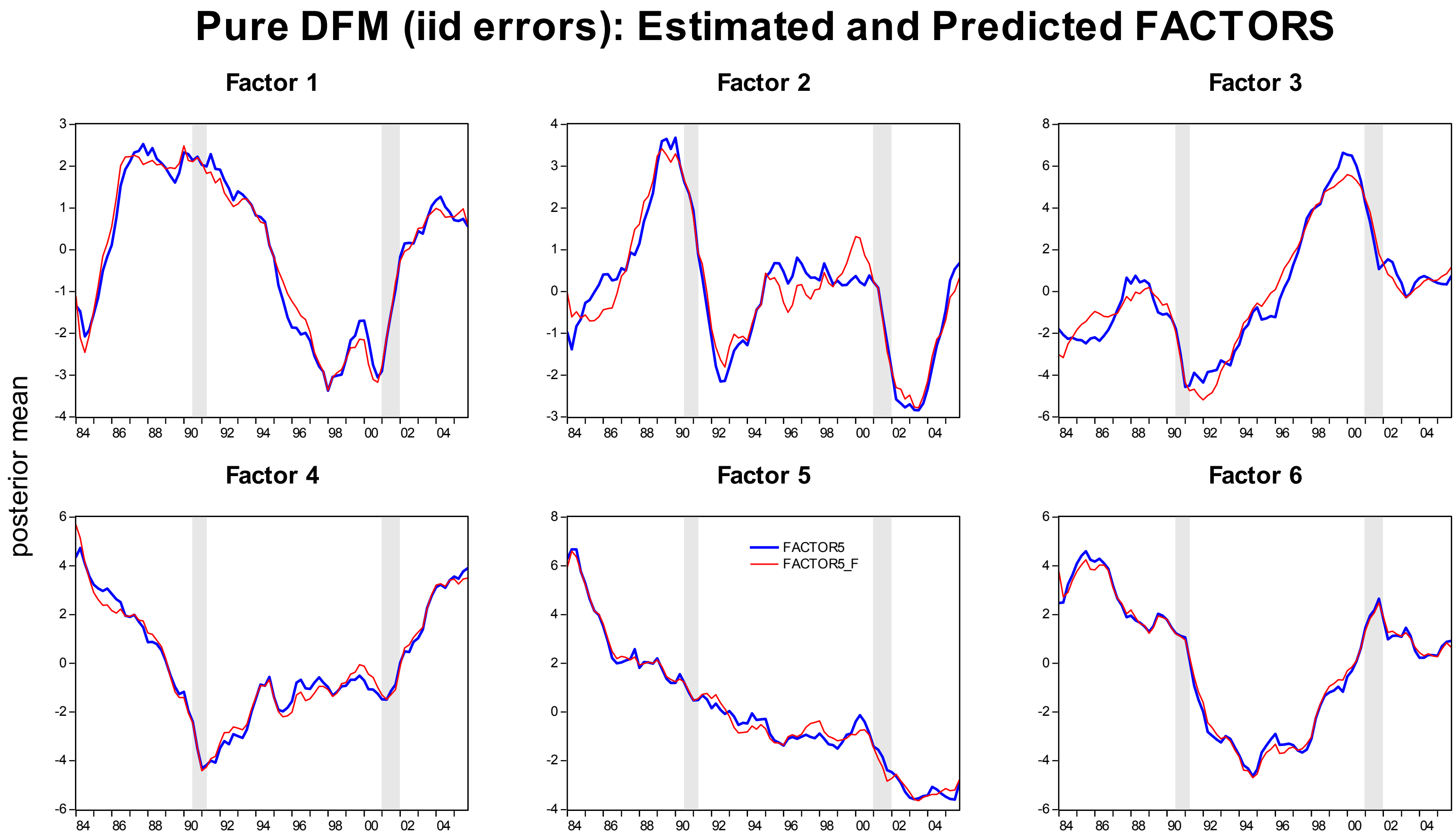
Notes: Source – Kryshko (2011). Figure depicts the posterior means and 90% credible intervals of the data-rich DSGE model state variables (blue line & bands): inflation (PI_T, π_t), nominal interest rate (R_T, R_t), real consumption (X_T, x_t), government spending shock (GOV_T, g_t), money demand shock (CHI_T, χ_t), and neutral technology shock (Z_T, Z_t). Red line corresponds to the smoothed versions of the same variables in a *regular* DSGE model estimation derived by Kalman smoother at posterior mean of deep structural parameters (see notes to Table D3 in Kryshko (2011) for definition of "regular DSGE estimation").

Figure C3. Pure DFM (iid errors): Estimated Factors



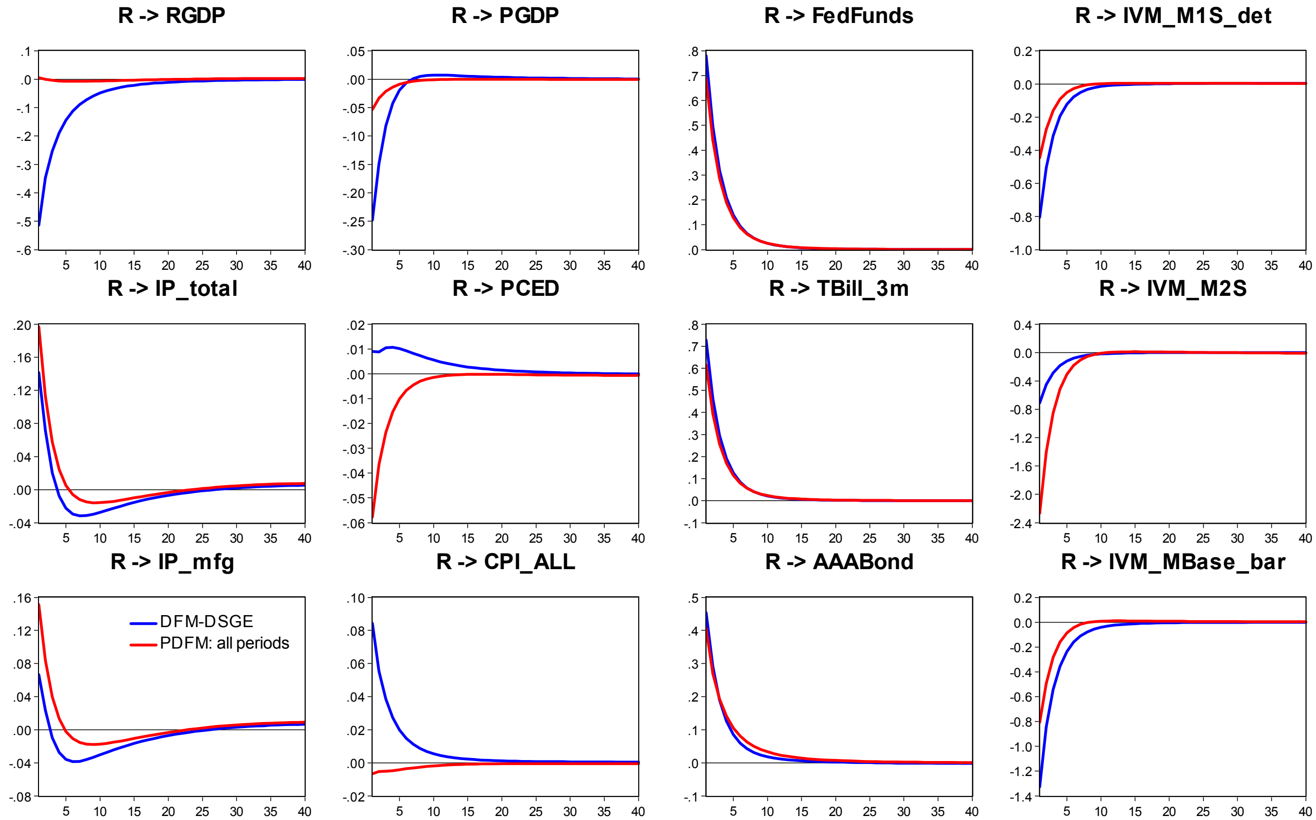
Notes: The figure plots the posterior means and 90% credible intervals of the latent empirical factors extracted by the empirical DFM (7)-(9). Normalization: block diagonal. Algorithm: Jungbacker-Koopman (2008).

Figure C4. Do Empirical Factors and DSGE Model State Variables Span the Same Space?



Notes: The figure plots the actual empirical factors extracted by the DFM (7)-(9) (blue line) and the empirical factors predicted by the data-rich DSGE model state variables using (18) in the main text (red line).

Figure C5. Impact of Monetary Policy Innovation on Core Macro Series

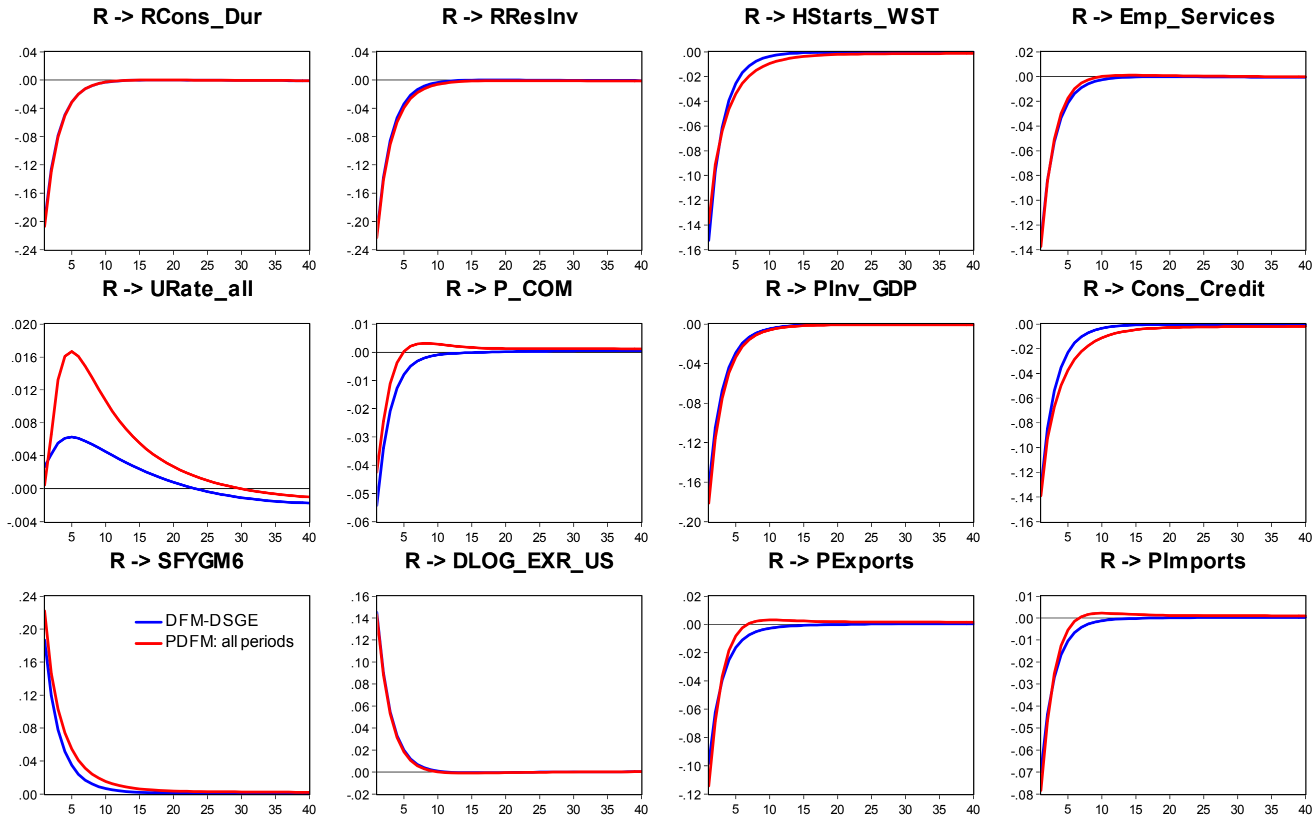


Notes: The figure plots the impulse responses of data indicators to a 1-standard-deviation **monetary policy** innovation $(\varepsilon_{R,t})$ computed in the data-rich DSGE model (blue line, "DFM-DSGE") and in empirical pure DFM (red line, "PDFM: all periods") according to (19) and (20), respectively.

The impact of structural shock is mapped from data-rich DSGE model into empirical DFM every period.

Data indicators are real GDP (RGDP), industrial production: total (IP_total), industrial production: manufacturing (IP_mfg), GDP deflator inflation (PGDP), PCE deflator inflation (PCED), CPI inflation (CPI_ALL), Federal Funds rate (FedFunds), 3-month T-Bill rate (TBill_3m), yield on AAA rated corporate bonds (AAABond), real money balances based on M1S aggregate (IVM_M1S_det), on M2S aggregate (IVM_M2S), and on adjusted monetary base (IVM_MBase_bar). See the corresponding mnemonics in Appendix B, p.29.

Figure C6. Impact of Monetary Policy Innovation on Non-Core Macro Series

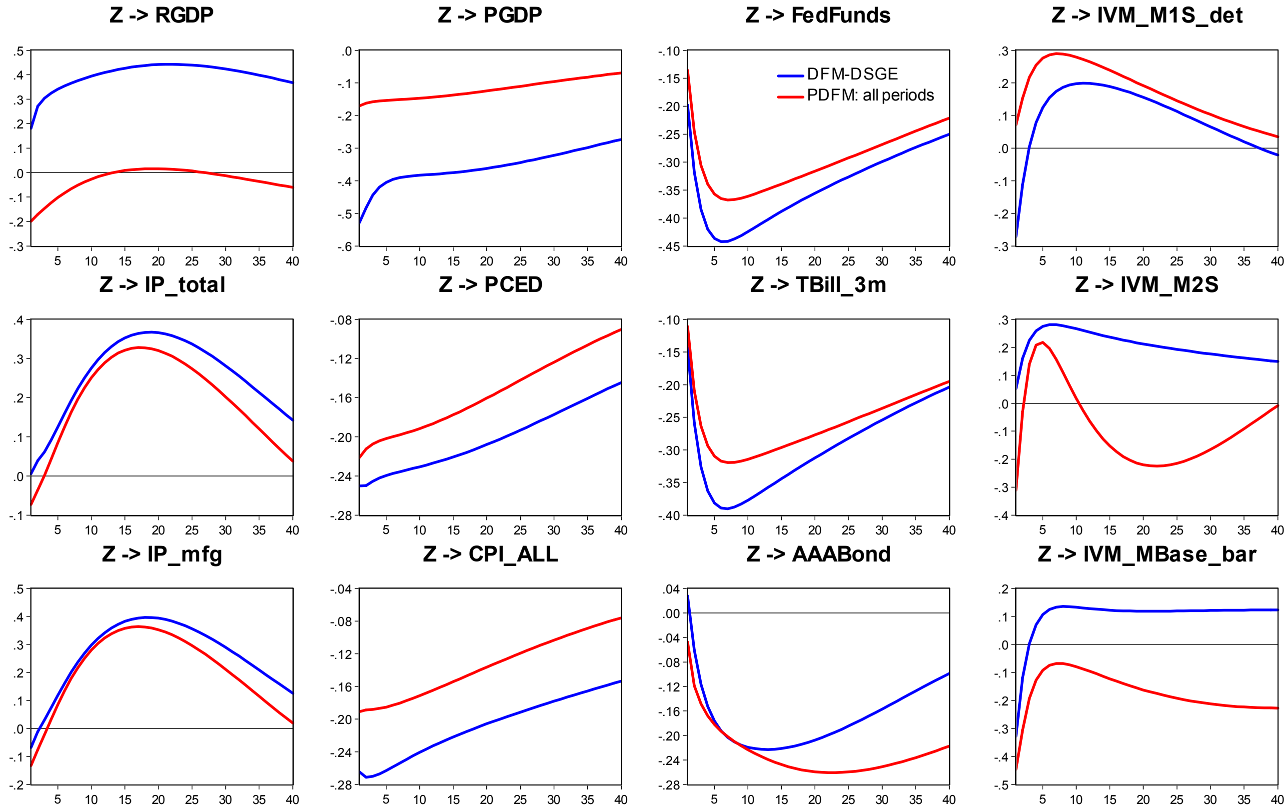


Notes: The figure plots the impulse responses of data indicators to a 1-standard-deviation **monetary policy** innovation $(\varepsilon_{R,t})$ computed in the data-rich DSGE model (blue line, "DFM-DSGE") and in empirical pure DFM (red line, "PDFM: all periods") according to (19) and (20), respectively.

The impact of structural shock is mapped from data-rich DSGE model into empirical DFM every period.

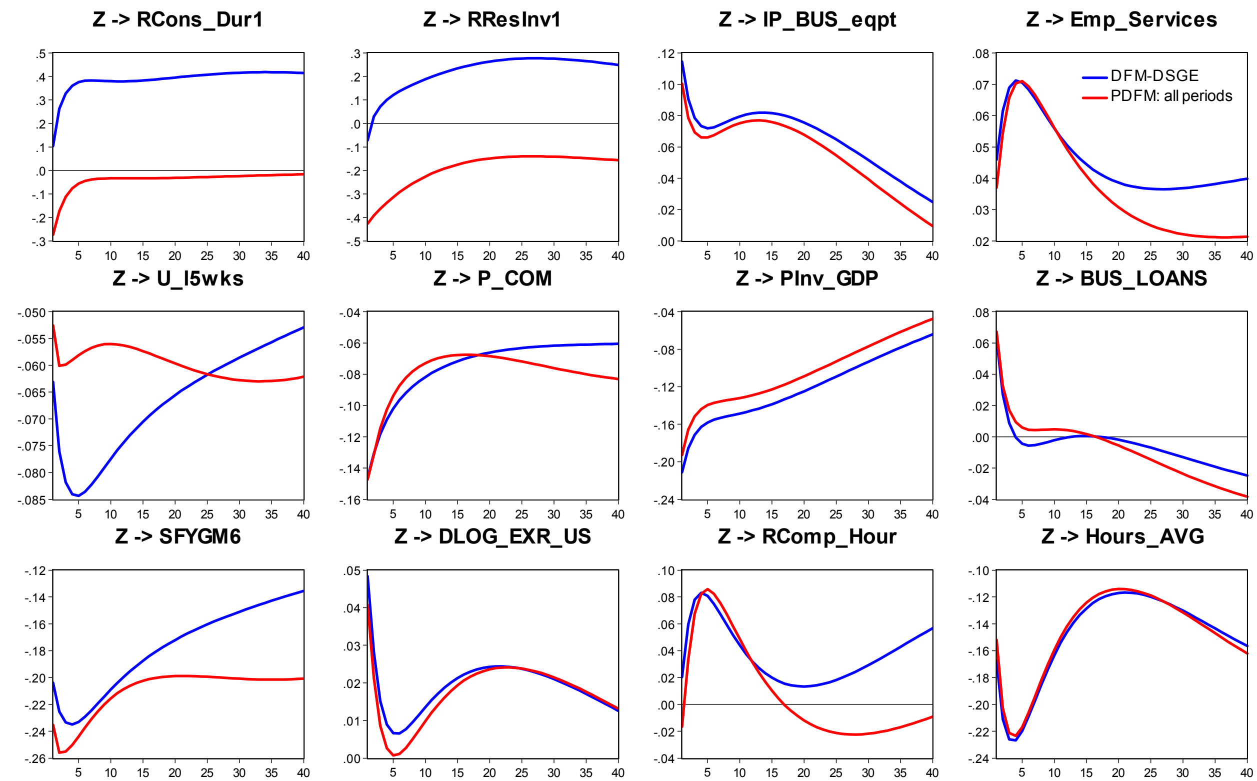
Data indicators are real consumption of durables (RCons_Dur), real residential investment (RResInv), housing starts: West (HStarts_WST), employment in services sector (Emp_Services), unemployment rate (URate_all), commodity price inflation (P_COM), investment deflator inflation (PInv_GDP), consumer credit outstanding (Cons_Credit), 6-month over 3-month T-Bill rate spread (SFYGM6), US effective exchange rate depreciation (DLOG_EXR_US), exports price index (PExports), imports price index (PImports). See the corresponding mnemonics in Appendix B, p.29.

Figure C7. Impact of Technology Innovation on Core Macro Series



Notes: The figure plots the impulse responses of data indicators to a 1-standard-deviation **technology** innovation $(\varepsilon_{Z,t})$ computed in the data-rich DSGE model (blue line, "DFM-DSGE") and in empirical pure DFM (red line, "PDFM: all periods") according to (19) and (20), respectively.
The impact of structural shock is mapped from data-rich DSGE model into empirical DFM every period.
Data indicators are real GDP (RGDP), industrial production: total (IP_total), industrial production: manufacturing (IP_mfg), GDP deflator inflation (PGDP), PCE deflator inflation (PCED), CPI inflation (CPI_ALL), Federal Funds rate (FedFunds), 3-month T-Bill rate (TBill_3m), yield on AAA rated corporate bonds (AAABond), real money balances based on M1S aggregate (IVM_M1S_det), on M2S aggregate (IVM_M2S), and on adjusted monetary base (IVM_MBase_bar). See the corresponding mnemonics in Appendix B, p.29.

Figure C8. Impact of Technology Innovation on Non-Core Macro Series



Notes: The figure plots the impulse responses of data indicators to a 1-standard-deviation **technology** innovation $(\varepsilon_{Z,t})$ computed in the data-rich DSGE model (blue line, "DFM-DSGE") and in empirical pure DFM (red line, "PDFM: all periods") according to (19) and (20), respectively.
The impact of structural shock is mapped from data-rich DSGE model into empirical DFM every period.
Data indicators are real consumption of durables (RCons_Dur1), real residential investment (RResInv1), industrial production: business equipment (IP_BUS_eqpt), employment in services sector (Emp_Services), persons unemployed less than 5 weeks (U_l5wks), commodity price inflation (P_COM), investment deflator inflation (PInv_GDP), commercial and industrial loans (BUS_LOANS), 6-month over 3-month T-Bill rate spread (SFYGM6), US effective exchange rate depreciation (DLOG_EXR_US), real compensation per hour (RComp_Hour), average weekly hours worked (Hours_AVG). See the corresponding mnemonics in Appendix B, p.29.

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