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Data-rich DSGE model forecasts of the great recession and its recovery

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A B S T R A C T

I investigate the extent to which modern dynamic stochastic general equilibrium (DSGE) models can produce macroeconomic and labor market dynamics in response to a financial crisis that are consistent with the experience of the Great Recession. Using the methods of Boivin and Giannoni (2006) and Kryshko (2011), I estimate two DSGE models in a data-rich environment. The two models estimated in this paper include close variations of the Smets and Wouters (2003; 2007) New Keynesian model and the FRBNY (Del Negro et al., 2013) model that augments the Smets & Wouters model with a financial accelerator. I find the model with a financial accelerator that is estimated in a data-rich environment is able to significantly out-forecast modern DSGE models not estimated in a data-rich environment and the Survey of Professional Forecasters (SPF) in regard to core macroeconomic growth variables and many labor and financial metrics including the unemployment rate, total number of employees by sector and business loans.

1. Introduction

Modern day macroeconomic theory has greatly leaned on structural dynamic stochastic general equilibrium (DSGE) modeling. These models give policymakers a workshop in which co-movements of aggregate macroeconomic time series can be evaluated over the business cycle. The Smets and Wouters (2003; 2007) model (henceforth, SW) in particular is widely considered the “workhorse” of the DSGE literature. However, Del Negro and Schorfheide (2013) have found this model to be limited in identifying the financial crisis for most of 2008, including the 4th quarter of 2008, when the crisis was in full swing.

A model that was better equipped to identify the Great Recession a few months earlier than the SW model is a variant of the SW model with financial frictions (henceforth, SWFF). The SWFF model introduces a Bernanke et al. (1999) financial accelerator mechanism and closely follows the entrepreneurial sector of the FRBNY model outlined by Del Negro et al. (2013). Del Negro and Schorfheide (2013) compared the SW and SWFF models' forecasting performance over the past two decades when the models were estimated under a standard set of seven or eight macroeconomic data series. They found that during the Great Recession the modified SWFF model was better at forecasting output and inflation when compared to the original SW model, however, this forecast model ranking was not consistent in time frames outside of the Great Recession.

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In this paper, I compare the forecasting performance of both the SW and SWFF DSGE models when they are estimated in a data-rich environment using the techniques of Boivin and Giannoni (2006) and Kryshko (2011). To my knowledge, this is the first time the SWFF model has been estimated in this fashion. Given the construction of traditional DSGE model estimation (henceforth, DSGE-Reg) Del Negro and Schorfheide (2013) were only able to compare the two models along a few key macroeconomic series. However, the estimation technique of Boivin and Giannoni (henceforth, DSGE-DFM) allows DSGE models to be estimated using a large data vector of macroeconomic time series and it provides an avenue through which these two models can be used to study the dynamics of such series as the unemployment rate, unemployment duration and employees by sector; even when no such series are directly incorporated into the structural model. Instead, the series that are not directly incorporated inside the DSGE model are allowed to load on economic variables and structural processes that are inside the DSGE model.

In addition, the DSGE-DFM estimation technique may provide different estimates of some structural parameters in the model that could produce better forecasts of variables that are directly modeled inside the DSGE model, such as GDP, consumption, investment growth, inflation and interest rates.

After conducting the DSGE-DFM and DSGE-Reg estimations on both the SW and SWFF models, I compare the forecasts of the four models, SW-Reg, SW-DFM, SWFF-Reg, SWFF-DFM. Comparing these four models helps answer three important questions. First, do DSGE-DFM models help in forecasting core macroeconomic variables before and during the Great Recession when compared to DSGE-Reg models? Second, when I compare the SW-DFM and SWFF-DFM models do we see similar results for other key macroeconomic variables not directly incorporated in either model as Del Negro and Schorfheide (2013) found for the variables of output growth and inflation? Third, does DSGE-DFM estimation help eliminate the time varying forecast dominance of the SW and SWFF models?

I first closely examine the period surrounding the Great Recession and its recovery and find compelling evidence that the answer to the first two questions is **yes**. I find that both DSGE-DFM models are better equipped to replicate the dynamics of the Great Recession than their DSGE-Reg counterparts are, when it comes to output, consumption, hours worked and investment. In addition, the SWFF-DFM model is able to foresee the downturn in output and investment as early as February of 2008. I also find that the SWFF-DFM model was able to foresee the decrease in the number of overall jobs, number of jobs in the manufacturing and construction sectors and the rise in the unemployment rate beginning in the fall of 2008.

When comparing the four models along a wider time frame horizon (1998–2011), I find that both DSGE-DFM models predict the dynamics associated with the core macroeconomic growth variables more accurately when compared to the two DSGE-Reg models. I also find that many of the in-sample forecasts generated by the SW-DFM and SWFF-DFM models do not differ much in tranquil economic times. It is only in times of financial volatility that I see the simulated paths from the two DSGE-DFM models begin to differ. As a result of this the SWFF-DFM model out ranks the SW-DFM model in terms of forecasting for the entire sample period not just in times of financial volatility as was the case with the SWFF-Reg and SW-Reg models as illustrated in Del Negro and Schorfheide (2013).

These results suggest that the SWFF model estimated in a data-rich environment (SWFF-DFM) would have predicted the labor market and production dynamics associated with the Great Recession and its proceeding recovery. In addition to generating the most accurate dynamics, the SWFF-DFM model also has similar or smaller root mean squared errors (henceforth, RMSEs) when compared to the Survey of Professional Forecasters' (henceforth, SPF) forecasts of output, consumption and investment growth. This implies the SWFF-DFM not only wins the horserace amongst the four models but that it should also be taken seriously as a forecasting and policy analysis tool.

Lastly, I examine both DSGE-DFM models for clues on why they could have foreseen the Great Recession earlier than their DSGE-Reg counterparts. I conduct an historical decomposition of the SWFF model and find that the Great Recession can mainly be attributed to negative investment, negative preference and negative finance shocks (corresponding to an increased spread between the risk and risk-free interest rates inside the model). When I look at the impulse response functions (IRFs) generated for the SWFF-Reg and SWFF-DFM models, I find that the different structural parameter estimates help generate more persistent declines in output from these types of shocks and I see that the investment-consumption tradeoff that can occur from these shocks diminishes in the SWFF-DFM model. This diminishing tradeoff results in slower recoveries in both real investment and real consumption and thus, a slower recovery in real GDP, as was seen with the recovery from the Great Recession.

The macro-financial time series I use to estimate both the SW and SWFF models is a near replica of the Stock and Watson (2003) dataset used in estimating their dynamic factor model. It includes labor and financial data series that are usually not utilized in DSGE-Reg estimation. These include employment by sector, stock price indexes, housing starts and many price and wage indexes beyond the standard CPI index and GDP deflator.

This DSGE-DFM method has been most recently used by Gali et al. (2012), Brave et al. (2012), Justiniano et al. (2013), and Barsky et al. (2014); who have all expanded the observable vector to improve the identification of unobservable and observable states and thus improve the estimation of the structural parameters. Gali et al. (2012) and Justiniano et al. (2013) promotes the use of multiple series for the measurement of wages, while Brave et al. (2012) and Barsky et al. (2014) uses multiple measures of inflation to estimate their perspective models. However, these papers used the method to allow for multiple data variables measuring the same model concepts and I will use the methodology to allow a large vector of macro-financial data to load on all DSGE model states.

In addition to these papers, my paper also fits into the structural DSGE literature of labor market dynamics around the Great Recession. Gali et al. (2012), Christiano et al. (2015; 2016) incorporate a more advanced labor market in their perspective DSGE models than either the SW or SWFF model. The models of Gali et al. (2012) and Christiano et al. (2015) are able to simulate and/or forecast the dynamics of employment, unemployment and other aggregate labor market statistics quite nicely, as does the SWFF-DFM model of this paper. However, the SWFF-DFM model in this paper is able to also capture the labor market and output dynamics of less aggregate statistics, such as employment and production by sector.

The remainder of this paper is structured as follows. Section 2 briefly explains the features of each DSGE model and outlines the estimation technique used to incorporate the large set of economic and financial series. Also included in this section is a description of the priors for the state-space and structural parameters as well as an overview of the data series. Section 3 presents the simulated output growth paths of all four models around the Great Recession and the paths for both the SW-DFM and SWFF-DFM models for various production growth, labor, output and finance series around the trough and recovery of the Great Recession. Also included in this section are Diebold Mariano test statistics of out-of-sample forecasts for all four models around the 1998–2011 time frame. Section 4 discusses the important dynamics of the SWFF-DFM model and discusses why the SWFF-DFM was able to predict a slow recovery in employment and production markets. Section 5 concludes and discusses future extensions.

2. The DSGE models and estimation technique

I consider two DSGE models in this paper, the first model is based on the FRBNY model outlined by Del Negro et al. (2013). This model is an extension of the Smets and Wouters (2003; 2007) New Keynesian model with the addition of a credit market with frictions that closely follows the financial accelerator model created by Bernanke et al. (1999). The second model has no credit channel and closely follows the Smets and Wouters (2003) model. This model will be referred to as SW, while the model with financial frictions will be referred to as SWFF.

In the second part of this section, I present the steps needed to generate Bayesian estimates of the parameters of the linearized models. For the Bayesian estimation, I adopt two techniques, the first being the standard Random Walk Metropolis-Hasting algorithm whose results will be referred to as SW-Reg and SWFF-Reg for the respective models. The second is a data-rich estimation method proposed by Boivin and Giannoni (2006) whose results will be referred to as SW-DFM and SWFF-DFM for the respective models.

2.1. General outline of DSGE models

The SWFF model involves a number of exogenous shocks, economic agents, and market frictions. The agents include households, intermediate and wholesale firms, banks, entrepreneurs, capital producers, employment agencies, and government agencies. In all, the SWFF model has price, wage and financial frictions, habit persistence in consumption, investment adjustment costs, capital utilization costs and eight exogenous shocks. The SW model is identical to the SWFF model without the entrepreneur and banking sectors. Instead, households own the capital, decide the utilization rate and rent it to intermediate firms. Further, the SW model does not have any financial frictions or financial risk shocks. In Appendix A, I present the linearized equations for both models around their respective steady states that I use to produce my results.

2.2. Regular DSGE estimation

The state space representation of the solved model consists of a transition equation, which is calculated by solving the linearized system of the given model one wishes to evaluate for a given set of structural model parameters (θ):

$$S_t = G(\theta)S_{t-1} + H(\theta)v_t \quad \text{where } v_t \sim NID(0, I) \tag{2.1}$$

and the measurement equation:

$$X_t^{reg} = \Lambda S_t \tag{2.2}$$

Here X_t^{reg} are the economic data sets and Λ is a matrix matching the observed data to the definitions of the model's state variables S_t.

The description of the data sets and individual elements of Λ for the regular estimation technique can be found in Appendix B.[1]

2.3. DSGE-DFM estimation

Bayesian estimation of a DSGE model in a data-rich environment incorporates the state space model discussed above with a few modifications. The assumption that all relevant information for the estimation is summarized by a relatively small number of data sets needs to be met in order for accurate estimates and forecasts to be obtained when a DSGE model is estimated as described in Section 2.2. However, the development of Dynamic Factor Models proposed by

[1] For more detail on Bayesian DSGE estimation techniques please see An and Schorfheide (2007).

Sargent and Sims (1977) and further advanced by the works of Stock and Watson (1989; 2003; 2009; 2011) have shown that large data sets can hold valuable information in identifying unobserved common factors of the economy.

Further, the abundance of data series that can stand in as a measurable metric of a particular economic variable can be large as well, for example, inflation can be measured in multiple data sets including CPI, PCE, GDP deflator and other series. The econometrician's choice of which data set(s) to use in the estimation process can have an impact on the results as shown by Guerron-Quintana (2010).

The set up for DSGE-DFM estimation is characterized by equations (2.3)–(2.5).

$$S_t = G(\theta)S_{t-1} + H(\theta)v_t \text{ where } v_t \sim NID(0, I_m) \tag{2.3}$$

$$X_t = \Lambda S_t + e_t \tag{2.4}$$

$$e_t = \Psi e_{t-1} + \epsilon_t \text{ where } \epsilon_t \sim NID(0, R) \tag{2.5}$$

Here e_t follows an AR(1) process and is often referred to as measurement error. The matrix X is $J \times T$ where J is the number of data series used in estimation and T is the number of observables for each series. The Matrix Λ is now no longer assumed to be known by the econometrician, but instead is estimated within the MCMC routine. The matrices Ψ and R that govern the measurement error's stationary processes for each series are assumed to be diagonal and are also estimated within the MCMC routine.

The measurement equation (2.4) has the following structure:

$$\begin{bmatrix} Output\,\#1 \\ Output\,\#2 \\ Inflation\,\#1 \\ Inflation\,\#2 \\ \vdots \\ ------- \\ [Housing\ Market] \\ [Labor\ Market] \\ [Output\ Components] \\ [Financial\ Market] \\ [Investment] \\ [Price/Wage\ Indexes] \\ [Other] \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \lambda_{Y_1} & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ 0 & \lambda_{\pi_2} & \dots & 0 \\ -- & ---- & --- & -- \\ [\lambda_{H_1}] & [\lambda_{H_2}] & \dots & [\lambda_{H_n}] \\ [\lambda_{L_1}] & [\lambda_{L_2}] & \dots & [\lambda_{L_n}] \\ \vdots & \vdots & \dots & \vdots \end{bmatrix} \begin{bmatrix} \hat{Y}_t \\ \hat{\pi}_t \\ \vdots \\ \epsilon_t^f \end{bmatrix} + \begin{bmatrix} e_{t,1} \\ e_{t,2} \\ \vdots \\ e_{t,J} \end{bmatrix}$$

where X_t is partitioned into core series and non-core series separated by the dashed line. The core series are series that are only allowed to load on one particular variable of the state vector S_t to which there is a known sole relationship between series and state (for instance, GDP to Y). Further, the factor loading coefficient for the first series of each core variable that corresponds to a particular known state is assumed to be perfectly tight, this is represented by the 1's in the Λ matrix. This anchors the estimated states of the DSGE model and ensures that they don't drift too far away from their theoretical foundation. I check to see if indeed this is the case for the SWFF-DFM model in Appendix C.

The non-core series consist of the remaining 97 data sets not in the core series and are grouped into eight subgroups. These series are allowed to "load" on all time t states in the state vector. Non-core series may have up to n (where n is the number of elements in S_t) non-zero elements for their corresponding row in Λ unlike the core series whose corresponding row in Λ may only have one non-zero element.

Following the work of Boivin and Giannoni (2006) and Kryshko (2011), a Metropolis-within-Gibbs algorithm is used to estimate the state space parameters $\Gamma = [\Lambda, \Psi, R]$ and the structural DSGE parameters θ. The likelihood functions of the DSGE-DFM models appear to have many peaks and cliffs that can cause the MCMC algorithm to get "stuck." To make sure the algorithm explores the entirety of the parameter space, I have implemented an adaptive element into the Metropolis step of the algorithm along the lines of Roberts and Rosenthal's (2009) adaptive within Gibbs example. The adaptive Metropolis-within-Gibbs algorithm used follows the following steps:

1. Specify Initial values of $\theta^{(0)}$, and $\Gamma^{(0)}$, $\Gamma = \{\Lambda, \Psi, R\}$
2. Repeat for g=1...G
   - 2.1 Solve the DSGE model numerically and obtain $G(\theta^{(g-1)})$ and $H(\theta^{(g-1)})$
   - 2.2 Draw from $p(\Gamma | G(\theta^{(g-1)}), H(\theta^{(g-1)}); X_{1:T})$
     - 2.2.1 Generate unobserved states $S^{1:T,(g)}$ from $p(S^T | \Gamma^{(g-1)}, G(\theta^{(g-1)}), H(\theta^{(g-1)}); X_{1:T})$ using the Carter–Kohn forward–backward algorithm
     - 2.2.2 Generate state-space parameters $\Gamma^{(g)}$ from $p(\Gamma | S^{1:T,(g)}; X_{1:T})$ by drawing from a set of known conditional densities $[R|\Lambda, \Psi; S^{1:T,(g)}]$, $[\Lambda | R, \Psi; S^{1:T,(g)}]$, $[\Psi | \Lambda, R; S^{1:T,(g)}]$.
   - 2.3 Draw DSGE parameters $\theta^{(g)}$ from $p(\theta | \Gamma; X_{1:T})$ using adaptive Metropolis Hastings
     - 2.3.1 Propose $\theta^* = \theta^{(g-1)} + \bar{c}\,\varepsilon_\ell$ where $\varepsilon_\ell \sim NID(0, \Sigma^{-1})$

2.3.2 Calculate $P(X_{1:T}|\theta^*, \Gamma^{(g)})$ using the Kalman Filter

2.3.3 Calculate the acceptance probability ω

$$\omega = min\left\{\frac{P(X_{1:T}|\theta^*, \Gamma^{(g)})P(\theta^*)}{P(X_{1:T}|\theta^{(g-1)}, \Gamma^{(g)})P(\theta^{(g-1)})}, 1\right\}$$

2.3.4 $\theta^{(g)} = \theta^*$ with probability ω and $\theta^{(g)} = \theta^{(g-1)}$ with probability $(1-\omega)$

2.4 Calculate acceptance rate of proposed θ for 1 to g draws. If the acceptance rate is lower than target acceptance rate decrease $\bar{c}$ by w (iff $\bar{c} > w$). If acceptance rate is greater than target acceptance rate increase $\bar{c}$ by w. This target acceptance rate adaption can be implemented every n iterations of g. In addition the condition $w \to 0$ as $g \to \infty$ must be satisfied

3. Return $\{\theta^{(g)},\ \Gamma^{(g)}\}_{g=1}^{G}$

A few comments are in order. First, regarding step 2.2 which is the Gibbs portion of the algorithm. This step uses the Carter and Kohn (1994) algorithm which first requires a forward pass of the Kalman filter to collect the generated states, S, and their corresponding cov/var matrices, P. The backward pass of the algorithm then smooths out the estimated states using both S and P from the forward pass.[2] Step 2.2.2 then performs line-by-line OLS for each series in X given the generated states $S^{1:T}$. With the use of the proper conjugate priors the distributions of step 2.2.2 are known using the approach of Chib and Greenberg (1994).

The algorithm must first be initialized with $\theta^{(0)}$, $\Gamma^{(0)}$ and Σ. The values of $\theta^{(0)}$ are retrieved by taking the mean of $P(\theta|X^{reg})$ when estimated as described in Section 2.2. Once $\theta^{(0)}$ is obtained it is then used to calculate $S^{1:T,(0)}$. The estimated states are then used to run line-by-line OLS for each series in X to back out initial values of $\Gamma^{(0)}$. Σ^{-1} is the inverse Hessian of the DSGE model evaluated at its posterior mode under regular estimation.

The applied algorithm is based on 500,000 draws (2 parallel chains of 250,000 draws discarding the initial burn-in period of 100,000 iterations). The calibrations regarding the adaptive step include the acceptance target rate which is set at 27%, an initial $\bar{c}$ which is set to .1, the adaptive jump size w which is set at .005[3] and an adjustment rate n which is set at 25. The adjustment rate n determines how many iterations take place between changing $\bar{c}$ as described in step 2.4.

2.4. Data and parameter priors

To estimate both the SW and SWFF models in a data-rich environment a total of 97 quarterly data series are used.[4] These series cover the time period of 1984Q2 to 2011Q4. The complete set of series encompasses many of the economic and financial series used by Stock and Watson (2003) and Kryshko (2011). The evaluation window of the data series is significant for multiple reasons. First, Kim and Nelson (1999) have argued that a structural break in economic growth volatility occurred in 1984Q1. Further, Lubik and Schorfheide (2004) assert that it was not until the early 1980's that monetary policy of the Taylor-rule form was consistent with a determinate equilibrium.

The SWFF-DFM (SW-DFM) estimation consists of 17 (15) core series and 80 (82) non-core series. The core series for both models include three measures each of GDP, inflation, employment and nominal interest rates. Also included in the core series are real consumption and investment expenditures and hourly wages. In addition, the core series for the SWFF-DFM model include 2 measures of the interest rate spread. The series that hold a perfectly tight loading factor are the 8 (7) series used in regular estimation of each model. These include real per capita GDP, the GDP price deflator, per capita real consumption and private investment expenditures, real average hourly wage, hours worked, the annualized federal funds rate and the quarterly spread between BAA corporate bond yields to the 10 year Treasury bond yield. All per capita variables are calculated using the adult population of 16 years and older. These series are either demeaned, linearly detrended log level or log first differenced and demeaned.

The non-core series are grouped into eight categories. The first being *Output Components* which include series that explain deviations from per capita linear trends of different GDP and production output components. The *Labor Market* category includes employment by sector as well as unemployment rates and durations. The *Housing Market* group includes regional housing starts and the residential investment series. The *Financial Market* classification includes a number of different interest rates, loan and credit quantities and asset prices. The *Exchange Rate* group includes exchange rates of the US dollar to other foreign currencies. The *Investment* grouping includes inventory indexes and other investment series. The *Price and Wage* category includes a number of pricing indexes, wage indexes and commodity prices. The final category *Other* includes money supply measures and consumer and producer sentiment surveys.

As is common in the Dynamic Factor Model literature, all non-core series sample standard deviation is normalized to 1. In addition, these series are either demeaned, linearly detrended log level or log first differenced and demeaned. A complete list and transformation rubric of each core and non-core series is found in Appendix B.

[2] The backwards pass draws states S using a cov/var matrix that is a transformation of the P matrix. It is necessary that P be a symmetric and positive semi-definite matrix. However, it is sometimes necessary to computationally transform the P matrix using the procedure by Rebonato and Jäckel (1999).

[3] In order to accord with the condition of step 2.4, $w = min\left(.005, \left(\frac{g}{n}\right)^{-.5}\right)$.

[4] A 3-month average is used to obtain quarterly data from monthly series.

Table 1
Priors for DSGE-DFM Γ Parameters.

	Description	Distribution	Mean	Std.
Γ Parameters				
$\Psi_{i,i}$	AR(1) coef. of measurement error	Normal	0	1
$R_{i,i}$	Variance of measurement error	Inv. Gamma	0.001	3*
$\Lambda_{i,j}$	Factor loadings of Non-core data sets	Normal	0	$R_{i,i}I$
$\Lambda_{i,j}$	Factor loadings of Core data sets	Normal	1	$R_{i,i}I$

The structural parameter marginal priors are in accordance to the Smets and Wouters (2003; 2007) priors. Some structural parameters are fixed including the discount rate, share of capital, depreciation rate, and the steady state share of government and investment to total output. The latter parameters being calibrated to the average proportion of investment and government purchases of GDP over the sample period. In the SWFF model the steady state default rate is set to .0075 which corresponds to Bernanke et al. (1999) annualized default rate of 3%. The quarterly survival rate of entrepreneurs is fixed at .99 which corresponds to an average entrepreneur life of 68 quarters or 17 years. The steady state spread is calibrated to 140 basis points which is roughly the sample median spread between the BAA corporate bond yield and 10 year Treasury bond yield. This value is in line with the estimated values of Del Negro et al. (2013) who estimated the steady state spread to be between 73 and 150 basis points. A complete list of calibrated structural parameters as well as the prior mean, standard deviation and description of the estimated structural parameters can be found in Table D.1 and Table D.2 of the appendix.

The priors for the state space parameters include the elements of Λ and the diagonal elements of Ψ and R. The elements of Λ can be separated between core and non-core elements. Core series may only have a single non-zero row element of Λ whose prior is normally distributed and centered around 1.[5] Each non-core series corresponding row elements[6] of Λ has a multivariate normal prior centered around zero.

The prior for each ith row of the non-core series follows the work of Boivin and Giannoni (2006) and Kryshko (2011), who use a Normal-Inverse-Gamma prior distribution for $(\Lambda_i, R_{i,i})$ so that $R_{i,i} \sim IG_2(.001, 3)$ and the prior mean of factor loadings for the ith row is given by $\Lambda_i|R_{i,i} \sim N(0, R_{i,i}I)$ where the mean is a vector of zeros and I is the identity matrix. The prior for the ith measurement equation's autocorrelation parameter, $\Psi_{i,i}$ is $N(0, 1)$ for all rows. The autocorrelation parameter prior is truncated to values inside the unit circle to ensure all error processes are stationary.

Priors regarding the core series are still Normal-Inverse-Gamma but instead the mean of the factor loadings of the ith row of Λ is centered at the DSGE models implied theoretical loading. As discussed earlier the first data set of each core series category has a perfectly tight loading prior. The priors for Ψ and R whose diagonal elements correspond to core series remains the same. In the spirit of Boivin and Giannoni (2006) who fix the measurement equation of the federal funds rate error term to be zero, I truncate $R_{13,13}$ which correspond to the federal funds rate error term to be no greater than 0.05. This assures that the nominal interest rate of the DSGE model will not drift far away from the federal funds rate observed in the economy (see Table 1).

3. Model implied forecast evaluation

In this section I perform a similar exercise as Del Negro and Schorfheide (2013) of comparing the simulated and forecasting ability of the SW-Reg and SWFF-Reg models but I also add the SW-DFM and SWFF-DFM models to the model comparison pool. Further, instead of just focusing on output and inflation, I also pay particular attention to series related to the labor and finance markets. Of course, many of these series can only be forecasted using the SWFF-DFM and SW-DFM models that were estimated in a data-rich environment.

I first present the model implied forecasts of core macroeconomic growth series for all four models at different time periods around the Great Recession, I then compute pseudo out-of-sample forecasts for all four models for the time period of 1998–2011 and use Diebold–Mariano test statistics to evaluate their forecasting performance around this selected sample period. Finally, I examine the model implied forecasts of the SW-DFM and SWFF-DFM models around the Great Recession for variables related to the labor and finance markets that are not directly modeled in either DSGE model.

3.1. Forecasts of output component growth

I compare the growth forecasts of the SW-Reg, (magenta) SWFF-Reg (green), SW-DFM (red), SWFF-DFM (blue) and the median forecast given by the Survey of Professional Forecasters (dashed-cyan) for real output, consumption and investment growth against actual realized growth for these three series (black).

In particular, I take the estimated posterior distributions of the models' structural parameters and loading coefficients of the Λ matrix and create simulated paths for the different time series for both models. I estimate the models at six different time periods, one at which all data related from 1984Q2 to 2007Q4 is available to the econometrician, one at which the

[5] The core interest rate series priors are centered around 4 since all data are in APR.
[6] The elements of Λ that correspond to $t-1$ states of the S_t vector are assumed to be zero.

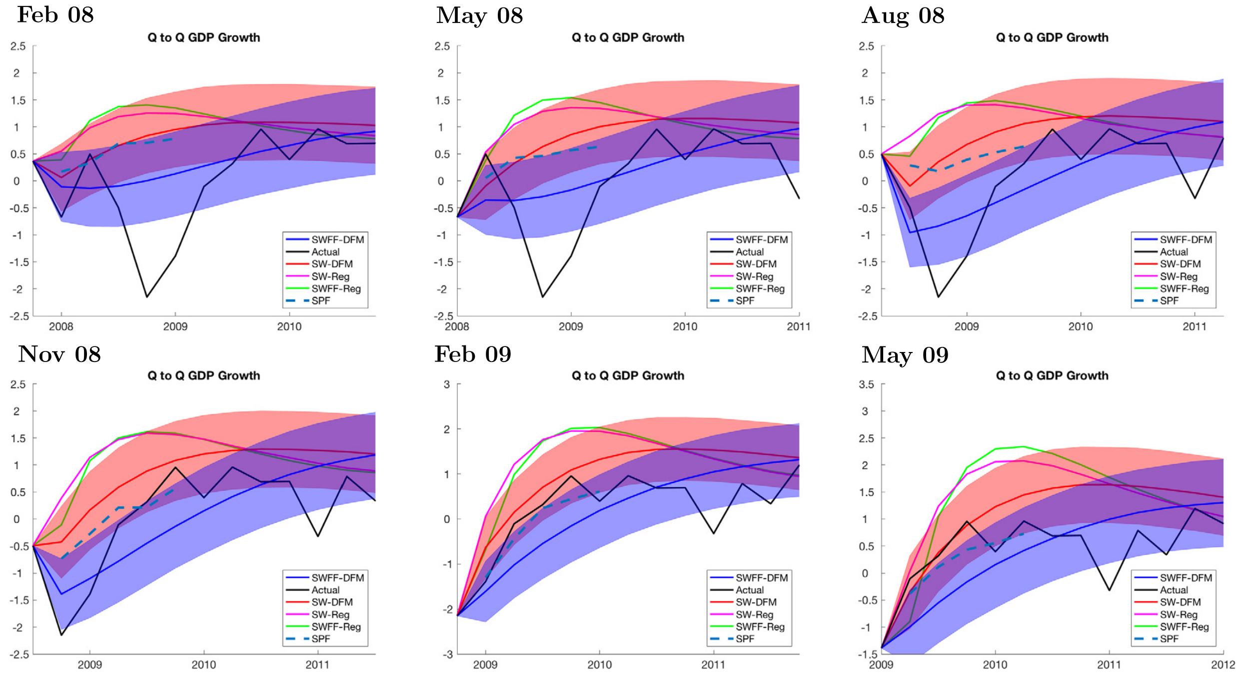

Fig. 1. Forecasts for Quarter to Quarter Real GDP Growth. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

econometrician can see quarterly data related to 2008Q1, one in which they have 2008Q2 data values available to them and so forth. When the new data are revealed, the new values are inserted into the Kalman filter and are used as the new starting points for each of the simulations. The models' posterior parameters are re-estimated after data for 2008Q3 is available.

In total each forecast is generated by 500,000 simulations, 5,000 draws from the posterior parameter distribution and each parameter draw is simulated using 100 draws of future structural shocks for 16 quarters. In all simulations the zero lower bound is established using shadow monetary policy shocks using an algorithm outlined by Holden and Paetz (2012).

Figs. 1–3 show the median forecast as well as the 68% forecast posterior density intervals for the three expenditure series at six different staring times. The six time periods start when data for the first quarter (2007Q4) of the Great Recession would have been available and end when data for 2009Q1 would have been available to the econometrician.

Of note, both the DSGE-DFM models outperform the DSGE-Reg models in terms of forecast accuracy for real GDP and real consumption growth around the Great Recession and its recovery. In addition, the SWFF-DFM model can foresee negative GDP growth starting in May 2008 and foresees the magnitude of the Great Recession starting in November 2008. The SWFF-DFM also foresee the sluggish growth in consumption throughout the next three years as can be seen by the bottom panel of Fig. 2. It does overstate the decline in real GDP in the year 2009, however, this may be due to the model's inability to capture the unconventional fiscal and monetary policy that took place over this time period.

Further, notice that the SWFF-DFM forecasts are better or comparable to the SPF forecasts and are a stark contrast to the overly optimistic SW-Reg and SWFF-Reg models which each predict a quick and robust recovery. This is a remarkable result given that the SWFF-DFM model generates these forecasts with no real time data available to it unlike the forecasts generated by the SPF. The SWFF-DFM November 2008 forecast only uses 20008Q3 data, it does not incorporate any real-time data that would be available for 2008Q4 in November like interest rates or other financial data.

Fig. 3 shows the median forecast for real investment at six different staring times. Regarding this variable none of the four models can foresee the depths of decline in investment, although, both DSGE-DFM models predict multiple quarters of negative investment growth starting in August 2008 and are in line with the estimates generated by the SPF.[7] However, once the depth of the decline in investment had been realized, the SWFF-Reg model does the best job in predicting the dynamics of the real investment recovery.

When evaluating Figs. 1–3 it is important to note how they relate to the results of Del Negro and Schorfheide (2013). First, the SW-Reg and SWFF-Reg models of the paper are most comparable to the SWπ and SWπ-FF models of Del Negro

[7] The SPF does not have a comparable forecast for real gross private investment so I use the median SPF forecasts levels for real residential investment, real non-residential investment and real change in investment inventories and calculate an implied SPF forecast of real gross private investment and its growth rate.

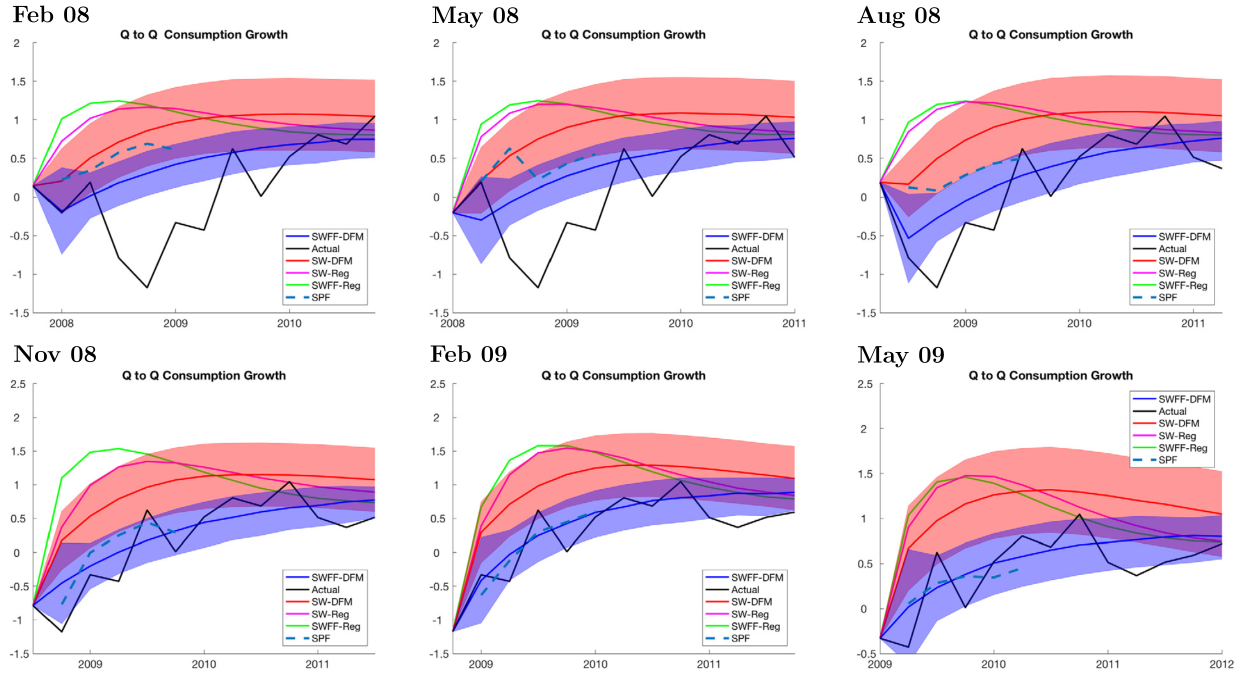

Fig. 2. Forecasts for Quarter to Quarter Real Consumption Growth.

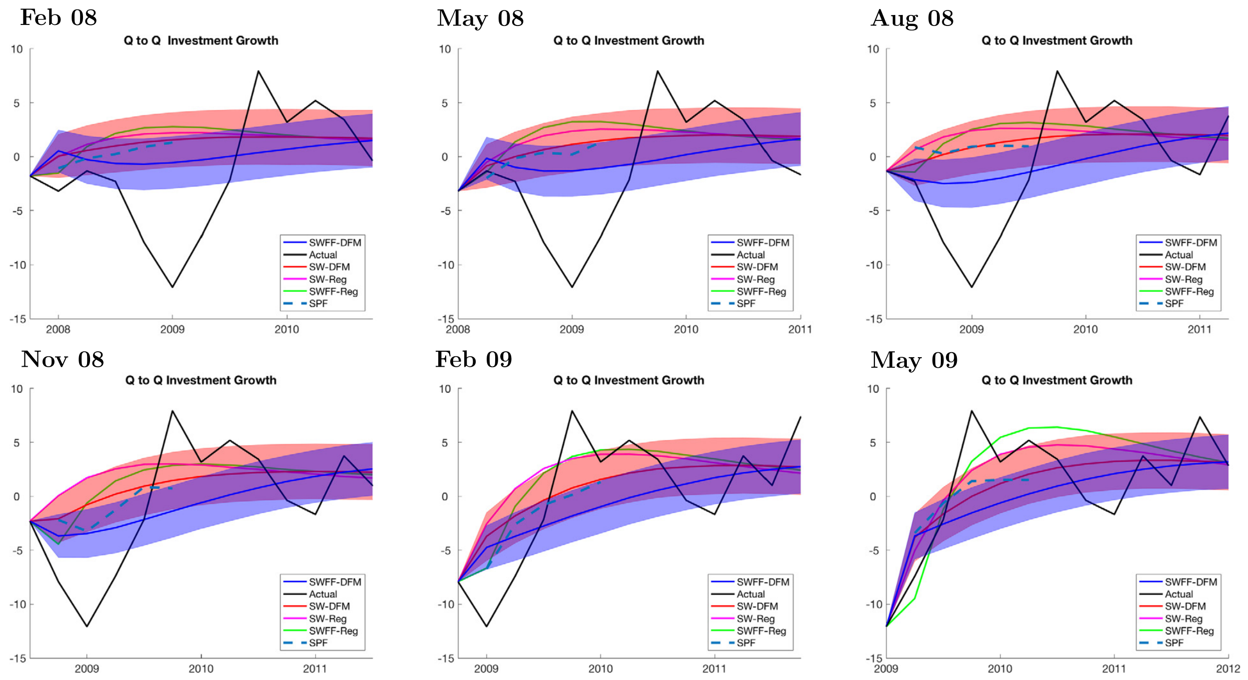

Fig. 3. Forecasts for Quarter to Quarter Real Investment Growth.

and Schorfheide and are in line with the one and two quarter ahead forecasts for output. The SWπ-FF model like the SWFF-Reg model of this paper does not see negative growth until the end of 2008.

Nevertheless, the SW-Reg and SWFF-Reg models both forecast robust economic growth three to five quarters ahead. This is contrary to both the models used in the Del Negro and Schorfheide paper, both of which actually underestimate the growth rate during the recovery. The reasoning behind this is that the models in Del Negro and Schorfheide are detrended along a stochastic growth path while all the models in this paper are detreneded along a constant growth path. As a result, when variables are far from the steady state in the models of this paper they are expected to grow faster, while the models

Table 2
Diebold–Mariano Test Statistics for Output Growth.

	Entire sample 1998Q1–2011Q4			Pre-recession 1998Q1–2007Q2			Great Recession 2007Q3–2011Q4		
	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4
SW-Reg vs SWFF-Reg	−0.8	−1.0	−0.8	−0.9	−2.6*	−1.5	1.0	−0.1	−0.1
SW-Reg vs SW-DFM	1.4	1.8	2.0*	−1.5	−0.8	0.8	2.7*	2.7*	15.9*
SWFF-Reg vs SWFF-DFM	2.9*	2.4*	2.3*	1.4	1.7	1.4	2.8*	2.8*	14.8*
SW-DFM vs SWFF-DFM	3.2*	2.3*	2.0*	2.7*	1.2	0.6	2.0*	2.6*	2.4*
SPF vs SW-Reg	−3.1*	−2.1*	−1.7	−0.8	0.2	0.1	−3.6*	−3.4*	−8.1*
SPF vs SWFF-Reg	−2.8*	−2.3*	−1.8	−0.9	−0.6	−0.2	−3.1*	−3.0*	−8.4*
SPF vs SWFF-DFM	1.1	0.7	1.0	0.0	0.8	0.8	1.5	0.1	0.8

Note: * denotes a DM statistic where the null hypothesis of equal predictive accuracy is rejected at the 5% level.

in the Del Negro and Schorfheide paper have the potential to move the steady state growth path closer to the variables, resulting in the need for less "catch-up" growth. Given this modeling assumption, the median forecasts of the SW-Reg and SWFF-Reg models are different than the models of the Del Negro and Schorfheide paper.

I opt to not use the stochastic growth path assumption for all four models because introducing it into DSEG-DFM estimation is non-trivial and I want to be able to directly compare the dynamics of all models assuming the same DSGE modeling assumptions. Furthermore, the DSGE-Reg models of this paper are capable of producing similar results of Del Negro and Schorfheide for immediate forecasting horizons around the Great Recession. Likewise, the forecasts generated by the DSGE-DFM models are still significantly better than the median forecast from the SPF around the Great Recession. This implies that they would also out-forecast the Del Negro and Schorfheide models around this time period because they found that the RMSE's for the models in that paper were equivalent to or higher than the median professional blue-chip forecasts for output.

3.2. *Comparing the point forecasts of the four models*

In the previous subsection, I placed particular attention on the forecasting performance of each model around the Great Recession. In this subsection, I wish to examine the point forecasts for all four models for a wider out-of-sample forecasting window of 1998–2011. Since the out-of-sample forecasting evaluation window includes time periods that the zero lower bound binds, I augment the SW and SWFF models starting in 2008Q4 with anticipated monetary policy shocks. These shocks are identified by Federal Fund Rate market expectations, as measured by OIS rates, following the approach described in Del Negro et al. (2013).

I conduct this "pseudo" out-of-sample forecast evaluation, by first estimating each model using 1984Q2–1997Q4 revised data and conduct one, two and four quarter ahead forecasts for core macroeconomic variables. I then add additional data each quarter and generate new forecasts. I re-estimate the model parameters twice a year.

After collecting median point forecasts for each quarter and each model, I assess their forecasting ability using Diebold–Mariano (DM) tests. DM test statistics for GDP are located in Table 2. A positive DM test statistic implies that the "model" on the right of column one has lower squared forecast errors than the "model" on the left. A negative DM test statistic implies that the "model" on the left of column one has lower squared forecast errors than the "model" listed on the right.

In evaluating the model's forecasts, four clear patterns appear. First, I find a similar result obtained by Del Negro and Schorfheide (2013), that the SWFF-Reg model's forecasts of GDP only improve upon the SW-Reg model's forecasts after the Great Recession. As the squared forecast errors for all forecast horizons are lower for SW-Reg model for the entire sample period and significantly lower for the pre-Great Recession error of 1998–2007Q2 sample period.

The second noteworthy implication of this application is the beneficial use of large data sets when I compare the output growth forecasts for the SW-Reg and SWFF-Reg models to the SW-DFM and SWFF-DFM forecasts. I see that the use of the extra data series substantially lowers the squared forecasts errors for output growth as shown in the second and third rows of Table 2. All DM tests for 1, 2 and 4-quarter ahead forecasts of output growth are statistically significant at the 5% level. In addition, the DSGE-DFM models significantly out forecasts their DSGE-Reg counter parts in terms of short-term consumption and investment growth as can be seen in Tables D.3 and D.4 of the appendix.

In addition to the DSGE-DFM models outperforming the DSGE-Reg models throughout the forecast evaluation window (1998–2011), I also see that the "predictive performance enhancing" effects of large data sets used in DSGE-DFM estimation start to amplify starting in the third quarter of 2007.

Thirdly, when I compare the SW-DFM and SWFF-DFM models in row four of Table 2, I see that the introduction of financial frictions and the use of a larger data vector allows the SWFF model to better compete with the SW model through the 1998–2011 forecasting time frame. This is suggested by the Diebold–Mariano tests which are either significantly positive or inconclusive for most *h* period ahead forecasts. This suggests that the extra data used in estimation helps solve the time-varying forecast ranking of the SW and SWFF implied by Del Negro and Schorfheide (2013).

Finally, rows five through seven of Table 2 show the competitiveness of the different models against the real-time forecast generated by the median forecast of leading professional forecasters of the SPF. As one can see the SW-Reg and SWFF-Reg

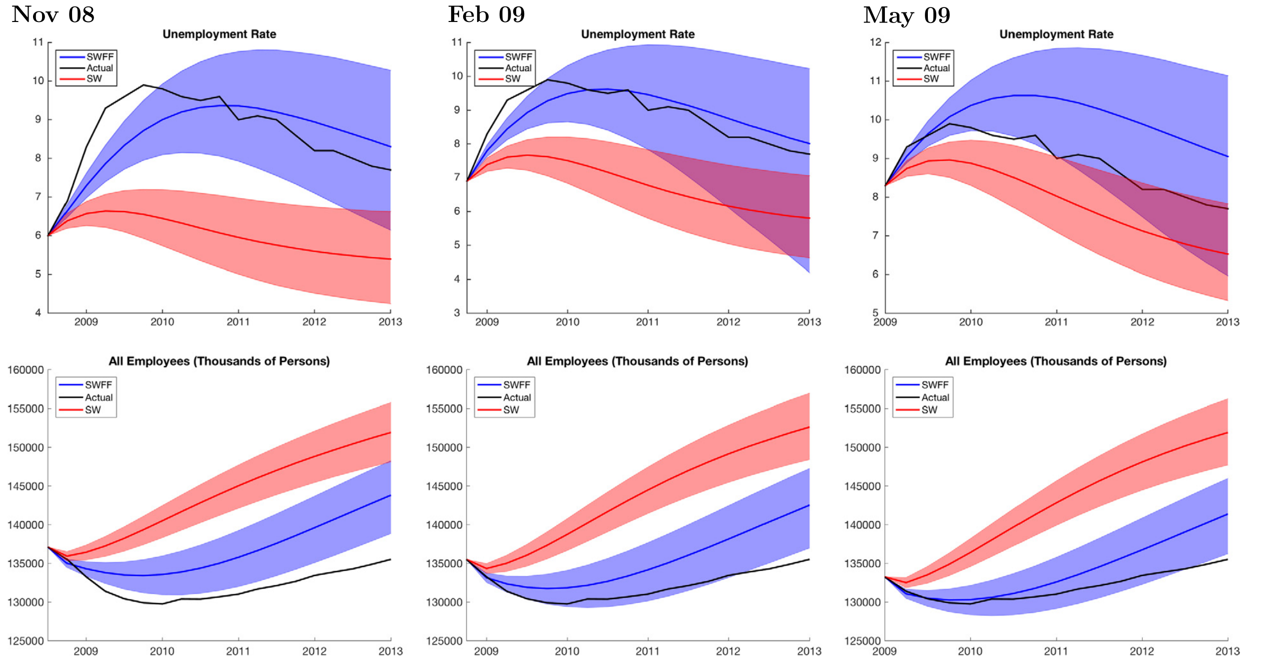

Fig. 4. Forecasted Paths for Aggregate Labor Market.

models produced competitive forecasts prior to 2007, but significantly fall behind the SPF forecast during the Great Recession. The rise in forecast errors is so large for the DSEG-Reg models that it makes the forecast accuracy of both significantly worse for the entire sample period. However, when I compare the SPF forecasts to the forecasts generated by the SWFF-DFM model, I see that it has marginally lower squared forecast errors for output growth for the entire sample and both pre and post Great Recession periods. In addition, the squared forecast errors of consumption and investment growth from the SWFF-DFM model are statistically insignificantly different from the squared forecast errors generated by the pooled SPF forecasts.

In summary, I see that the SWFF-Reg model only outperforms the SW-Reg model during the Great recession and its recovery; the use of a large data set significantly improves the forecasts of output and its components when compared to regular DSGE estimation; the large data vector eliminates the time-varying forecast ranking between the SW and SWFF models; and the SWFF-DFM produces competitive growth forecasts that are analogous to the median forecasts of the SPF before, during and after the Great Recession.

3.3. Forecasts of labor, housing, and credit markets

I next look at the forecasted paths of some labor market metrics including employment by sector, the unemployment rate, credit levels and housing starts, all of which are not directly incorporated in either DSGE model. The SWFF-DFM forecasted paths are in blue and the SW-DFM forecasted paths are in red, while the actual series values are shown in black. All forecasts have been transformed into actual levels.

When I examine forecasts for the unemployment rate and the number of overall employees in the economy in Fig. 4 and forecasts for the number of employees by sector in Fig. 5, I find that the model with a modeled finance market (SWFF-DFM) is able to pick up the upcoming increase of the unemployment rate as early as the fall of 2008. In contrast, the SW-DFM does not forecast an unemployment rate above 9% until after data from the 1st quarter of 2009 had been realized.

Further, the SWFF-DFM model significantly out forecasts the SW-DFM model when it comes to overall employees and employees in the professional services, retail trade, construction, manufacturing and wholesale trade sectors. Although the SWFF-DFM model constantly outperforms the SW-DFM model in predicting the future paths of all of these series, it is still overly optimistic about the number of jobs in the economy 3–4 years into the future. This may be a result of aging demographic changes seen around the country. Under their current construction both models have no ability to see such a demographic change as they use the population of 16 years and older (not prime-working age population) to transform variables in per capita terms.

Fig. 6 shows the forecasted paths of housing starts, consumer credit outstanding and business loans. Once again I see that the SWFF-DFM model soundly outperforms the SW-DFM model when it comes to housing starts. As far as consumer and business loans, the SWFF-DFM model is a good predictor of both for the first 4–6 quarters of each forecast. However, the SWFF-DFM model is unable to forecast the significant increases in both consumer and business loans that starts in the

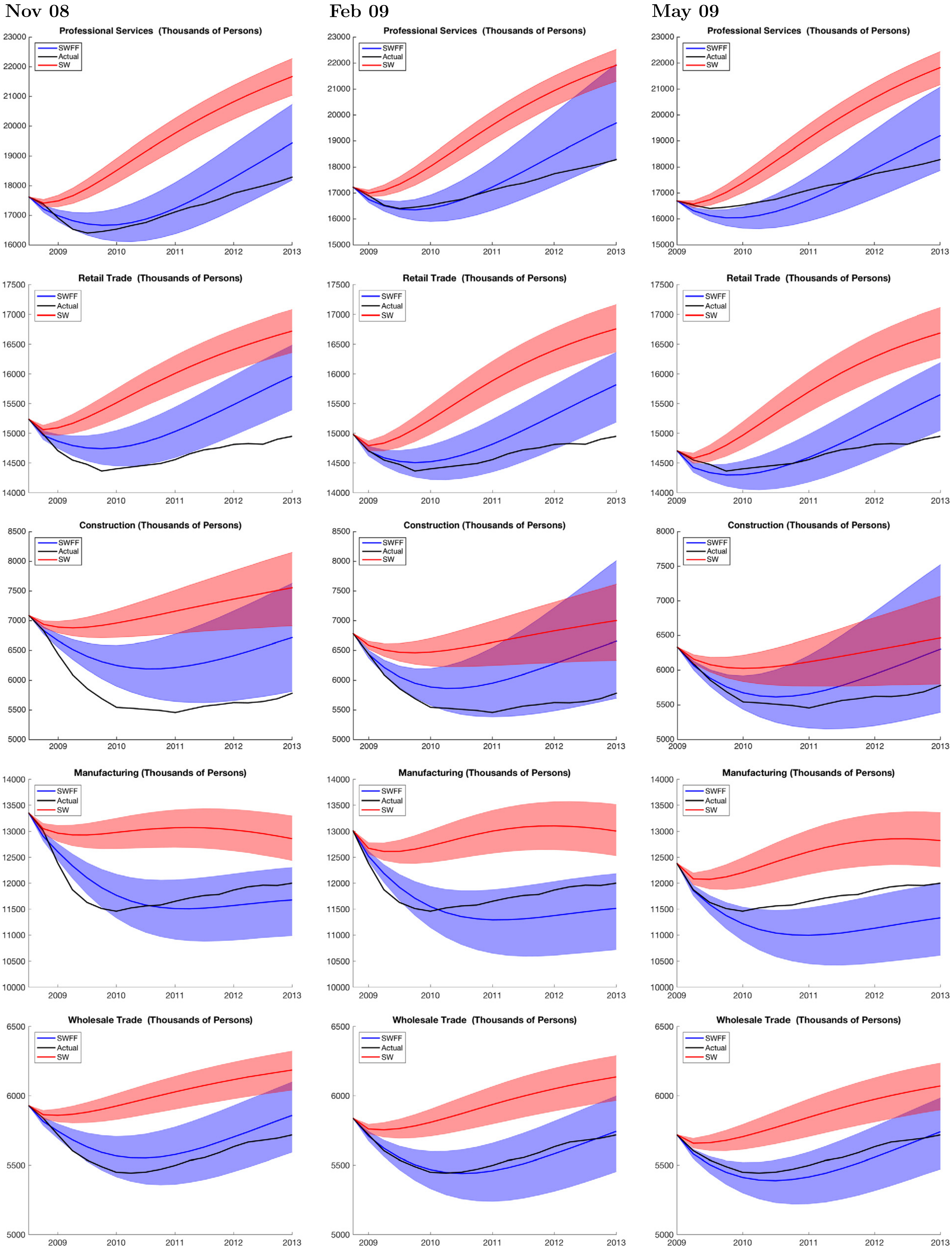

Fig. 5. Forecasted Paths for Labor Market Sectors.

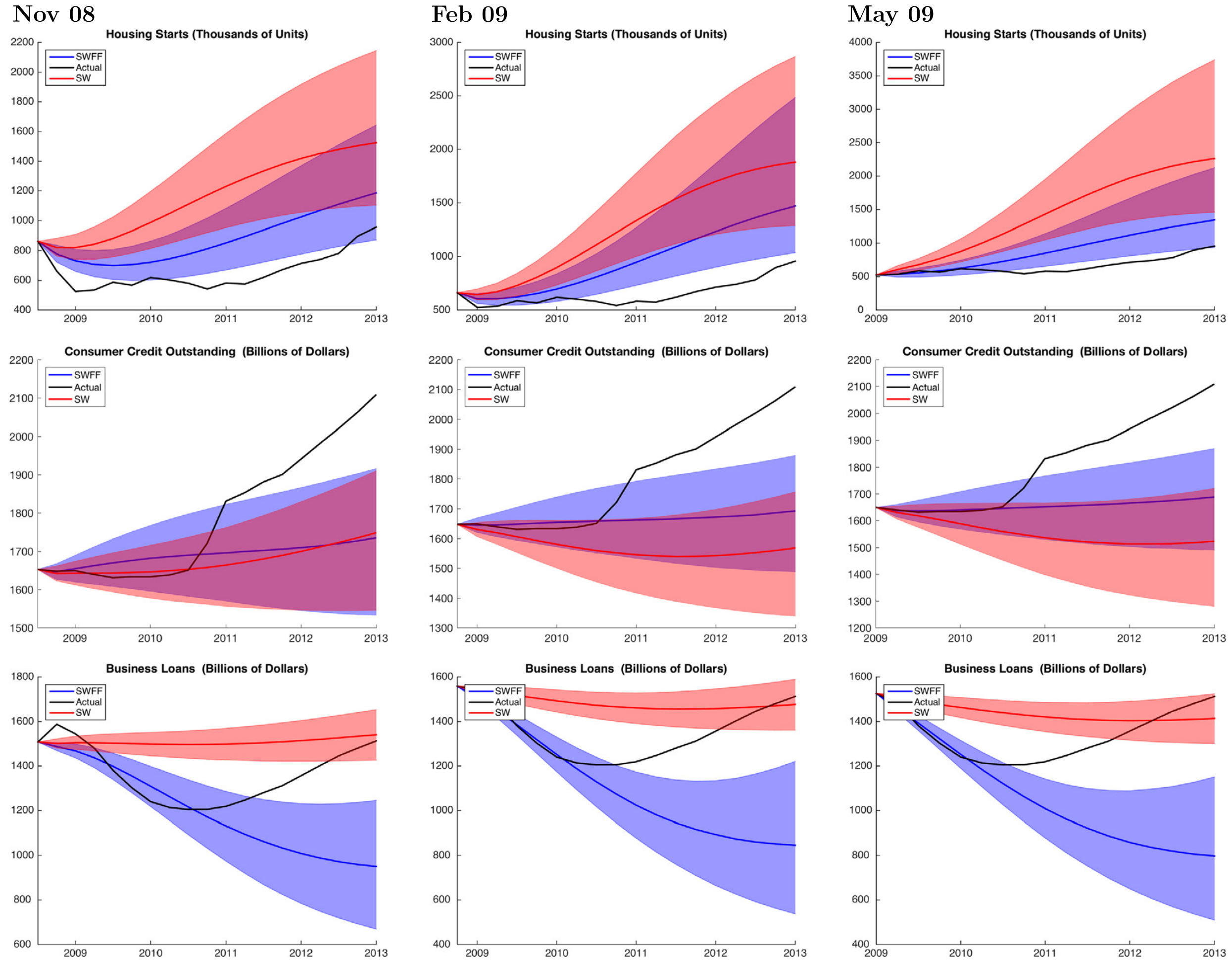

Fig. 6. Forecasted Paths for Financial Metrics.

middle of 2010. One possible explanation for the increase in both could be QE2, which started in August 2010. Of course neither model has a mechanism to foresee or incorporate such a policy change.

In summary, the SWFF-DFM model is able to see the decrease in jobs and the increase in the unemployment rate starting in November 2008. Additionally the SWFF-DFM model foresees the slower rate of overall jobs and jobs in particular sectors. There is a significant difference in the forecasted paths between the two models for the 2008–2013 time period. Yet this is not always the case for previous time periods, if I examine periods in which the financial spread was low and financial volatility was also low the forecasted paths between the models share similar posterior density intervals as can be seen in Fig. D.1 of the appendix. This would suggest that in addition to real output, the SWFF model is better at identifying the dynamics of the labor and finance markets in times of high financial volatility, yet still competitive with the SW model in times of low financial volatility.

4. Mechanisms behind the results

To better understand why the SWFF-DFM model was able to foresee the output and labor dynamics associated with the Great Recession more accurately and quicker than the SWFF-Reg, SW-Reg and SW-DFM models, it is important to compare the structural parameter estimates across the estimation techniques. Table D.5 reports the posterior estimates for all the structural parameters in the SWFF model while Fig. 7 plots the posterior distributions when fitted to a normal distribution for a select number of structural parameters for the SWFF model estimated using data from 1984Q2–2008Q3 (see Table D.6 for the SW model).

A few observations emerge when we compare the parameter estimates of the SWFF-Reg and SWFF-DFM models. First, the price and wage Calvo estimates share little to no overlap between the estimation techniques. The average length of contract negotiation for prices and wages is six quarters under the DSGE-Reg estimation compared to about every three quarters in the DSGE-DFM estimation. These smaller, yet still significant, price and wage rigidities are more in line with the findings of Klenow and Kryvtsov (2008) who examined monthly price changes by industry and found that the mean

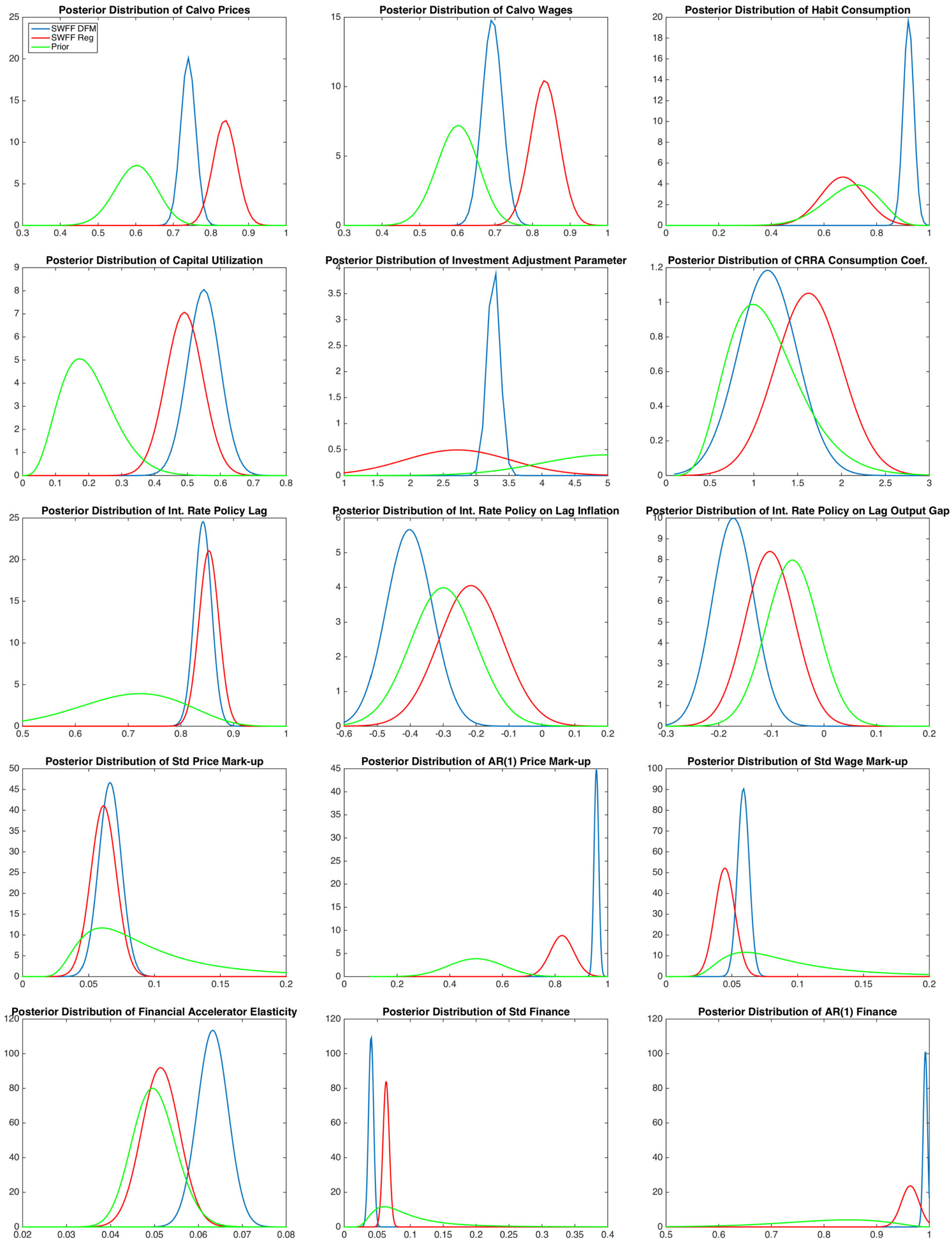

Fig. 7. Posterior Distribution Estimates of Structural Parameters in SWFF.

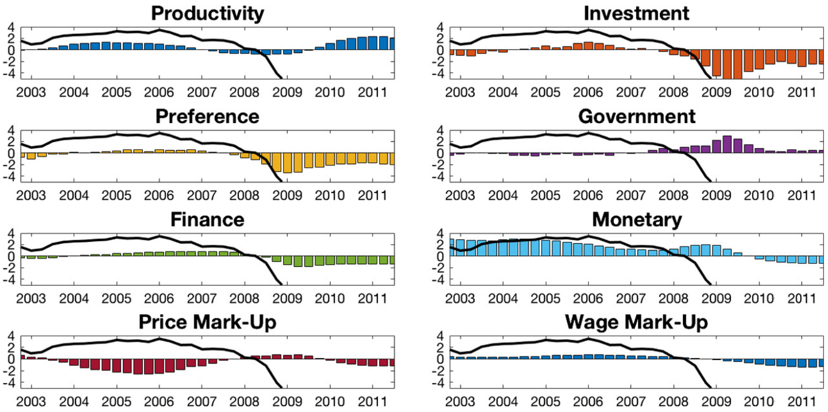

Fig. 8. Historical Decomposition of Output in the SWFF Model.

price duration is about 7 months. The parameter that governs habit formation consumption substantially increases in the DSGE-DFM estimation for both the SW and SWFF models when compared to its estimate under DSGE-Reg estimation. This helps explain why the SWFF-DFM model is able to forecast the sluggish growth in consumption during the recovery shown in Fig. 2.

Taylor Rule policy parameters are found to be more responsive to lagged inflation and the lagged output gap when estimated in the data-rich environment implying more inertia and persistence in the model. The policy parameters regarding the contemporaneous output gap and inflation levels are estimated to be less responsive in the data-rich environment.

Many of the parameters linked to the exogenous shocks of the model are different across the estimation techniques of the SWFF model. Foremost, price and wage mark-up shocks are estimated to be much more persistent in the SWFF-DFM estimation technique. The presence of many other price and wage indexes, including oil prices, drive this result as the estimates return to DSGE-Reg values when the SWFF-DFM is estimated without the Price and Wage Index data component.

The parameters that preside over the financial accelerator also change when estimated in a data-rich environment. There is more inertia in the financial accelerator as the spread elasticity is found to be larger and the finance shock is found to be smaller but much more persistence. The extra estimated persistence in nearly all structural shocks in the SWFF-DFM coupled with its modeled financial market can explain why the SWFF-DFM was able to anticipate the slow recovery in GDP, consumption and sector employment after large negative financial, investment and preference shocks were seen in 2008.

4.1. Driving forces behind the great recession

Essentially a generated forecast of any variable is a weighted average of the various IRFs controlling for initial conditions. Historical decomposition of GDP for the SWFF model shows that negative financial, investment and preference shocks were the main drivers of the decline in GDP as illustrated in Fig. 8. Examining the IRFs associated with these types of shocks help us better understand why the SWFF-DFM model foresaw the Great Recession earlier than other DSGE models and why it produces output and labor market dynamics in accordance with the recovery period of the Great Recession.

Fig. 9 gives the IRFs and 80% posterior density band of a one unit negative finance shock (positive spread shock), negative investment shock and a negative preference shock. The red IRFs correspond to the same one unit shocks for the DSGE-Reg estimation. Although all shocks are unitary the estimated standard deviation for the shock can differ. As expected real GDP falls for all three types of negative shock as is seen in the first row of Fig. 9. With regard to finance shocks, the impact on the spread is smaller in the SWFF-DFM model but its impact is larger on real GDP when compared to the SWFF-Reg model. This is due to the higher estimate of habit consumption in the SWFF-DFM model. This higher persistence in consumption does not cause consumption to increase in the SWFF-DFM model as it does in the SWFF-Reg model, creating a deeper decline in real GDP.

As expected real investment falls from a negative investment shock and real consumption falls from a negative preference shock in both the SWFF-Reg and SWFF-DFM models. However, the degree to which they fall and how fast they recover is quite substantial. This is due to the smaller estimates of the average size of an investment and preference shock and larger estimates of investment and preference shock persistence in the SWFF-DFM model. In the SWFF-DFM model it takes an extra two to three quarters before the component begins to recover when compared to the SWFF-Reg model. Further, real GDP does not recover as fast from both of these type of shocks because the tradeoff between consumption and investment that occurs from both investment and preference shocks in the SWFF-Reg model diminishes or disappears in the SWFF-DFM model.

The slower recoveries and diminishing or disappearing trade-off between consumption and investment that occurs in the SWFF-DFM model from these three types of shocks that depict the Great Recession helps explain why the SWFF-DFM model was able to forecast the output dynamics of the Great Recession and it ensuing recovery so well when compared

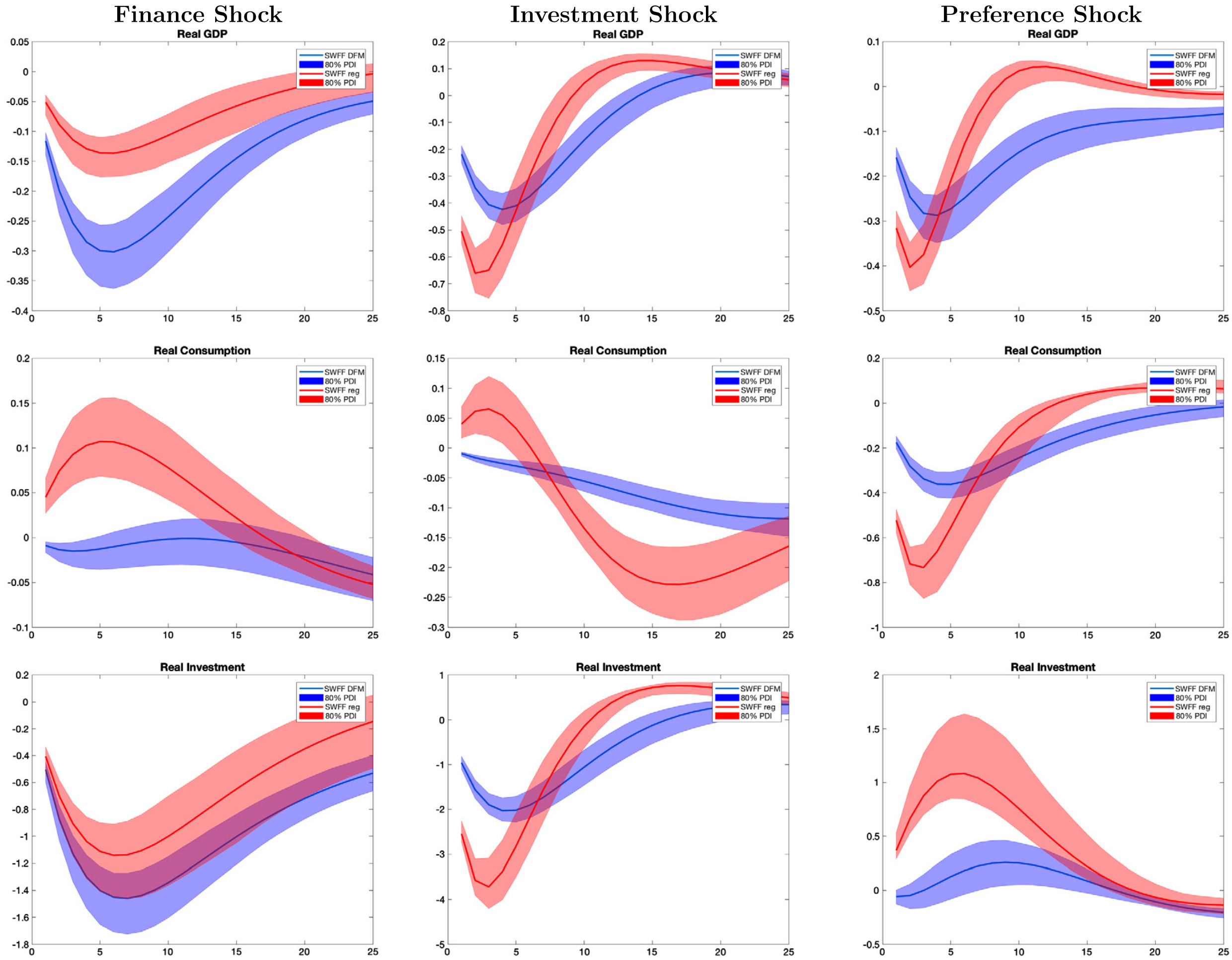

Fig. 9. IRFs of the Great Recession Shocks.

to the SWFF-Reg model. The SWFF-Reg model's estimated structural parameters predict slightly larger declines in real GDP from the three Great Recession shocks but a quicker recovery because the estimated structural parameters make the consumption/investment tradeoff larger, thus mitigating the decline in real GDP that initially takes place.

5. Conclusion

In this paper, the Smets and Wouters (2003; 2007) New Keynesian Dynamic Stochastic General Equilibrium (DSGE) model augmented with a financial accelerator (SWFF) is estimated using a large set of economic and financial series following the work of Boivin and Giannoni (2006) and Kryshko (2011). I then conduct similar exercises comparing the four models (SW-Reg, SWFF-Reg, SW-DFM and SWFF-DFM) as was done for the SW-Reg and SWFF-Reg models in the Del Negro and Schorfheide (2013) paper. I find that the SWFF-DFM model is better in capturing the dynamics of many economic series including output, consumption and many labor market metrics around the time of the Great Recession and its ensuing recovery.

In addition, the SWFF-DFM model generates dominant out-of-sample forecasts for the entire examined sample period (1998–2011), not just in the time period surrounding the Great Recession (2008–2011), as was the case for the SWFF-Reg model in Del Negro and Schorfheide (2013). The paper suggests that a structural DSGE model embedded with a modeled financial market and estimated in a data-rich environment would have predicted the output and labor market severity of the Great Recession and its aftermath, as well as foreseen the downturn in economic growth as early as February 2008. Further, such a model produces competitive forecasts of output, consumption, employment and unemployment when compared to the forecasts generated by the Survey of Professional Forecasters.

The continuing advancements in computational programming and the ever growing number of macroeconomic and financial series available allows DSGE-DFM estimation to be a bountiful area of future research.

Appendix A. Log linear equations

Both models are linearized around the non-stochastic steady state and then solved using the Sims (2002) method. This solution is the transition equation in the state-space set-up of Sections 2.2 and 2.3. Variables denoted with a hat are defined as log deviations around the steady state. $\left(\hat{Y}_t = log\left(\frac{Y_t}{Y}\right)\right)$ Variables denoted without a time script are steady state values. In all, the SWFF model is reduced to 12 equations and eight exogenous shocks all of which are listed below.

Physical capital $\bar{K}_t$ accumulates according to:

$$\hat{\bar{K}}_t = (1-\tau)\hat{\bar{K}}_{t-1} + \tau\hat{I}_t + \tau(1+\beta)S''\hat{\varepsilon}_t^I \tag{A.1}$$

where ε_t^I is an AR(1) investment shock and τ is the depreciation rate and S'' is a parameter that governs investment adjustment costs. A large S'' implies that adjusting an investment schedule is costly.

Labor Demand is given by

$$\hat{L}_t = -\hat{w}_t + (1+\tfrac{1}{\psi})\hat{r}_t^k + \hat{\bar{K}}_{t-1} \tag{A.2}$$

where r_t^k is the real rental rate of capital and ψ is a parameter that captures utilization costs of capital. A large ψ infers that capital utilization costs are high. The economy's resource constraint and production function take the form:

$$\hat{Y}_t = C_y\hat{C}_t + I_y\hat{I}_t + \frac{r^k\bar{k}_y}{\psi}\hat{r}_t^k + \mathcal{M}_t + \hat{\varepsilon}_t^G \tag{A.3}$$

$$\hat{Y}_t = \phi\hat{\varepsilon}_t^a + \phi\alpha\hat{\bar{K}}_{t-1} + \frac{\phi\alpha}{\psi}\hat{r}_t^k + \phi(1-\alpha)\hat{L}_t \tag{A.4}$$

where C_y and I_y are the steady state ratio of consumption and investment to output and $\mathcal{M}$ is the monitoring costs faced by banks. $\mathcal{M}$ is assumed to be negligible and is left out in the estimation process. ϕ resembles a fixed cost of production and is assumed to be greater than 1.

The Linearized Taylor Equation that determines the nominal interest rate is

$$\hat{R}_t = \rho\hat{R}_{t-1} + (1-\rho)\left[r_{\pi_1}\hat{\pi}_t + r_{y_1}\hat{Y}_t + r_{\pi_2}\hat{\pi}_{t-1} + r_{y_2}\hat{Y}_{t-1}\right] + \hat{\varepsilon}_t^r \tag{A.5}$$

The consumption and investment transition equations are

$$\hat{C}_t = \frac{h}{1+h}\hat{C}_{t-1} + \frac{1}{1+h}E_t[\hat{C}_{t+1}] - \frac{1-h}{(1+h)\sigma_c}\left(\hat{R}_t - E_t[\hat{\pi}_{t+1}]\right) + \hat{\varepsilon}_t^b \tag{A.6}$$

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{I}_{t+1}] + \frac{1}{(1+\beta)S''}\hat{q}_t + \hat{\varepsilon}_t^I \tag{A.7}$$

where $\hat{\varepsilon}_t^I$ and $\hat{\varepsilon}_t^b$ are exogenous stochastic stationary processes that effect the short term dynamics of consumption and investment. q_t is the relative price of capital and β is the discount rate.

The entrepreneurial return on capital is characterized by

$$\hat{\bar{R}}_t^k - \hat{\pi}_t = \frac{1-\tau}{1-\tau+r^k}\hat{q}_t + \frac{r^k}{1-\tau+r^k}\hat{r}_t^k - \hat{q}_{t-1} \tag{A.8}$$

The model yields a phillips curve equal to:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\iota_p}E_t[\hat{\pi}_{t+1}] + \frac{\iota_p}{1+\beta\iota_p}\hat{\pi}_{t-1} + \frac{(1-\beta\xi_p)(1-\xi_p)}{(1+\beta\iota_p)\xi_p}\left(\alpha\hat{r}_t^k + (1-\alpha)\hat{w}_t - \hat{\varepsilon}_t^a\right) + \hat{\varepsilon}_t^p \tag{A.9}$$

where ξ_p is the degree of price stickiness, ι_p is the degree of price indexation to last period's inflation rate and $\hat{\varepsilon}_t^a$, $\hat{\varepsilon}_t^p$ are exogenous processes that affect the productivity of production and the price mark up over marginal cost respectively.

Wages in the economy evolve according to:

$$\begin{aligned}\hat{w}_t = {} & \frac{\beta}{1+\beta}E_t[\hat{w}_{t+1}] + \frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{\pi}_{t+1}] - \frac{1+\beta\iota_w}{1+\beta}\hat{\pi}_t + \frac{\iota_w}{1+\beta}\hat{\pi}_{t-1} \\ & - \frac{(1-\beta\xi_w)(1-\xi_w)}{(1+\beta)\left(1+\nu_l\frac{1+\lambda_w}{\lambda_w}\right)\xi_w}\left(\hat{w}_t - \nu_l\hat{L}_t - \frac{\sigma_c}{1-h}(\hat{C}_t - h\hat{C}_{t-1})\right) + \hat{\varepsilon}_t^w\end{aligned} \tag{A.10}$$

where ξ_w is the degree of wage stickiness, ι_w is the degree of wage indexation to last period's inflation rate and $\hat{\varepsilon}_t^w$, is an exogenous process that affect monopoly power households hold over labor.

The finance market is characterized by two equations, the first being the spread of the return on capital over the risk free rate:

$$\hat{S}_t \equiv E_t\left[\hat{\tilde{R}}^k_{t+1} - \hat{R}_t\right] = \chi\left(\hat{q}_t + \hat{\bar{K}}_t - \hat{n}_t\right) + \hat{\varepsilon}^F_t \tag{A.11}$$

where χ is the elasticity of the spread with respect to the capital to net worth ratio and $\hat{\varepsilon}^F_t$ is a finance shock that effects the riskiness of entrepreneurs and thus the riskiness of banks being paid back in full.

The second financial equation contains the evolutional behavior of entrepreneur net worth:

$$\hat{n}_t = \delta_{\tilde{R}^k}(\hat{\tilde{R}}^k_t - \hat{\pi}_t) - \delta_R(\hat{R}_{t-1} - \hat{\pi}_t) + \delta_{qK}(\hat{q}_{t-1} + \hat{\bar{K}}_{t-1}) + \delta_n\hat{n}_{t-1} - \delta_\sigma\hat{\varepsilon}^F_{t-1} \tag{A.12}$$

where the δ coefficients are functions of the steady state values of the loan default rate, entrepreneur survival rate, the steady state variance of the entrepreneurial risk shocks, the steady state level of revenue lost in bankruptcy, and the steady state ratio of capital to net worth. The value of χ, which will be estimated, along with the calibrated steady state spread will determine the steady state level of the variance of the exogenous risk shock, the steady state value of the percentage of revenue lost in bankruptcy and the steady state level of leverage. Therefore, given a steady state spread the value of χ will determine the values of the δ coefficients.[8]

The SWFF model has eight exogenous shocks, seven of which are AR(1) processes the lone exception being the monetary policy shock which is simply white noise. All processes are assumed to be i.i.d. with mean zero and standard deviation σ_i and autocorrelation parameters ρ_i, where $i = \{a, b, G, r, I, F, p, w\}$

SW Model

The SW model is identical to the SWFF model without the entrepreneur and banking sectors. Instead households own the capital, decide the utilization rate of capital, rent it to intermediate firms and sell it to capital producers. As a result the household budget constraint includes income received by renting and selling capital. In addition, households must choose how much capital to own.

The linearized first order condition of capital is given by

$$\hat{q}_t = -(\hat{R}_t - E_t[\hat{\pi}_{t+1}]) + \frac{1-\tau}{1-\tau+r^k}E_t[\hat{q}_{t+1}] + \frac{r^k}{1-\tau+r^k}E_t[\hat{r}^k_{t+1}] + \hat{\varepsilon}^Q_t \tag{A.13}$$

This equation will replace the linearized equation (A.8). Since the equations (A.11) and (A.12) do not exist in the SW model there is a loss of an exogenous shock. In order to be able to directly compare misspecification error of the two models it is best that both models have the same amount of exogenous shocks. This is accomplished by adding a idiosyncratic equity premium price shock represented by $\hat{\varepsilon}^Q_t$ to replace the finance shock $\hat{\varepsilon}^F_t$ of the SWFF Model. Equation (A.13) is nested in the SWFF model if there exists no finance spread (i.e. $\hat{\tilde{R}}^k_{t+1} = R_t$). This assumption implies (A.8) forwarded ahead one period is identical to (A.13).

Appendix B. Data and transformations

	Kryshko shorthand	FRED code	Trans*	long description	Used in reg estimation
Core Sets					
	Core Output				
1	RGDP	GDPC1	2	Real GDP	*
2	IP_TOTAL	INDPRO	2	Industrial Production Index:total	
3	RGDI	A261RX1Q020SBEA	2	Real Domestic Income	
	Core Inflation				
4	PGDP	GDPDEF	3	GDP Price deflator	*
5	PCED	PCECTPI	3	PCE_ALL Price deflator	
6	CPI_ALL	CPIAUCSL	3	CPI_ALL Price index	
	Core Consumption				
7	RCONS	PCECC96	2	Real Personal Consumption Expenditures	*
	Core Investment				
8	RINV	GDPI	2	Real Private Domestic Investment	*
	Core Wages				
9	RWAGE	AHETPI	4	Real Average Hourly wages:production:total private	*
	Core Labor Employment				
10	HOURS	HOANBS	2	Hours Worked	*
11	EMP_CES	PAYEMS+USGOVT	2	Employees:Total Nonfarm	
12	EMP_CPS	CE160V	2	Civilian Labor Force:Employed, Total	
	Core Interest Rate				
13	FedFunds	FEDFUNDS	0	Federal Funds Rate (effective)	*
14	Tbill_3m	TB3MS	0	Interest Rate U.S. Treasury bill 3 month	

[8] For a comprehensive look at the functional forms of all the δ coefficients used in coding the model, one must look at the working appendix of Del Negro and Schorfheide available at http://economics.sas.upenn.edu/~schorf/research.htm.

(*continued*)

	Kryshko shorthand	FRED code	Trans*	long description	Used in reg estimation
15	AAABond	AAA	0	Bond Yield: Moody's AAA corporate	
	Core Spread*				
16	SFYBAAC	BAA-GS10	0	Spread of BAA corporate yield to 10 year Treasury	*
17	SFYAAAC	AAA-GS10	0	Spread of AAA corporate yield to 10 year Treasury	
Non-Core Sets					
	Output Components				
18	IP_FINAL	IPS299	2	Industrial Production Index:final products	
19	IP_CONS_DBLE	IPDCONGD	2	Industrial Production Index:Durable Consumer Goods	
20	IP_CONS_NONDBLE	IPNCONGD	2	Industrial Production Index:NonDurable Consumer Goods	
21	IP_BUS_EQPT	IPBUSEQ	2	Industrial Production Index:Business Equipment	
22	IP_DRBLE_MATS	IPDMAT	2	Industrial Production Index:Durable Goods Materials	
23	IP_NONDRBLE_MATS	IPNMAT	2	Industrial Production Index:NonDurable Goods Materials	
24	IP_MFG	IPMAN	2	Industrial Production Index:Manufacturing	
25	IP_FUELS	IPUTIL	2	Industrial Production Index:Fuels	
26	PMP	NAPMPI	0	NAPM Production index	
27	RCONS_DRBLE	DDURRA3Q086SBEA	2	Real Personal Consumption Expenditures index:Durables	
28	RCONS_NONDRBLE	DNDGRA3Q086SBEA	2	Real Personal Consumption Expenditures index:NonDurables	
29	RCONS_SERV	DSERRA3Q086SBEA	2	Real Personal Consumption Expenditures index:Sevices	
30	REXPORTS	B020RA3Q086SBEA	2	Real Exports Quantity Index	
31	RIMPORTS	B255RA3Q086SBEA	2	Real Imports Quantity Index	
32	RGOV	B823RA3Q086SBEA	2	Real Government Consumption & Investment Quantity Index	
	Labor Market				
33	EMP_Mining	USMINE	2	Employees:Mining & Logging	
34	EMP_CONST	USCONS	2	Employees:Construction	
35	EMP_MFG	MANEMP	2	Employees:Manufacturing	
36	EMP_SERVICES	SRVPRD	2	Employees:Service Providing	
37	EMP_TTU	USTPU	2	Employees:Trade, Transportation, Utilities	
38	EMP_WHOLESALE	USWTRADE	2	Employees:Wholesale Trade	
39	EMP_RETAIL	USTRADE	2	Employees:Retail Trade	
40	EMP_FIN	USFIRE	2	Employees:Financial Activities	
41	EMP_GOVT	USGOVT	2	Employees:Government	
42	EMP_PROSERV	USPBS	2	Employees:Professional Services	
43	EMP_LEISURE	USLAH	2	Employees:Leisure & Hospitality	
44	URATE	UNRATE	0	Unemployment Rate	
45	U_DURATION	UEMPMEAN	0	Average Duration of Unemployment (weeks)	
46	U_L5WKS	UEMPLT5	2	Unemployment Duration:Persons:Less than 5 Weeks	
47	U_5_14WKS	UEMP5TO14	2	Unemployment Duration:Persons:5–14 Weeks	
48	U_15_26WKS	UEMP15T26	2	Unemployment Duration:Persons:15–26	
49	U_M27WKS	UEMP27OV	2	Unemployment Duration:Persons:27 weeks +	
50	HOURS_AVG	CES0600000007	0	Average Weekly Hours:Goods Producing	
51	HOURS_AVG_OT	AWOTMAN	0	Average Weekly Overtime Hours:Manufacturing	
	Housing Market				
52	HSTARTS_NE	HOUSTNE	1	Housing Starts:Northeast	
53	HSTARTS_MW	HOUSTMW	1	Housing Starts:Midwest	
54	HSTARTS_SOU	HOUSTS	1	Housing Starts:South	
55	HSTARTS_WST	HOUSTW	1	Housing Starts:West	
56	RRRESINV	B011RA3Q086SBEA	2	Real Private Domestic Investment:Residential Quantity Index	
	Financial Market				
57	SFYGM6	TB6MS-TB3MS	0	Spread of 6 month Tbill to 3 month Tbill	
58	SFYGT1	GS1-TB3MS	0	Spread of 1 year Treasury to 3 month Tbill	
59	SFYGT10	GS10-TB3MS	0	Spread of 10 year Treasury to 3 month Tbill	
60	TOT_RES	TOTRESNS	2	Total Reserves of Depository Institutions	
61	TOT_RES_NB	NONBORRES	5	Total Reserves Of Depository Institutions, Nonborrowed	
62	BUS_LOANS	BUSLOANS	2	Commercial and Industrial Loans at All Commercial Banks	
63	CONS_CREDIT	NONREVSL	2	Total Nonrevolving Credit Owned and Securitized, Outstanding	
64	SP500	SP500	3	S&P 500 Stock Price Index	
65	DJIA	DJIA	3	Dow Jones Industrial Average	
	Exchange Rates				
66	EXR_US	TWEXMMTH	3	Trade Weighted U.S. Dollar Index: Major Currencies	
67	EXR_SW	EXSZUS	3	Switzerland / U.S. Foreign Exchange Rate	
68	EXR_JAN	EXJPUS	3	Japan / U.S. Foreign Exchange Rate	
69	EXR_UK	EXUSUK	3	U.S. / U.K. Foreign Exchange Rate	
70	EXR_CAN	EXCAUS	3	Canada / U.S. Foreign Exchange Rate	
	Investment				
71	NAPMI	NAPM	0	Purchasing Managers Index	
72	NAPM_NEW_ORDERS	NAPMNOI	0	NAPM New Orders Index	

(*continued on next page*)

(*continued*)

	Kryshko shorthand	FRED code	Trans*	long description	Used in reg estimation
73	NAPM_SUP_DEL	MAPMSDI	0	NAPM Supplier Deliveries	
74	NAPM_INVENTORIES	NAPMII	0	NAPM Inventories Index	
75	RNONRESINV	B009RA3Q086SBEA	2	Real private fixed investment: Nonresidential quantity index	
	Price & Wage Indexes				
76	RAHE_CONST	CES3000000008	4	Real Avg. Hourly wages:construction (Deflated w/GDP Deflator)	
77	RAHE_MFG	CES3000000008	4	Real Avg. Hourly wages:manufacturing (Deflated w/GDP Deflator)	
78	RCOMP_HR	COMPRNFB	4	Real Compensation Per Hour (index)	
79	ULC	ULCNFB	4	Unit Labor Cost (index)	
80	CPI_CORE	CPILFESL	3	CPI:Less food and energy	
81	PCED_DUR	DDURRA3Q086SBEA	3	PCE:Durable goods price index	
82	PCED_NDUR	DNDG RA3Q086SBEA	3	PCE:NonDurable goods price index	
83	PCED_SERV	DSERRG3Q086SBEA	3	PCE:Services price index	
84	PINV_GDP	GPDICTPI	3	Gross private domestic investment price index	
85	PINV_NRES_STRUCT	B009RG3Q086SBEA	3	GPDI:price index:structures	
86	PINV_NRES_EQP	B010RG3Q086SBEA	3	GPDI:price index:Equiptment and software	
87	PINV_RES	B011RG3Q086SBEA	3	GPDI:price index:Residential	
88	PEXPORTS	B020RG3Q086SBEA	3	GDP:Exports Price Index	
89	PIMPORTS	B021RG3Q086SBEA	3	GDP:Imports Price Index	
90	PGOV	B822RG3Q086SBEA	3	Government Consumption and gross investment price index	
91	P_COM	PPIACO	3	PPI:All commodities price index	
92	P_OIL	PPICEM/PCEPILFE	3	PPI:Crude (Divided by PCE Core)	
	Other				
93	UTL11	MCUMFN	0	Capacity Utilization-Manufacturing	
94	LABOR_PROD	OPHNFB	4	Output per hour all persons:business sector index	
95	UMICH_CONS	UMCSENT	1	University of Michigan Consumer Expectations	
96	M_1	M1SL	2	M1 Money stock	
97	M_2	M2SL	2	M2 Money stock	

* Transformation codes are described in the data transformation rubric.

Note: Since there is no Spread variable in the SW Model, data set 16 is not used in the SW-Reg estimation and data sets 16 and 17 are moved to the Financial Market grouping for SW-DFM estimation.

Data Transformation Rubric

Code	Description
0	Demeaned
1	Log() and demeaned
2	Linear detrended Log() per capita
3	Log() differenced and demeaned
4	Detrended Log()
5	Detrended per capita level

Note: All per capita variables are calculated using the adult population series (CNP16OV).

Measurement Equations for DSGE-Reg Estimation

The measurement equation (2.2) is specified as follows where the 8th row is omitted for the SW model:

$$\begin{bmatrix} \text{RGDP} \\ \text{PGDP} \\ \text{RCONS} \\ \text{RINV} \\ \text{RWAGE} \\ \text{HOURS} \\ \text{FedFunds} \\ \text{SFYBAAC/4} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & \dots & 0 \end{bmatrix} \begin{bmatrix} y_t \\ \pi_t \\ c_t \\ I_t \\ w_t \\ L_t \\ R_t \\ S_t \\ \vdots \end{bmatrix}$$

Appendix C. Estimated state variables

I examine the in-sample dynamics of the model to ensure that our SWFF-DFM model is consistent (in terms of the conduct of macroeconomic series) with the in-sample dynamics of the SWFF-Reg model. Using the Carter–Kohn algorithm, it is straightforward to calculate the estimates of the endogenous variables of the model over the sample time period. These are plotted for the SWFF model in Fig. C.1. The blue line and shaded area represent the posterior mean and 90% density interval of the variable under SWFF-DFM estimation and the red line represents the posterior mean of the variable under SWFF-Reg estimation. The y-axis of all plots is representing percentage deviations away from the variable's steady state values.

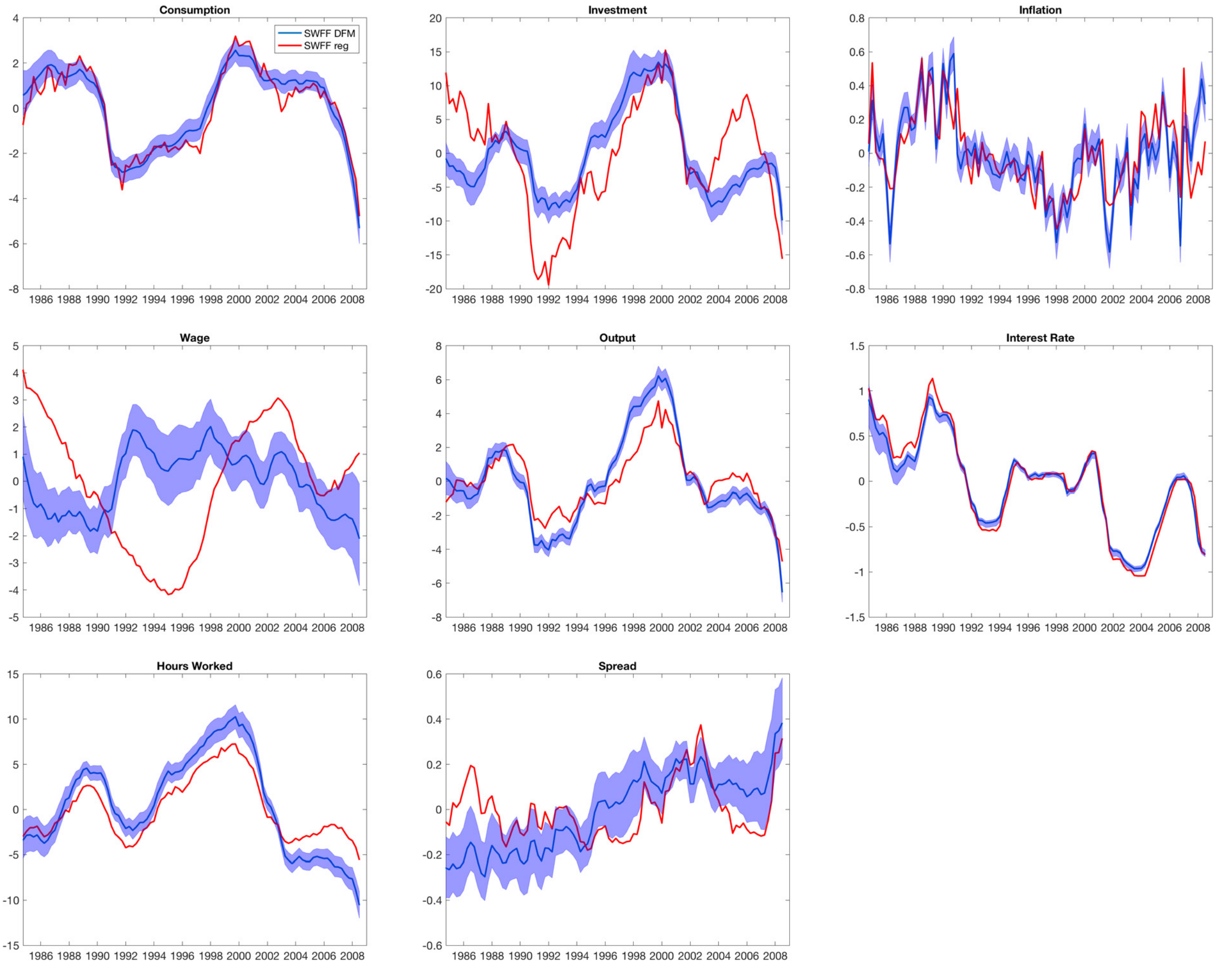

Fig. C.1. Simulated States of Endogenous Variables of SWFF.

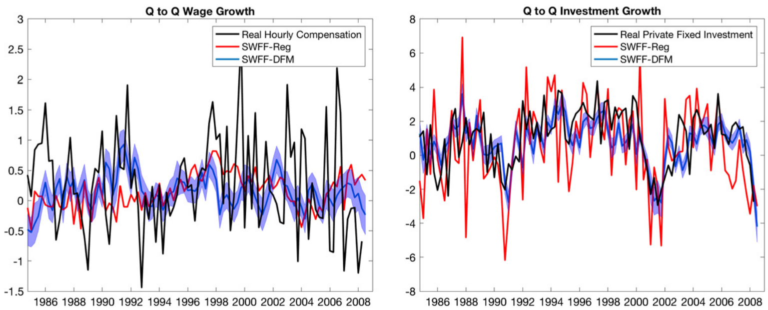

Fig. C.2. Simulated Growth Rates of Real Investment and Real Wages.

The eight plots of Fig. C.1 represent endogenous variables that are directly related to a data series in the core. Recall, eight of the series have a perfectly tight loading prior to ensure that the variable is “anchored” to its economic definition. As the plots show this is mostly the case with two exceptions, wage and investment. The endogenous variables of consumption, inflation, output, interest rate, hours worked and financial spread in the SWFF-DFM track the core data series that is associated with these variables.

When I look at the plots for wage growth and investment growth in Fig. C.2, I see a pattern emerge. First, the growth rates of both real wage and investment in the SWFF-DFM model match the endogenous variables each is associated with more closely. In certain periods when the model implied endogenous variable in the SWFF-DFM model is not in the neighborhood as the data series it is directly related to, I see that it is very close to other series that could be used as an alternative data series to match the endogenous variable in the model. For example, two periods in which real wage growth in the SWFF-DFM model differs from the core data set are 1990–1992 and 1998–2002. During both these periods real wage growth in the SWFF-DFM model more closely aligns with the growth rate of real compensation per hour.

Additionally, the endogenous variable of real investment growth in the SWFF-DFM model seems to be smoother than the actual growth rate of Real Gross Private Domestic Investment as seen in the right hand plot of Fig. C.2. However, the growth rate of Real Private Fixed Investment seems to match the endogenous variable of real investment growth in the SWFF-DFM model quite well.

Appendix D. Tables & figures

Table D.1
Calibrated Parameters.

	Description	Value
β	Discount rate	0.99
α	Share of capital	0.3
τ	Depreciation rate	0.025
I_y	S.S. investment proportion of output	0.18
g_y	S.S. government proportion of output	0.19
λ_w	Degree of wage markup	0.3
Specific to SWFF		
γ	Survival rate of entrepreneur	0.99
F^*	Loan default rate	0.0075
S	S.S. Spread (Annual %)	1.4

Table D.2
Priors for DSGE Models' Parameters.

	Description	Distribution	Mean	Std.
Structural Parameters				
ψ	Capital utilization costs	Beta	0.2	0.08
ι_p	Degree of indexation on prices	Beta	0.5	0.15
ι_w	Degree of indexation on wages	Beta	0.5	0.15
ξ_p	Calvo price stickiness	Beta	0.6	0.05
ξ_w	Calvo wage stickiness	Beta	0.6	0.05
ν_l	CRRA coef. on labor	Gamma	1.4	0.45
σ_c	CRRA coef. on consumption	Gamma	1.2	0.45
h	Habit consumption	Beta	0.7	0.1
ϕ	Fixed cost of production	Gamma	0.5	0.3
S''	Capital adjustment cost	Normal	5	1
Policy Parameters				
r_{π_1}	Taylor Rule coef. on inflation	Gamma	2	0.33
r_{y_1}	Taylor Rule coef. on output gap	Gamma	0.2	0.1
r_{π_2}	Taylor Rule coef. on past inflation	Normal	−0.3	0.1
r_{y_2}	Taylor Rule coef. on past output gap	Normal	−0.06	0.05
ρ	Lagged interest rate in Taylor Rule	Beta	0.7	0.1
Exogenous Processes Parameters				
ρ_a	AR(1) coef. on productivity shock	Beta	0.8	0.1
ρ_b	AR(1) coef. on preference shock	Beta	0.8	0.1
ρ_G	AR(1) coef. on gov't spending shock	Beta	0.8	0.1
ρ_I	AR(1) coef. on investment shock	Beta	0.8	0.1
ρ_w	AR(1) coef. on wage mark-up shock	Beta	0.5	0.1
ρ_p	AR(1) coef. on price mark-up shock	Beta	0.5	0.1
σ_a	Std. of productivity shock	Inv. Gamma	0.1	2*
σ_b	Std. of preference shock	Inv. Gamma	0.1	2*
σ_G	Std. of gov't spending shock	Inv. Gamma	0.1	2*
σ_r	Std. of monetary policy shock	Inv. Gamma	0.1	2*
σ_I	Std. of investment shock	Inv. Gamma	0.1	2*
σ_p	Std. of price mark-up shock	Inv. Gamma	0.1	2*
σ_w	Std. of wage mark-up shock	Inv. Gamma	0.1	2*
σ_q	Std. of equity premium shock	Inv. Gamma	0.1	2*
Parameters Specific to SWFF				
$\chi*$	Spread Elasticity	Beta	0.05	0.005
ρ_F	AR(1) coef. on finance shock	Beta	0.8	0.1
σ_F	Std. of finance shock	Inv. Gamma	0.1	2*

Note: The auxiliary parameter χ is estimated with $\chi^* = .0225 + .0825\chi$.
Note: All inverse gamma distributions list degrees of freedom instead of std.

Table D.3
Diebold–Mariano Test Statistics for Consumption Growth.

	Entire sample 1998Q1–2011Q4			Pre-recession 1998Q1–2007Q2			Great Recession 2007Q3–2011Q4		
	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4
SW-Reg vs SWFF-Reg	2.7*	2.0*	2.2*	2.0*	1.7	1.6	2.2*	1.4	2.4*
SW-Reg vs SW-DFM	1.7	2.5*	2.3*	1.2	1.1	1.4	3.5*	3.7*	10.2*
SWFF-Reg vs SWFF-DFM	1.1	1.7	1.5	1.5	0.4	0.2	2.3*	2.0*	2.3*
SW-DFM vs SWFF-DFM	0.4	0.6	0.3	0.8	0.8	−0.2	−0.1	0.2	0.3
SPF vs SW-Reg	−2.6*	−2.8*	−1.8	−0.3	−2.1	−0.2	−3.1*	−2.9*	−4.4*
SPF vs SWFF-Reg	−1.9	−2.2*	−1.2	0.2	−2.1*	0.3	−2.4*	−2.1*	−2.1*
SPF vs SWFF-DFM	−1.5	−1.7	−0.5	−1.1	−1.1	0.4	−1.1	−1.2	−1.3

Table D.4
Diebold–Mariano Test Statistics for Investment Growth.

	Entire sample 1998Q1–2011Q4			Pre-recession 1998Q1–2007Q2			Great Recession 2007Q3–2011Q4		
	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4	h = 1	h = 2	h = 4
SW-Reg vs SWFF-Reg	0.7	−0.1	−2.0*	0.7	−1.1	−1.3	0.6	0.1	−1.8
SW-Reg vs SW-DFM	2.8*	1.6	1.1	1.9	2.1*	1.3	2.3*	1.6	1.1
SWFF-Reg vs SWFF-DFM	2.1*	1.1	1.4	1.5	0.7	1.4	1.6	1.0	1.2
SW-DFM vs SWFF-DFM	−0.3	0.7	0.8	−0.0	−1.6	−0.1	−0.2	1.1	0.9
SPF vs SW-Reg	−3.0*	−1.5	−0.9	−2.7*	0.8	0.5	−2.0*	−2.0*	−4.3*
SPF vs SWFF-Reg	−2.7*	−1.4	−1.4	−2.5*	0.2	−0.2	−1.6	−1.7	−3.1*
SPF vs SWFF-DFM	−1.0	−0.2	0.3	−1.6	0.7	0.9	−0.2	−0.7	−0.1

Note: * denotes a DM statistic where the null hypothesis of equal predictive accuracy is rejected at the 5% level.

Table D.5
Posterior Estimates of SWFF Model.

	Regular estimation			DSGE-DFM estimation		
	Mean	5%	95%	Mean	5%	95%
Structural Parameters						
ψ	0.491	0.414	0.595	0.550	0.471	0.649
ι_p	0.261	0.099	0.495	0.106	0.040	0.181
ι_w	0.250	0.128	0.389	0.426	0.240	0.676
ξ_p	0.837	0.783	0.887	0.739	0.708	0.776
ξ_w	0.833	0.759	0.882	0.693	0.654	0.740
ν_l	1.782	1.127	2.545	1.244	0.785	1.849
σ_c	1.624	1.057	2.323	1.157	0.725	1.843
h	0.672	0.525	0.806	0.921	0.888	0.951
ϕ	0.467	0.219	0.760	0.176	0.052	0.380
S	2.716	1.471	4.138	3.267	3.074	3.394
χ	0.051	0.044	0.059	0.063	0.057	0.069
Policy Parameters						
r_{π_1}	2.196	1.832	2.602	1.539	1.397	1.706
r_{y_1}	0.336	0.235	0.443	0.131	0.070	0.209
r_{π_2}	−0.216	−0.383	−0.056	−0.403	−0.536	−0.289
r_{y_2}	−0.103	−0.179	−0.024	−0.172	−0.252	−0.110
ρ	0.853	0.821	0.883	0.842	0.810	0.864
Exogenous Processes AR(1) Parameters						
ρ_a	0.910	0.877	0.940	0.944	0.928	0.955
ρ_b	0.755	0.623	0.863	0.726	0.673	0.776
ρ_G	0.971	0.951	0.987	0.867	0.838	0.890
ρ_I	0.664	0.549	0.766	0.843	0.765	0.913
ρ_F	0.964	0.932	0.986	0.993	0.985	0.998
ρ_p	0.826	0.745	0.891	0.957	0.941	0.969
ρ_w	0.600	0.432	0.781	0.911	0.853	0.952
Exogenous Processes Standard Deviation Parameters						
σ_a	0.487	0.431	0.550	0.428	0.343	0.500
σ_b	0.094	0.063	0.131	0.026	0.019	0.034
σ_G	0.327	0.290	0.372	0.230	0.179	0.289
σ_r	0.127	0.111	0.145	0.130	0.119	0.148
σ_I	0.955	0.801	1.129	0.241	0.192	0.308
σ_F	0.063	0.056	0.072	0.041	0.035	0.047
σ_p	0.061	0.047	0.078	0.066	0.052	0.081
σ_w	0.045	0.033	0.058	0.059	0.051	0.065

Note: Parameters estimated using data from 1984Q2–2008Q3.

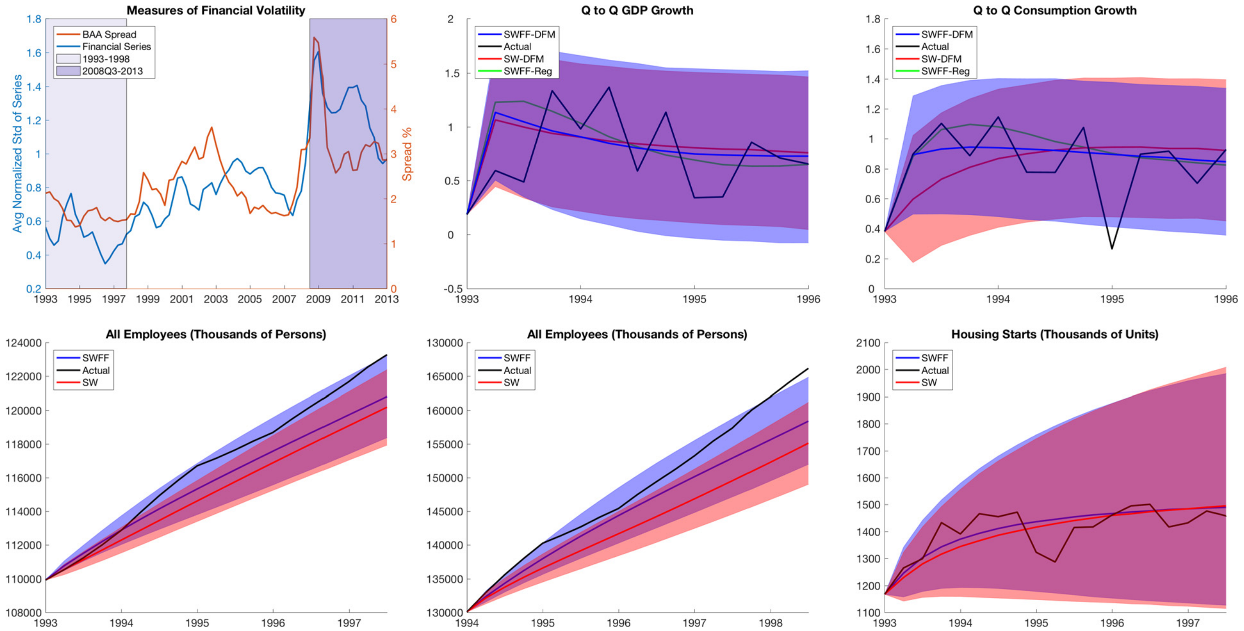

Fig. D.1. Forecasted Paths of the Mid-1990's.

Table D.6
Posterior Estimates of SW Model.

	Regular estimation			DSGE-DFM estimation		
	Mean	5%	95%	Mean	5%	95%
Structural Parameters						
ψ	0.345	0.208	0.497	0.284	0.155	0.442
ι_p	0.261	0.102	0.493	0.229	0.093	0.411
ι_w	0.223	0.108	0.356	0.442	0.210	0.672
ξ_p	0.838	0.787	0.885	0.689	0.609	0.766
ξ_w	0.853	0.804	0.888	0.756	0.634	0.828
ν_l	2.009	1.307	2.880	1.363	0.729	2.225
σ_c	1.678	1.115	2.316	1.233	0.710	1.922
h	0.688	0.552	0.816	0.910	0.852	0.954
ϕ	0.445	0.201	0.750	0.128	0.036	0.254
S	5.348	3.841	6.898	5.243	4.560	6.104
Policy Parameters						
r_{π_1}	2.161	1.775	2.556	2.107	1.744	2.498
r_{y_1}	0.345	0.238	0.460	0.206	0.116	0.291
r_{π_2}	−0.222	−0.383	−0.063	−0.231	−0.383	−0.085
r_{y_2}	−0.084	−0.166	−0.005	−0.166	−0.238	−0.093
ρ	0.867	0.835	0.896	0.831	0.796	0.860
Exogenous Processes AR(1) Parameters						
ρ_a	0.911	0.879	0.939	0.945	0.901	0.979
ρ_b	0.772	0.654	0.864	0.755	0.671	0.821
ρ_G	0.974	0.956	0.987	0.968	0.949	0.989
ρ_I	0.710	0.593	0.813	0.848	0.785	0.906
ρ_p	0.827	0.748	0.890	0.600	0.418	0.734
ρ_w	0.524	0.381	0.684	0.588	0.415	0.886
Exogenous Processes Standard Deviation Parameters						
σ_a	0.500	0.442	0.567	0.209	0.155	0.277
σ_b	0.085	0.056	0.120	0.036	0.023	0.053
σ_G	0.322	0.287	0.362	0.292	0.217	0.353
σ_r	0.125	0.110	0.142	0.119	0.104	0.139
σ_I	0.737	0.603	0.881	0.263	0.214	0.317
σ_q	0.104	0.039	0.244	0.583	0.467	0.713
σ_p	0.061	0.047	0.078	0.098	0.075	0.125
σ_w	0.048	0.036	0.060	0.106	0.070	0.150

Note: Parameters estimated using data from 1984Q2–2008Q3.

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