INCORPORATING HIGH DIMENSIONAL DATA VECTORS INTO STRUCTURAL MACROECONOMIC MODELS

by

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DISSERTATION ABSTRACT

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Title: Incorporating High Dimensional Data Vectors into Structural Macroeconomic Models

In this dissertation I incorporate high dimensional data vectors in estimated Dynamic Stochastic General Equilibrium (DSGE) models, evaluating the labor market dynamics incorporated inside such data vectors, out-of-sample forecasting performance of many models estimated with such data vectors and analytically examining the reduction of macroeconomic volatility that can occur when such data vectors are used in the formation of expectations about the future.

The second chapter investigates the extent to which modern DSGE models can produce labor market dynamics in response to a financial crisis that are consistent with the experience of the Great Recession. I estimate two New-Keynesian models, one with and one without financial frictions, in a data-rich environment. I find that negative financial shocks are associated with longer recoveries in real investment, capital-intensive sectors of the labor market and average unemployment duration. I also find the model with a financial accelerator is equipped with better tools to identify the dynamics associated with the Great Recession and its recovery in regard to many labor and financial metrics.

The third chapter compares the out-of-sample forecasting performance of the two DSGE models of Chapter II when they are estimated both out of and in a data-rich environment. This chapter finds that many financial time series variance decomposition are significantly better explained using the structural set-up of the New-Keynesian model with financial frictions. DSGE models estimated with high dimensional data vectors significantly out forecast their regularly estimated counterpart in regard to output, investment and consumption growth. Lastly, the use of real-time optimal pool model weighting significantly out-forecasts traditional macroeconomic models as well as an equally weighted weighting scheme in terms of many macroeconomic variables.

The fourth chapter examines the role forecasts derived by high dimensional data vectors can have on lowering macroeconomic volatility. Bounded rational agents are introduced into the Chapter II DSGE model with financial frictions and are given the

option to use or ignore professionally generated forecasts from a dynamic factor model in their perceived forecasting model. In simulations, I find that professionally generated forecasts can significantly lower the volatility of many macroeconomic variables including inflation and hours worked.

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CHAPTER I

INTRODUCTION

Today, the macroeconometrician works in a world where many economic time series are available, yet many macroeconomic models only use, or are concerned with, a small handful of these series. The goal of this dissertation is to examine the inferences that can be made when one incorporates a large quantity of economic time series into structural macroeconomic models. In this dissertation I incorporate high dimensional data vectors in estimated Dynamic Stochastic General Equilibrium (DSGE) models, evaluating the out-of-sample forecasting performance of many models estimated with such data vectors. Also, I analytically examine the reduction of macroeconomic volatility that can occur when such data vectors are used in the formation of economic expectations about the future.

The second chapter is titled "Financial Crises and Labor Market Dynamics: Evidence from a Data-Rich DSGE Model." In this chapter I investigate the extent to which DSGE models can produce labor market dynamics in response to a financial crisis that are consistent with the experience of the Great Recession. The two DSGE models include close variations of the Smets & 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. Using the methods of Boivin and Giannoni (2006) and Kryshko (2011), I estimate both models using a high dimensional data vector of 97 quarterly observables over the time period of 1984Q2-2008Q3. This allows me to examine the dynamics of economic series not obtainable in traditional DSGE model estimation. I find that negative financial shocks are associated with longer recoveries in real investment, capital intensive sectors of the labor market and average unemployment duration when compared to other negative output shocks. These results hold when the recession magnitude is normalized across the shocks. I also find that the FRBNY model with a financial accelerator is equipped with better tools to identify the dynamics associated with the Great Recession and its recovery in regard to many labor and financial metrics including the unemployment rate, total number of employees by sector and consumer loans.

This chapter includes an outline of both models, an overview of the DSGE-DFM estimation technique and posterior estimates of the structural parameters of both models. The DSGE-DFM estimation technique allows me to examine the labor market impacts of different "types" of recessions. I find that financial crises are associated with longer periods of unemployment duration and a larger increase in the economy's unemployment rate when compared to identical declines of output driven by consumer, monetary or supply side shocks.

The third chapter is titled "Evaluating the Forecasting Performance of Model Averaging DSGE-DFM Models." Procedures of this chapter include an out-of-sample forecast of all four models estimated in Chapter II. The results suggest that estimating the model in a data-rich environment yields significantly better forecasts for output growth in the time period of 1998-2012. In this chapter, I also replicate the finding of Del Negro and Schorfheide (2012) that the forecasting rank of output growth and inflation of the DSGE models with financial frictions and without is not stable over time. I evaluate the out-of-sample forecasting performance of these four models against that of other forecasting models, including vector autoregression models of different lag specifications and dynamic factor models. I find that the DSGE-DFM model estimation outperforms many of these models throughout the 1998-2012 window, with larger outperformance centered around the financial crisis and its recovery.

One potential reason for such results is highlighted by examining the forecast error variance decomposition and historical decomposition of each model. I find that the model with a financial accelerator mechanism explains more of the variance decomposition of financial data series through its structural shocks when compared to its counterpart's structural shocks. Historical decompositions of output show that periods that correspond to large financial volatility correspond to large exogenous misspecification error in the model without financial frictions and large financial spread shocks in the model with financial frictions. This suggest that the DSGE model with financial frictions is equipped with better tools in identifying the dynamics associated with the Great Recession.

Lastly, this chapter explores the forecasting value of real-time optimal pool (RTOP) model weighting when DSGE-DFM models are included in the model pool. The use of each forecasting model's density forecast is used to assign the optimal weight to each model. RTOP model weighting results in better out-of-sample point forecasting results for many macroeconomic variables and results in probability integral transformations (PIT) histograms that are more uniformly distributed when compared to the PITs of most DSGE models. Furthermore, when the volatility of the financial markets is accounted for by using a model prior with RTOP weighting, out-of-sample point forecasts are again improved upon. This RTOP model weighting that accounts for the state of the world introduced in this chapter expands upon the RTOP weighting scheme proposed by Amisano and Geweke (2013).

The fourth chapter is titled “Effects of Professional Forecast Dissemination on Macroeconomic Volatility.” This chapter explores the role that professional public forecast announcements can have on macroeconomic volatility. Boundedly rational agents are used inside the medium scale DSGE model with financial frictions outlined in Chapter II. Modeled agents must select between three simple linear forecasting specifications, some that contain the inclusion of a professional“publicly” announced forecast of the endogenous economic variable and some that do not. When the model is simulated these publicly announced forecasts are generated using a dynamic factor model whose parameters are derived by a high dimensional data vector. Historically calibrated simulations of the model show that the inclusion of a professionally derived forecast by the agents in their adaptive learning forecast specifications can reduce the economic volatility in inflation and hours worked by as much as 25% and 10%. If however, the professionally derived forecast is not disseminated well to the agents or biased by the public sector, agents will learn to ignore the announcement and macroeconomic volatility will increase. I find that the inclusion of very noisy professional forecasts can result in “coordinated volatility cascades” where agents could reduce macroeconomic volatility by ignoring the professional forecast, but choose not to, because of its past forecast performance.

CHAPTER II

FINANCIAL CRISIS AND LABOR MARKET DYNAMICS: EVIDENCE FROM A DATA-RICH DSGE MODEL

II.1 Introduction

Unemployment and labor market fluctuations surrounding the business cycle have a significant impact on household welfare. Empirical work suggests that sluggish labor market recoveries may be directly linked to what initiated the preceding recession. In particular, Boeri et al. (2012) used firm-level balance sheets and employment records and found that firms in industries that use more temporary financing in every-day business operations adjust employment levels much more when credit shocks decrease liquidity than firms with less financing on their balance sheet. This liquidity channel leads to larger job loses and slower hiring when a decrease in economic output is caused by a financial shock rather than a demand or supply shock.

The relationship of job destructions and liquidity is not only found at the firm-level but is also seen at the aggregate labor market level. Calvo et al. (2012) studied economic data from thirty-five emerging and advanced economies and found that the unemployment rate rose higher and remained higher for longer periods of time in recessions caused by financial shocks when compared to recessions caused by productivity shocks. Calvo et al. (2012) also examined wage dynamics and found that financial recessions can be associated with either jobless recoveries or wageless recoveries depending on the level of inflation observed in the economy during the recovery period.

These and other findings suggest that the underlying causes behind a recession produces different dynamics at both the aggregate and sub-aggregate macroeconomic levels. The understanding of these dynamics is important to policy makers, for example, types of recessions that have more of an impact on certain labor sectors than others need to be targeted more in fiscal policy prescriptions. Further, certain types of recessions may be associated with similar dynamics of economic output but very different labor market recoveries. As a result, monetary policy that accounts for heterogeneous labor market recoveries based upon the underlying cause of the recession may be enhanced when compared to policy prescriptions primarily focused on inflation and output dynamics.

To parse with more precision the results of Boeri et al. (2012) and Calvo et al. (2012) a medium-scale Dynamic Stochastic General Equilibrium (DSGE) model with a sophisticated labor market is needed. Yet, most prominent structural macroeconomic models do not include a sophisticated labor market. This has made inferences about recoveries and recessions in regard to labor markets difficult. The persistent level of unemployment, unemployment durations and jobs by sector associated with the Great Recession and its recovery represent a deficiency in the structural macroeconomic literature. This chapter utilizes an estimation technique developed by Boivin and Giannoni (2006) to compare labor market dynamics across different structural shocks in hopes of better understanding why recoveries from recessions can be so different. In particular, I take a close look at the Great Recession and why its initial recovery was classified by a historically slow labor market recovery.

Modern day macroeconomic theory has greatly leaned on structural 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 (SW) in particular is widely considered the "workhorse" of the DSGE literature. However, Del Negro and Schorfheide (2012) have found this model to be flawed 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 able to identify the Great Recession six months earlier than the SW model is a variant of the SW model with financial frictions (SWFF). The SWFF model introduces a Bernanke, Gertler and Gilchrist (1999) financial accelerator mechanism and closely follows the entrepreneurial sector of the DSGE model of Christiano et al. (2010) and the FRBNY model outlined by Del Negro et al. (2013). Del Negro and Schorfheide (2012) 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 data series. They found that during the financial crisis the modified SWFF model was better at forecasting output and inflation when compared to the original SW model.

A problem is that both these models do not have sophisticated labor markets embedded inside of them. Additionally, given the construction of traditional DSGE model estimation (DSGE-Reg) we are limited to examining only a handful of co-movements among these aggregate series. However, the techniques of Boivin and Giannoni (2006) and Kryshko (2011) provide an avenue through which DSGE environments can be used to study such series as the unemployment rate, unemployment duration and employees by sector even when no such series are directly incorporated into the structural model.

The Boivin and Giannoni (2006) technique (DSGE-DFM) allows DSGE models to be estimated using a large data vector of macroeconomic time series. 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. The estimated structural parameters and loadings allow me to examine the dynamic effects of the structural shocks inside the DSGE model as well as the dynamics of additional data indicators and series important to the policymaker; including the dynamics of various labor and financial market indicators.

In this chapter, I estimate both the SW and SWFF models using the DSGE-DFM method. The time series I use to conduct these estimations 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 neglected in regular DSGE model estimation. These include unemployment rates and durations, stock price indexes, housing starts and many price and wage indexes beyond the standard CPI index and GDP deflator.

This chapter addresses the question of why some recessions are associated with jobless or wageless recoveries and others are not. In particular, I investigate whether recently developed (and popular) structural models of the U.S. economy can generate labor market dynamics similar to those seen in the data. To explore the economic and labor market effects of various exogenous shocks I examine structural impulse response functions (IRF's) for series that are usually not obtainable inside DSGE models. Many of these IRF's are only obtainable if embedded in a dynamic factor model with little or no theoretical interpretation of the original shock by which they are generated. However, the DSGE-DFM estimation technique creates a structural foundation of what type of initial shock has created the disturbance.

After estimating both models in a data-rich environment, I calibrate the SWFF model to ensure that all shocks decrease real GDP by the same amount. I find evidence that financial crises (corresponding to an increased spread between the risk and risk-free interest rates inside the model) are associated with higher levels of unemployment and longer average unemployment duration in comparison to other types of recessions with identical output decreases. These results suggest that the relationship between unemployment and GDP growth implied by Okun's Law might be state-dependent. I also find that sectors associated with more capital intensive operations (manufacturing and construction sectors) are the very sectors that are slowest to recover from a financial shock. Labor market series are not the only series where such a pattern exists, decreases in real investment, exports and new orders are larger and last longer during financial recessions when compared to consumer, monetary, or supply shock driven recessions.

Given the above theoretical evidence distinguishing the difference between financial recessions and other types of recessions, I closely examine the period surrounding the Great Recession and its recovery. I conduct simulations and forecasts for 2008Q3, 2008Q4 and 2009Q1 of both DSGE-DFM models. I find that the SWFF 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. In comparison to the SW model, the SWFF model was able to predict these declines earlier and more accurately. These results suggest that the SWFF model would have predicted the labor market dynamics associated with the Great Recession and its proceeding recovery. I also find that many of the in-sample forecasts of such variables do not differ from each other in tranquil economic times. It is only in times of financial volatility that we see the simulated paths from the two models begin to differ.

The remainder of this chapter is structured as follows. Section II.2 explains each sector of the economy for both models including its micro-foundations and optimization problems. The linearized equations for both models needed to replicate the results of this chapter are also given in this section. Section II.3 outlines the estimation technique used to incorporate the large set of economic and financial series including the adaptive Metropolis-within-Gibbs algorithm used in estimating both models in the data-rich environment. 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 and how they were collected, transformed, and grouped. Section II.4 discusses the main findings of the chapter including estimated IRF's for different "types" of normalized recessions induced by the various structural shocks inside the SWFF model. Section II.5 shows the simulated paths of both the SW and SWFF models for various labor and finance series around the trough and recovery of the Great Recession. Section II.6 concludes and discusses future extensions.

II.2 The DSGE Models

I consider two DSGE models in this chapter, 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, Gertler and Gilchrist (1999). It incorporates many of the features of Christiano, Motto and Rostagno (2010). 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 SWFF. This section proceeds as follows, I first outline the agents in the SWFF model and discuss their choices and optimization problems. Next, I present the linearized equations of the model around the steady state that I use to produce my results. Finally, I introduce the components of the SW model that differ from the SWFF model, as well as any linearized equations that change as a result of how the SW model is microfounded.

II.2.1 General Outline of SWFF Model

The 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. The agents and their choice behavior decisions along with what shocks impact which agents directly are illustrated in Figure 1.

Households supply household-specific labor to employment agencies. Households maximize a CRRA utility function over an infinite horizon with additively separable utility in consumption, leisure and money. Utility from consumption has habit persistence as it is realized by a relative measure of total consumption in the last time period. Labor is differentiated over households, and is not perfectly competitive implying households hold some monopoly power over wages. The model includes sticky nominal wages set in a Calvo (1983) manner with wage indexation to those who can not freely optimize their wage. In addition to holding money, households can save in Government bonds and/or deposits in banks. Households are subject to an exogenous preference shock that can be viewed as a shock in the consumer's consumption and saving decisions.

Employment Agencies package and sell labor bought from the household to intermediate-firms. Employment agencies are perfectly competitive but must buy specialized labor from households who hold some monopoly power over wages. Households and Employment Agencies may only renegotiate wages with a certain probability but are subject to inflation indexation. Employment agencies are subject to wage mark-up shocks that capture exogenous changes in the monopolistic power households hold over their specialized labor.

Firms come in two forms, intermediate good producing firms and final good producing firms. There is a continuum of intermediate good firms, who supply intermediate goods in a monopolistically competitive market. Intermediate firms produce differentiated goods, decide on labor and capital inputs, and set prices in a Calvo-like manner. As with wages, those firms unable to change their prices, are able to partially index them to past inflation rates. Intermediate firms face two exogenous shocks, the first is a productivity shock that affects their production ability and the second is a price mark-up shock. The price mark-up shock captures the degree of competitiveness in the intermediate goods market. Final goods use intermediate goods in production and are produced in perfect competition. The final good is sold to the households and capital producers in the form of consumption.

Capital Producers buy consumption output from the final goods sector and transform it into new capital. The creation of new capital (Investment) requires both the newly bought consumption output and the previous stock of capital in the economy which they buy from entrepreneurs. The investment procedure is subject to convex adjustment costs making it more expensive to produce more capital in times of large investment growth. Capital producers are subject to investment shocks that affect the marginal efficiency of investment as in Justiniano et al. (2011).

Financial Sector centers around two economic agents, banks and entrepreneurs. Entrepreneurs enter the period with some level of net worth. They must use their net worth and an agreed upon loan from the bank to buy capital from the capital producers. Once the capital is bought they are affected by an idiosyncratic risk shock that can decrease or increase their overall level of capital just purchased. The entrepreneur must then decide the utilization of the new level of capital and rent it out to intermediate firms to be used in their production process. Once the capital has been used in the production process the non-depreciated capital is purchased by the capital producers. If entrepreneurs received enough revenue they pay back the agreed upon loan with interest to the bank. If entrepreneurs do not have enough revenue a proportion of their revenue is seized by the bank. Banks incorporate the risk of default by charging entrepreneurs an interest rate higher than the deposit rate payed to households. Entrepreneurs face a probability of death after each time period and the banking sector is perfectly competitive. Figure 2 describes the sequence of events amongst all relevant agents when it comes to the financial sector.

Government Agencies are composed of a monetary authority and a fiscal authority. The short term nominal interest rate is determined by the monetary authority, which is assumed to follow a generalized Taylor Rule and is subject to monetary policy shocks. The monetary authority supplies the corresponding money demanded by the household to support the targeted nominal interest rate. The fiscal authority sets government spending and collects lump sum taxes. It is subject to exogenous government spending shocks. Finally, there is a resource constant that states that all final output must equal consumption, investment, government purchases, loan monitoring costs and capital utilization costs.

Let's now examine each economic agents optimization problem and constraint. All relevant first order conditions can be found in Appendix A of this dissertation.

Households

There is a continuum of households indexed by j. The objective function for household j is given by:

$$E_t \sum_{s=0}^{\infty} \beta^s b_{t+s} \left[\frac{(C_{t+s}(j) - hC_{t+s-1})^{1-\sigma_c}}{1-\sigma_c} - \frac{(L_{t+s}(j))^{1+\nu_l}}{1+\nu_l} + log\left(\frac{M_{t+s}(j)}{P_{t+s}}\right) \right] \quad \text{(II.2.1)}$$

where $C_t(j)$ is household consumption, $L_t(j)$ is supply of a household differentiated type of Labor and $M_t(j)$ is household money holdings. Households face a stochastic shock b_t that can be viewed as an intertemporal preference shock that creates a wedge between the marginal utility of consumption and the real return to risk-free government bonds. h is an identical parameter across households that captures consumption persistence. All parameters not indexed by j are assumed to be identical across all households. Household j's budget constraint is:

$$\begin{aligned} P_{t+s}C_{t+s}(j) + B_{t+s}(j) + D_{t+s}(j) + M_{t+s}(j) \leq R_{t+s-1}B_{t+s-1}(j) \\ + R^d_{t+s-1}D_{t+s-1}(j) + M_{t+s-1}(j) + W_{t+s}(j)L_{t+s}(j) + \Pi_{t+s}(j) - T_{t+s} + Trans_{t+s} \end{aligned} \quad \text{(II.2.2)}$$

where P_t is the price index of the economy, $B_t(j)$ is holdings of government bonds, $D_t(j)$ is the amount of deposits in the banking sector, R_t is the nominal interest rate on government bonds, R_t^d is the nominal interest rate banks pay on deposits, Π_t is the profit households get from owning the intermediate firms, $W_t(j)$ is the wage earned, T_t are lump sum taxes payed to/by the government and $Trans_t$ are wealth transfers to/from the entrepreneurial agents. Household j chooses $\{C_t(j), L_t(j), M_t(j), B_t(j), D_t(j)\}_{t=0}^{\infty}$ that maximizes expected utility (II.2.1) subject to the household budget constraint (II.2.2). Further, households may purchase state-contingent securities (not indicated in the budget constraint) which implies that all households choose the same amount of consumption, money holdings, bond purchases and bank deposits.

Employment Agencies

Households sell their specialized labor $L_t(j)$ to employment agencies who then bundle it and sell it to intermediate firms as L_t. The composite labor good of the economy is a CES aggregator of the households specialized labor.

$$L_t = \left(\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}} \, dj \right)^{1+\lambda_{w,t}} \tag{II.2.3}$$

The parameter $\lambda_{w,t}$ is a stochastic process centered around λ_w that measures the monopoly power a household holds in selling its specialized labor. The first order condition of the agencies' profit maximization equation (A.4) leads to the following demand for specialized labor $L_t(j)$:

$$L_t(j) = \left(\frac{W_t(j)}{W_t} \right)^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} L_t \tag{II.2.4}$$

Households choose the optimal wage subject to the labor demand function. However, in every time period a probability exists ξ_w that households can not freely readjust their wage. If a household can not readjust their wage, their wage is automatically indexed to a weighted average of steady state inflation and last periods inflation as in Erceg, Henderson, and Levin (2000).

$$W_t(j) = \left(\pi_{t-1}^{\iota_w} \pi^{1-\iota_w} \right) W_{t-1}(j) \tag{II.2.5}$$

For households who are able to adjust $W_t(j)$, they face the following optimization problem:

$$\max_{W_t^*(j)} \quad E_t \sum_{s=0}^{\infty} (\xi_w \beta)^s \left[-\frac{b_{t+s} L_{t+s}(j)^{1+\nu_L}}{1+\nu_L} + \Lambda_{t+s} W_t(j) L_{t+s}(j) \right] \tag{II.2.6}$$

$s.t$ equation II.2.4 and

$$W_{t+s}(j) = \prod_{k=1}^{s} \left(\pi_{t+k-1}^{\iota_w} \pi^{1-\iota_w} \right) W_t(j) \tag{II.2.7}$$

Households are maximizing the expected discounted utility from consuming future wage income minus the expected discounted disutility of all future labor while factoring in their labor demand rule and wage indexation rule. (Λ_t is the Lagrange multiplier associated with the households' budget constraint.)

Final Good Producers

Final good producers operate in a perfectly competitive market. They buy intermediate goods $Y_t(i)$, package them into final output Y_t and resell it to consumers. The final good of the economy is a CES production function of a continuum of intermediate goods.

$$Y_t = \left(\int_0^1 Y_t(i)^{\frac{1}{1+\lambda_{f,t}}} \, dj \right)^{1+\lambda_{f,t}} \tag{II.2.8}$$

The parameter $\lambda_{f,t}$ is a stochastic process centered around λ_f that gauges the monopoly power an intermediate firm has in selling its specific good i. The first order condition of the final good producers profit maximization equation (A.9) leads to the following demand for good $Y_t(i)$:

$$Y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} Y_t \tag{II.2.9}$$

Intermediate Good Producers

Intermediate good producers are the first stage of production. Intermediate firms use utilized capital and labor packaged by the employment agencies to produce differentiated intermediate goods that they sell to the final goods producers. A continuum of these firms indexed by i exist and use the following production process:

$$Y_t(i) = \varepsilon_t^a K_t(i)^{\alpha} L_t(i)^{1-\alpha} - f \tag{II.2.10}$$

where f is a fixed cost of the production process, K_t is utilized capital and ε_t^a is a stationary stochastic productivity shock that alters the production process. Firms hire labor and rent capital in perfectly competitive markets and pay identical wages and rental rates. The intermediate firms' profit is given by:

$$P_t(i)\left(\varepsilon_t^a K_t(i)^\alpha L_t(i)^{1-\alpha} - f\right) - W_t L_t(i) - R_t^k K_t(i) \tag{II.2.11}$$

Intermediate firms choose the optimal price to sell their intermediate good i subject to good's demand function. However, in every time period a probability exists ξ_p that a firm can not freely optimize their price (Calvo, 1983). If a firm can not readjust their price it is indexed to a weighted average of steady state inflation and last period's inflation. For firms that are able to choose the optimal price, $P_t^*(i)$, solve the following maximization problem:

$$\max_{P_t^*(i)} \quad E_t \sum_{s=1}^{\infty} (\xi_p \beta)^s \Lambda_{t+s}[(P_{t+s}(i) - MC_{t+s})Y_{t+s}(i)] + \Lambda_t[(P_t(i) - MC_t)Y_t(i)] \tag{II.2.12}$$

$s.t$ equation II.2.9 and

$$P_{t+s}(i) = \prod_{k=1}^{s} \left(\pi_{t+k-1}^{\iota_p} \pi^{1-\iota_p}\right) P_t(i) \tag{II.2.13}$$

where MC_t is the firms' marginal cost and equation (II.2.13) is the price indexation rule. Since all firms have the identical maximization problem firm indexation may be dropped from this time forth.

Capital Producers

Capital goods are produced in a perfectly competitive sector of the economy by purchasing final good output and transforming it into new capital. In addition to producing new capital, capital producers also buy and sell capital from entrepreneurs at price Q_t. At the end of time t capital producers purchase non-depreciated $t-1$ physical capital from entrepreneurs and investment goods from the final good producers and convert them to the time t capital stock. The time t physical capital stock is then purchased by entrepreneurs and used in time $t+1$ production. The physical capital stock evolves according to:

$$\bar{K}_t = (1-\tau)\bar{K}_{t-1} + \mu_t \left(1 - S\left(\frac{I_t}{I_{t-1}}\right)\right) I_t \tag{II.2.14}$$

where τ is the depreciation rate and I_t is the investment good purchased.

Capital producers face a stochastic exogenous process μ_t that alters the ability of producers to turn investment purchases into physical capital. In addition, capital producers face investment adjustment costs represented by the function S. Where $S(1) = S'(1) = 0$, $S'() > 0$ and $S''() > 0$. The capital producers profit maximization problem and first order condition are located in Appendix A.

Entrepreneurs and Banks

There exists a continuum of finite lived entrepreneurs indexed by e who are able to borrow from the perfectly competitive banking sector who obtain deposits from the households. At the end of period $t-1$, entrepreneurs buy physical capital $Q_{t-1}\bar{K}_{t-1}$ using their own nominal net worth N_{t-1} and a loan from the banking sector B^b_{t-1}.

$$Q_{t-1}\bar{K}_{t-1}(e) = B^b_{t-1}(e) + N_{t-1}(e) \tag{II.2.15}$$

In period t the entrepreneur is then subject to a stochastic 'productivity' shock $w_t(e)$ that increases or decreases the entrepreneur's physical capital stock. The productivity shock is drawn from the lognormal cumulative distribution $F(w)$ with mean $m_{w,t-1}$ and variance $\sigma^2_{w,t-1}$. The distribution is assumed to be known at $t-1$ and $m_{w,t-1}$ is such that $E[w_t(e)] = 1$. The standard deviation σ_w will follow an exogenous process and be considered as a financing shock as it will either increase or decrease the riskiness of loans. Entrepreneurs then choose the optimal utilization rate u_t that maximizes their time t profit.

$$\max_{u_t(e)} \quad \left[R^k_t u_t(e) - P_t a(u_t(e))\right] w_t(e)\bar{K}_{t-1}(e) \tag{II.2.16}$$

where R^k_t is the rental rate of utilized capital paid by the intermediate firms and $a()$ is the cost of capital utilization payed in final good output, with $a(u) = 0$, $a'() > 0$ and $a''() > 0$.

Entrepreneurs at the end of period t sell the non-depreciated physical capital to the capital producers resulting in the following period t revenue for entrepreneur e:

$$w_t(e)\tilde{R}_t^k(e)Q_{t-1}\bar{K}_{t-1}(e) \tag{II.2.17}$$

where

$$\tilde{R}_t^k(e) = \frac{R_t^k u_t(e) + (1-\tau)Q_t - P_t a(u_t(e))}{Q_{t-1}} \tag{II.2.18}$$

Entrepreneurs and banks agree upon a loan contract that consists of the size of the loan B_t^b, the interest rate of the loan R_t^c and the default threshold of the loan $\bar{w}_t$ below which entrepreneurs cannot pay back the loan and are obligated to turn over their time t revenues to the bank. However, banks are only able to recover a $(1-\mu)$ fraction of the defaulted revenue do to unmodeled bankruptcy costs.

$$\bar{w}_t(e)\tilde{R}_t^k Q_{t-1}\bar{K}_{t-1}(e) = R_t^c(e)B_{t-1}^b(e) \tag{II.2.19}$$

Banks abide by a zero profit condition since they operate in a perfectly competitive environment given by:

$$\begin{aligned}[1 - F_{t-1}(\bar{w}_t(e))]R_t^c(e)B_{t-1}^b(e) + (1-\mu)\int_0^{\bar{w}_t(e)} wdF_{t-1}(w)\tilde{R}_t^k Q_{t-1}\bar{K}_{t-1}(e) \\ = R_{t-1}^d B_{t-1}^b(e)\end{aligned} \tag{II.2.20}$$

where the first term on the left equals the expected revenue payed back to the banks, the second term equals the expected revenue a bank receives when a entrepreneur defaults and the term right of the equality is the amount paid by the bank to depositors held by the households. The optimal contract maximizes expected entrepreneur profits subject to the banks' zero profit condition and is laid out in more detail in Appendix A.

The aggregate equity, V_t, of entrepreneurs operating in the economy evolves according to

$$V_t = \tilde{R}_t^k Q_{t-1}\bar{K}_{t-1} - \left(R_{t-1} + \mu G_{t-1}(\bar{w}_t)\tilde{R}_t^k \tfrac{Q_{t-1}\bar{K}_{t-1}}{Q_{t-1}\bar{K}_{t-1} - N_{t-1}}\right)(Q_{t-1}\bar{K}_{t-1} - N_{t-1}) \tag{II.2.21}$$

where the first term on the right is the time t revenue of entrepreneurs minus the interest and principle payments entrepreneurs borrowed from the banking sector. Notice that the agreed upon contract interest rate of the loan will be higher than the risk less rate, R_{t-1}. This external finance premium will be a function of bankruptcy costs and exogenous entrepreneur risk. At the end of each period a fraction $1-\gamma$ of entrepreneurs exit the economy and are replaced by new entrepreneurs. Exiting entrepreneurs transfer some fraction of their net worth to households and the remaining net worth is transferred to newly born entrepreneurs symbolized as W_t^e. Therefore aggregate net worth, N_t, evolves as:

$$N_t = \gamma V_t + W_t^e \tag{II.2.22}$$

Government Agencies

The *monetary authority* follows a generalized Taylor rule to set the nominal interest rate that adjusts due to deviations of inflation and output from their steady state levels.[1]

$$\left(\frac{R_t}{R}\right) = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi}\right)^{R_{\pi_1}} \left(\frac{Y_t}{Y}\right)^{R_{y_1}} \left(\frac{\pi_{t-1}}{\pi}\right)^{R_{\pi_2}} \left(\frac{Y_{t-1}}{Y}\right)^{R_{y_2}}\right]^{1-\rho_R} e^{\varepsilon_t^R} \tag{II.2.23}$$

where R is the steady state nominal interest rate and ρ_R resembles the degree of interest rate smoothing set by the monetary institution. ε_t^R is a stochastic monetary policy shock that affects the nominal interest rate. The central bank supplies the corresponding money supply demanded by the household to achieve the targeted nominal interest rate R_t.

The *fiscal authority* has the following government budget constraint and where government purchases G_t is determined by the stochastic process $G\epsilon_t^G$ formally given by:

$$P_t G_t + R_{t-1} B_{t-1} + M_{t-1} = T_t + M_t + B_t \tag{II.2.24}$$

II.2.2 Log Linear Equations

The model is 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 Section II.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 model is reduced to 12 equations and eight exogenous shocks all of which are outlined in Appendix A and listed in this subsection.

[1]The Taylor rule used is different than the Taylor rule used by Smets and Wouters who had the monetary authority react to deviations in output and inflation from their completely flexible price equilibrium

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

$$\hat{\bar{K}}_t = (1-\tau)\hat{\bar{K}}_{t-1} + \tau\hat{I}_t + \tau(1+\beta)S''\hat{\varepsilon}_t^I \tag{II.2.25}$$

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

$$\hat{L}_t = -\hat{w}_t + (1+\tfrac{1}{\psi})\hat{r}_t^k + \hat{\bar{K}}_{t-1} \tag{II.2.26}$$

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:

$$\hat{Y}_t = C_y\hat{C}_t + I_y\hat{I}_t + \frac{r^k\bar{k}_y}{\psi}\hat{r}_t^k + \mathcal{M}_t + \hat{\varepsilon}_t^G \tag{II.2.27}$$

$$\hat{Y}_t = \phi\hat{\varepsilon}_t^a + \phi\alpha\hat{\bar{K}}_{t-1} + \frac{\phi\alpha}{\psi}\hat{r}_t^k + \phi(1-\alpha)\hat{L}_t \tag{II.2.28}$$

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

$$\hat{R}_t = \rho\hat{R}_{t-1} + (1-\rho)\left[r_{\pi_1}\hat{\pi}_t + r_{y_1}\hat{Y}_t + r_{\pi_2}\hat{\pi}_{t-1} + r_{y_2}\hat{Y}_{t-1}\right] + \hat{\varepsilon}_t^r \tag{II.2.29}$$

The consumption and investment transition equations are

$$\hat{C}_t = \frac{h}{1+h}\hat{C}_{t-1} + \frac{1}{1+h}E_t[\hat{C}_{t+1}] - \frac{1-h}{(1+h)\sigma_c}\left(\hat{R}_t - E_t[\hat{\pi}_{t+1}]\right) + \hat{\varepsilon}_t^b \tag{II.2.30}$$

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{I}_{t+1}] + \frac{1}{(1+\beta)S''}\hat{q}_t + \hat{\varepsilon}_t^I \tag{II.2.31}$$

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

$$\hat{\tilde{R}}_t^k - \hat{\pi}_t = \frac{1-\tau}{1-\tau+r^k}\hat{q}_t + \frac{r^k}{1-\tau+r^k}\hat{r}_t^k - \hat{q}_{t-1} \tag{II.2.32}$$

The model yields a phillips curve equal to:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\iota_p}E_t[\hat{\pi}_{t+1}] + \frac{\iota_p}{1+\beta\iota_p}\hat{\pi}_{t-1} + \frac{(1-\beta\xi_p)(1-\xi_p)}{(1+\beta\iota_p)\xi_p}\left(\alpha\hat{r}_t^k + (1-\alpha)\hat{w}_t - \hat{\varepsilon}_t^a\right) + \hat{\varepsilon}_t^p \tag{II.2.33}$$

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:

$$\begin{aligned}\hat{w}_t = &\frac{\beta}{1+\beta}E_t[\hat{w}_{t+1}] + \frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{\pi}_{t+1}] - \frac{1+\beta\iota_w}{1+\beta}\hat{\pi}_t + \frac{\iota_w}{1+\beta}\hat{\pi}_{t-1}\\ &- \frac{(1-\beta\xi_w)(1-\xi_w)}{(1+\beta)\left(1+\nu_l\frac{1+\lambda_w}{\lambda_w}\right)\xi_w}\left(\hat{w}_t - \nu_l\hat{L}_t - \frac{\sigma_c}{1-h}(\hat{C}_t - h\hat{C}_{t-1})\right) + \hat{\varepsilon}_t^w\end{aligned} \tag{II.2.34}$$

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:

$$\hat{S}_t \equiv E_t\left[\hat{\tilde{R}}_{t+1}^k - \hat{R}_t\right] = \chi\left(\hat{q}_t + \hat{\bar{K}}_t - \hat{n}_t\right) + \hat{\varepsilon}_t^F \tag{II.2.35}$$

where χ is the elasticity of the spread with respect to the capital to net worth ratio and $\hat{\varepsilon}_t^F$ 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:

$$\hat{n}_t = \delta_{\tilde{R}^k}(\hat{\tilde{R}}_t^k - \hat{\pi}_t) - \delta_R(\hat{R}_{t-1} - \hat{\pi}_t) + \delta_{qK}(\hat{q}_{t-1} + \hat{\bar{K}}_{t-1}) + \delta_n\hat{n}_{t-1} - \delta_\sigma\hat{\varepsilon}_{t-1}^F \tag{II.2.36}$$

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, 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, the value of χ will determine the values of the δ coefficients.[2] In all, 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 $i = \{a, b, G, r, I, F, p, w\}$

II.2.3 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 making their complete decision set equal to $\{C_t(j), L_t(j), M_t(j), B_t(j), \bar{K}_t(j)\}_{t=0}^{\infty}$. The new household budget constraint is now

$$\begin{aligned} P_{t+s}C_{t+s}(j) + B_{t+s}(j) + M_{t+s}(j) \leq R_{t+s-1}B_{t+s-1}(j) + M_{t+s-1}(j) + W_{t+s}(j)L_{t+s}(j) \\ +\Pi_{t+s}(j) - T_{t+s} + \bar{K}_{t+s}(j)\left(R^k_{t+s}u_{t+s}(j) - P_{t+s}a(u_{t+s}(j))\right) \\ +P_{t+s}q_{t+s}\left((1-\tau)\bar{K}_{t+s-1}(j) - \bar{K}_{t+s}(j)\right) \end{aligned} \tag{II.2.37}$$

The linearized first order condition of capital is given by

$$\hat{q}_t = -(\hat{R}_t - E_t[\hat{\pi}_{t+1}]) + \frac{1-\tau}{1-\tau+r^k}E_t[\hat{q}_{t+1}] + \frac{r^k}{1-\tau+r^k}E_t[\hat{r}^k_{t+1}] + \hat{\varepsilon}^Q_t \tag{II.2.38}$$

This equation will replace the linearized equation (II.2.32). Since the equations (II.2.35) and (II.2.36) 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

[2] 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.

by adding a idiosyncratic equity premium price shock represented by $\hat{\varepsilon}_t^Q$ to replace the finance shock $\hat{\varepsilon}_t^F$ of the SWFF Model. Equation (II.2.38) is nested in the SWFF model if there exists no finance spread (i.e $\hat{\tilde{R}}_{t+1}^k = R_t$). This implies (II.2.32) forwarded ahead one period is identical to (II.2.38).

II.3 Estimation Technique

This section presents the steps needed to generate Bayesian estimates of the parameters of the linearized models of the previous section. 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. The Kalman filter is used to construct the likelihood of the models in both estimation techniques. Following Boivin and Giannoni (2006) and Kryshko (2011), I outline the steps of the Adaptive Metropolis-within-Gibbs algorithm used to estimate the SW-DFM and SWFF-DFM models. Next the priors for the models' parameters are shown and lastly, the data-set and its transformations are outlined in the final subsection.

II.3.1 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):

$$S_t = G(\theta)S_{t-1} + H(\theta)v_t \quad \text{where } v_t \sim NID(0, I) \tag{II.3.1}$$

and the measurement equation:

$$X_t^{reg} = \Lambda S_t \tag{II.3.2}$$

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 matrices $G(\theta)$ and $H(\theta)$ are functions of the model's structural parameters and v_t is a vector of the i.i.d. components of the model's exogenous processes $\hat{\varepsilon}_t$.

The description of the data sets and individual elements of Λ for the regular estimation technique can be found in Appendix B. With the model set up in state-space form and all stochastic processes being distributed normally and independently the Kalman Filter is used to calculate the likelihood function. Using the given priors found in Section II.3.3, a Random-Walk Metropolis-Hastings[3] algorithm is then used to obtain the posterior distribution of the model's parameters $P(\theta|X^{reg})$.

II.3.2 DSGE-DFM Estimation

Bayesian estimation of a DSGE model in a data rich environment incorporates the state space model discussed earlier 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 II.3.1. However, the development of Dynamic Factor Models proposed by Sargent and Sims (1977) and further advanced by the works of Stock and Watson (1989, 2003, 2005, 2009) 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). It is for these reasons that DSGE-DFM estimation was introduced by Boivin and Giannoni (2006).

The state space set up for DSGE-DFM estimation is characterized by equations (II.3.3)-(II.3.5)

$$S_t = G(\theta)S_{t-1} + H(\theta)v_t \text{ where } v_t \sim NID(0, I_m) \tag{II.3.3}$$

$$X_t = \Lambda S_t + e_t \tag{II.3.4}$$

$$e_t = \Psi e_{t-1} + \epsilon_t \text{ where } \epsilon_t \sim NID(0, R) \tag{II.3.5}$$

where e_t follows an AR(1) process and is often referred to as measurement error. The matrix X is J x 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.

[3]For more detail on this and other Bayesian DSGE estimation techniques please see An and Schorfheide (2007)

The measurement equation (II.3.4) has the following structure:

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

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.

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. To help with convergence, 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-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.[4] Once the estimated

[4] 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 outlined by Rebonato (1999)

states have been generated S in equation (II.3.4) has been obtained. 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 II.3.1. 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.[5]

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[6] 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.

II.3.3 Data and Parameter Priors

To estimate both the SW and SWFF models in a data-rich environment a total of 97 quarterly[7] data series are used. These series cover the time period of 1984Q2 to 2008Q3. The complete set of series encompasses many of the economic and financial series used by Stock and Watson (2009) 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. Clarida et al. (2000) have shown that the stability of monetary policy of the form of equation (II.2.29) did not occur until the early 1980's. Further, Lubik and Schorfheide (2004) assert that it was not until the early 1980's that monetary policy of this form was consistent with a determinate equilibrium. Finally, 2008Q3 was the last quarter before nominal interest rates hit the zero lower bound.

The SWFF-DFM (SW-DFM) estimation consist of 17 (15) core series and 80 (82) non-core series. The core series for both models include three measures each of GDP,

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[5]The optimizer used is csminwel, initiated at the parameter prior means and available at http://sims.princeton.edu/yftp/optimize/

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

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

inflation, hours worked 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 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 bill 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[8]. A complete list and transformation rubric of each core series along with their corresponding Fred-II database code is found in Appendix B.

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 indicies, wage indicies 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, as were the core series, these series are either demeaned, linearly detrended log level or log first differenced and demeaned. A complete list and transformation rubric of each non-core series along with their corresponding Fred-II database code is found in Appendix B.

The structural parameter marginal priors are in accordance to the Smets and Wouters (2003, 2007) priors. The distribution of the prior along with its mean, standard deviation and description of the parameter are laid out in Table 2. The parameter priors include normal, beta, gamma, and inverse gamma distributions. All coefficients whose values lie within the unit interval are drawn from beta distributions, while all stan-

[8]This is to account for no intercept vector in the measurement equation

dard deviations of the structural shocks are drawn from inverse gamma distributions. The priors on the autocorrelation coefficients of the structural shock ensure that shocks will be persistent in the model economy. The joint prior is given by the products of the marginals and is truncated to parameter values that guarantee a determinate and unique model equilibrium.

In addition, 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, Gertler, Gilchrist (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 Tbill 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 can be found in Table 1.

The priors for the state space parameters include the elements of Λ and the diagonal elements of Ψ and R. First, 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[9]. Each non-core series corresponding row elements[10] 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-Invers-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 process are stationary.

Priors regarding the core series is still Normal-Inverse-Gamma but instead the mean of the factor loadings of the ith row Λ_i is centered at the DSGE models implied theoretical loading. As discussed earlier the first data set of each core series category has

[9]The core interest rate series priors are centered around 4 since the interest rates are in annualized percentage

[10]The elements of Λ that correspond to $t-1$ states of the S_t vector are assumed to be zero

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 and Kryshko (2011) who fixes all Taylor Rule policy parameters to be equal to the means of the posterior distributions estimated in the regular environment, 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 nominal interest rates observed in the economy.

II.4 Properties of the Estimated Models

This section is divided between estimation results and the economic inferences that DSGE-DFM estimation can tell us about financial recessions and their subsequent recoveries. Posterior estimates of the structural parameter and estimated states of the models are discussed first. Second, impulse response functions (IRF's) are presented and discussed along with the diagnostic inferences they bring when comparing economic downturns that are driven by different types of structural shocks.

II.4.1 Structural Parameters and Estimated State Variables

The posterior estimates for the structural parameters for both models and both estimation techniques are tabulated in Tables 4 and 5. We can examine some characteristics and trends across the estimation techniques by examining Figure 3. This figure plots the posterior distributions when fitted to a normal distribution for a select number of structural parameters for the SWFF model. A few observations emerge. 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 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.

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. However, 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 remain similar across the estimation techniques of the SWFF model. However, price and wage mark-up shocks are estimated to be much more persistent in the DSGE-DFM estimation technique. The presence of many other price and wage indexes, including oil prices, drive this result as different inflation dynamics are needed to describe them. The parameters that preside over the financial accelerator do 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 more persistence.

Using the Carter-Kohn algorithm which is applied in the DSGE-DFM estimation algorithm it is straightforward to calculate the estimates of the endogenous and exogenous variables of the model over the sample time period. These are plotted for the SWFF model in Figures 4 and 5. The blue line and shaded area represent the posterior mean & 90% density interval of the variable under SWFF-DFM estimation and the red line and shaded area represent the posterior mean & 90% density interval of the variable under SWFF-Reg estimation. The first eight plots of Figure 4 represent endogenous variables that are directly related to a data series in the core.[11] Recall, one of the series has a perfectly tight loading prior to ensure that the variable is "anchored" to its economic definition. As the plots show this is indeed the case, with the first eight endogenous variables within the same neighborhood of the SWFF-Reg endogenous variable estimations with the lone exception being wage growth.

The remaining five plots of Figure 4 and the eight plots of Figure 5 correspond to variables not directly linked to a particular class of economic variable. As a result, the percent deviations from steady state of the time plots of these variables exhibit noteworthy differences between the estimation techniques. These variables are where the large data set can most easily load and generate dynamic state factors to help explain the large set of data while still possessing the theoretical structure inside the DSGE model. Also of note is that these variables exhibit smoother and smaller posterior density intervals when estimated in the data-rich environment.

II.4.2 Impulse Response Functions

DSGE-DFM estimation allows for economic series not directly corresponding to any endogenous variables in the DSGE model to be related to the model's exogenous shocks.

[11]Since, there is assumed to be no measurement/misspecification error in the SWFF-Reg estimation there is no poster density interval around the first eight endogenous variables as they are assumed to be measured without error.

This allows IRF's to be generated for many economic series whose IRF's do not exist outside of structural VAR estimation. This can also act as a rudimentary diagnostic tool of how well the DSGE model is identified and specified. For example, if it is found that many of the price indexes included in the data set fall when there is a positive price shock it would tend to suggest an identification problem. Figures 6-9 represent such IRF's for the SWFF model and are discussed in this subsection.

Figure 6 gives the IRF's and 80% posterior density band of a one unit negative finance shock (positive spread shock). The red IRF's correspond to the same one unit finance shock but are only available for series used in DSGE-Reg estimation. Although all shocks are unitary the estimated standard deviation for the shock can differ. We see that the finance shock lowers Real GDP and increases the spread as the finance accelerator would predict. In addition, the unemployment rate increases and peaks about 7 quarters after the shock and results in a longer average unemployment duration in the future. The adverse finance shock results in the decrease of manufacturing employees captured by the 5th plot of the diagram and commercial loans begin to fall a few quarters after the finance shock. As the SWFF model theoretically predicts, a finance shock increases entrepreneurial risk and we will see investment loan quantities decrease inside the SWFF model.

Figure 7 gives the IRF's of a negative productivity shock in the economy. We see that Real GDP and Industrial Production Indexes all fall and are hump shaped with a trough around 6-8 quarters. Capacity Utilization in the manufacturing sector falls and output per hour of all persons falls as well. This is of particular note as it is the closest data series we have that could be thought of as a measurable for labor productivity.

The next set of IRF's plot a negative investment shock in Figure 8. As expected real investment falls in both the SWFF-Reg model and SWFF-DFM model. 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 shock in the SWFF-DFM model discussed earlier. We also see a decrease in non-residential investment, business inventories and new orders. The pro-cyclical relationship seen in the data between real wages and real GDP remains consistent inside the model. We also see that inventories initially decrease, but as the economy begins to recover, inventories begin to exceed their long-run averages about 8-12 quarters after the investment shock.

The final set of IRF's are plotted in Figure 9 and are associated with a negative preference shock (negative consumption shock). The IRF's show a downturn in real GDP, real personal consumption and consumption expenditures on non-durables. We see that it corresponds to a decrease in employees in the retail sector and a decrease in outstanding consumer credit. Interestingly, the negative preference shock also corresponds to a decrease in the University of Michigan's Consumer Expectations Survey.

In summary, all these negative structural shocks decrease output. A closer examination of related macroeconomic series show that these structural shocks are theory-consistent with series directly linked inside the model and series indirectly linked to the model. Supply shocks have a greater effect on firm level series at first while demand shocks tend to effect aggregate expenditures first. We see that the greatest and most persistent decreases in output are associated with negative financial and productivity shocks. Yet, these shocks and their resulting dynamics do not account for different magnitudes of decrease in output between the different shocks. In order to trace the dynamic effects of the structural shocks to additional data indicators we must normalize the structural shocks to assure that output falls by a similar magnitude across the menu of structural shocks. I conduct such an application in the proceeding subsection.

II.4.3 Comparing the Economic Effects of Normalized Structural Shocks

A major advantage to the DSGE-DFM estimation technique is that it permits us to consider the economic effects of structural shocks outside the scope of the standard variables of GDP, prices, and short-term interest rates. This can help in answering questions like: what makes financial recessions and subsequent recoveries so much different than other recessions and recoveries? I attempt to evaluate such a question by comparing the IRF's of different normalized structural shocks.

The SWFF model estimated in a data-rich environment creates an excellent framework to see if the results of Boeri et al. (2012) and Clavo et al. (2012) discussed earlier are also found in the SWFF model and if so what may be the driving forces behind them. In this application, I calibrate all parameters including the loading coefficients of the SWFF-DFM model to their estimated posterior median and normalize the size of the eight structural shocks to assure that the maximum decrease of real output is equal across the different shocks.[12] This assures any differences in the fluctuations of other variables or series are not due to an output level effect. Figure 10 examines the IRF's of each structural shock for nine different economic series. Since we are mainly focused on financially driven recessions, we highlight the IRF's equated to the financial shock

[12] The decrease of real output is normalized around the decrease associated with a two standard deviation financial spread shock.

by the thick green line in Figure 10. Further, unlike the financial shocks seen in 2008, none of these negative shocks create a deep enough recession to force the model below the zero lower bound.

The top panel of Figure 10 plots the IRF's of real GDP, Investment and Exports. We can see that by design real GDP decreases by the same amount for each of the structural shocks. However, we see that this decrease in GDP is quickest for monetary and consumer driven recessions, as recovery starts 4-5 quarters after the shock. Investment and financial driven recession recoveries start 5-6 quarters after the shock, while supply shock driven recessions (productivity and wage shocks) have more persistence, as recoveries do not begin until 7 or 8 quarters after the initial shock. We can also see that particular components of GDP react much differently to what has caused the recession. Real Investment and real Exports decrease by a much larger amount and are slower to recover to their steady state value in a financial recession. The decreases in both is similar to that of an investment productivity driven recession but recover at a much slower pace.

When we study the IRF's for different labor market measures, including the unemployment rate and average unemployment duration time, we see that the effect on both differ depending on what mechanism is behind the recession. Since the decrease in real GDP is identical, the different unemployment rate dynamics would suggest that the coefficient on Okun's Law is different depending on what the driving force behind the decrease in output is. The unemployment rate level is largest for investment and financial recessions, but the inertia rate associated with financial recessions is much greater, as the unemployment rate and the average duration of unemployment remains high for much longer when compared to any other type of recession.

If we examine the labor market in closer detail we can see why this phenomenon of a high and persistent unemployment rate may occur. We see that the decrease in inventories and real investment are largest and most persistence during a financial crisis. As a result the number of employees in manufacturing and construction decreases most significantly during financial recessions, while the decreases of service providing and retail trade jobs from a financial crisis are more consistent with those seen in monetary, consumption and investment driven recessions. This supports the findings of Boeri et al. (2012) as firms in the capital intensive manufacturing and construction sectors rely heaviest on financial markets to operate their businesses.

We see that financial recessions have the potential to create jobless recoveries and cause the unemployment rate and average duration of unemployment to remain high for a significant time period after the financial shock. A closer look at particular economic series suggests that sectors most likely associated with capital financing (manufacturing and construction) are the sectors that are slowest to recover and sectors less reliant on capital financing (retail trade and service providers) show little to no distinction between financial recessions and other demand and supply driven recessions.

II.5 Simulations and Forecasts

Del Negro and Schorfheide (2012) have found that the SWFF-Reg model significantly "outperformed" the SW-Reg model in regards of identifying and forecasting the output and inflation dynamics associated with the lead-up to the Great Recession and its recovery. In this section I perform a similar exercise of comparing the simulated and forecasting ability of the SW and SWFF models; but instead of just focusing on output and inflation, I pay particular attention to series related to the labor and finance markets. Of course these series can only be simulated using the SWFF-DFM and SW-DFM models that were estimated in a data-rich environment.

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 three different time periods, one at which all data related from 1984Q2 to 2008Q3 is available to the econometrician, one at which the econometrician can see quarterly data related to 2008Q4 and one in which they have 2009Q1 data values available to them. The models' posterior parameters are not re-estimated when the new data are revealed, instead the new values are inserted into the Kalman filter and are used as the new starting points for each of the simulations.

In total each forecast is generated by 50000 simulations, 500 draws from the posterior parameter distribution and each parameter draw is simulated using 100 draws of future structural shocks for 16 quarters. Figures 11-13 show the median forecast as well as the 68% forecast posterior density intervals for twelve different series at three different staring times. 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. In all simulations the zero lower bound is protected using shadow monetary policy shocks using an algorithm outlined by Holden and Paetz (2012).

Let's first look at the forecasted paths of some labor market metrics including the unemployment rate, average weekly hours and average real hourly wages. The forecasted paths of all of these series can be found in Figure 11. We see that the SWFF-DFM model 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 the 1st quarter of 2009. There is more forecast overlap between the models for average weekly hours and average hourly wages, yet the SWFF-DFM model is still better at picking up the initial decrease in weekly hours. The stagnation of real hourly wages over the last few years in not projected by either model, however, the SWFF-DFM model does predict a lower real wage when compared to the SW-DFM model.

When we examine the number of overall employees in the economy and the number of employees by sector in Figure 12 we find a similar story. The model with a modeled finance market (SWFF-DFM) significantly out forecasts the model without one (SW-DFM) 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 workforce demographic changes seen recently in the country. Under their current construction the models have no ability to see such a demographic change as they use the population of 16 years and older (not working age population) to transform variables in per capita terms.

Figure 13 shows the forecasted paths of housing starts, consumer credit outstanding and business loans. Again we 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 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 incorporate such an event.

In summary, the SWFF-DFM model is able to see the decrease in jobs and the increase in the unemployment rate quicker than the SW-DFM model. Additionally the SWFF-DFM model foresees the slower rate of overall jobs and jobs in particular sectors. We see that there is 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 we examine periods in which the financial spread was low and financial volatility was also low the forecasted paths between the models share a similar posterior density intervals. This would suggest that the SWFF model is better at identifying the dynamics of the labor and finance markets in times of high financial volatility.

II.6 Conclusion

In this chapter I follow the work of Boivin and Giannoni (2006) and Kryshko (2011) in order to estimate two popular Dynamic Stochastic General Equilibrium (DSGE) models in a data-rich environment. Using the data-rich estimation environment (DSGE-DFM) is appropriate here because it provides a framework where dynamic factor modeling can be introduced with latent factors that have the full theoretical structure of the DSGE model. This allows the structural shocks of the model to incorporate the dynamics of additional data series not modeled directly inside the DSGE model.

The Smets and Wouters (2003, 2007) New Keynesian model augmented with a financial accelerator (SWFF) is estimated using a large set of economic and financial series. To explore the economic and labor market effects of various exogenous shocks, I examine structural impulse response functions (IRF's) for series that are usually not obtainable inside DSGE models or only obtainable if embedded in a dynamic factor model with little or no theoretical interpretation of the original shock that they are generated by. However, the DSGE-DFM estimation technique creates a structural foundation of what type of initial shock has created the disturbance. An examination at calibrated IRF's suggests that financial crises have very different effects on the labor, finance and investment markets then do their structural counter-parts of monetary, consumer, government and supply shock driven recessions. Most notably, manufacturing and construction sectors are the very sectors that are slowest to recover from a financial shock. Further, the decreases in real investment, exports and new orders are larger and last longer during financial recessions.

I find that identical decreases of GDP generated by different structural shocks of the SWFF model creates different magnitudes in the change of the overall unemployment rate. These results suggest that the relationship between unemployment and GDP growth implied by Okun's Law may be state-dependent. Evidence of a state-dependent Okun's Law could have an impactful effect on past findings of many papers that use a constant coefficient in estimating Okun's Law when interchanging the output gap and the unemployment rate gap from its natural rate.

Comparing the original Smets and Wouters (2003, 2007) model (SW) and SWFF model, I find that the SWFF model is better in capturing the dynamics of many economic series including many labor market metrics around the time of the Great Recession and its subsequent recovery. This result suggests that a structural DSGE model embedded with a modeled financial market would have predicted the labor market severity of the Great recession and its aftermath. This finding is in concurrence with Del Negro and Schorfheide (2012) who have found a similar result in regards to the forecasts of output growth and inflation. Finally, I believe the continuing advancements in computational programming and the ever growing number of macroeconomic series available allows DSGE-DFM estimation to be a bountiful area of future research.

CHAPTER III

EVALUATING THE FORECASTING PERFORMANCE OF MODEL AVERAGING DSGE-DFM MODELS

III.1 Introduction

The advancement of computation in Bayesian estimation has resulted in a large pool of estimated models that policy makers can make inference from and forecasters can use in their prediction paths. The poor performance of many popular macroeconomic models around the financial crisis of 2008, has produced several papers evaluating the point and density forecasts generated by different macroeconomic models including those categorized as Dynamic Stochastic General Equilibrium (DSGE) Models. (Del Negro and Schorfheide, 2012; Stock and Watson, 2012; & Wolters, 2012)

Computational gains have led to additional estimation techniques to become possible for large scale models that were previously thought to be computationally burdensome. One example includes the estimation of DSGE models using a high dimensional data vector often referred to as Dynamic Factor Model DSGE estimation or DSGE-DFM estimation for short. Bekiros and Paccagnini (2014) have shown that DSGE-DFM model estimation of the SW model out-performs other estimated hybrid DSGE models and VAR models including Factor Augmented VAR specifications, when it comes to forecasting short-term GDP growth, inflation and short term interest rate paths from 1960 to 2010.

In the first part of this chapter, I conduct out-of-sample forecast covering the time periods of 1998Q1 to 2012Q1 for all four models in the previous chapter. These include the Smets & Wouters (2003, 2007) DSGE model referred to as SW-Reg and the Smets & Wouters model augmented with a financial accelerator (Del Negro et al., 2013) referred to as the SWFF-Reg model. The SW-DFM and SWFF-DFM models are also used which are the previously mentioned models estimated in a data-rich environment outlined in Chapter II.

The SW model with financial frictions (SWFF) introduces a Bernanke, Gertler and

Gilchrist (1999) financial accelerator mechanism and closely follows the entrepreneurial sector of the DSGE model of Christiano et al. (2010) and the FRBNY model outlined by Del Negro et al. (2013). Del Negro and Schorfheide (2012) compared the SW-Reg and SWFF-Reg models forecasting performance over the past two decades when the models were estimated under a standard set of seven or eight data series. They found that during the financial crisis, the SWFF model was better at forecasting output and inflation when compared to the original SW model. The SWFF was also able to identify a decline in output growth in the 2nd quarter of 2008, six months earlier when compared to the original SW model. However, they also found that this ranking is not stable over time, in fact over the past two decades, the model with financial frictions has only out-forecasted output and inflation on two occasions. These periods are centered around the financial crisis as well as the Dot-com bubble and early 2000's recession. These two events also coincide with the time periods that financial series were most volatile of the last two decades.

This chapter helps quantify and answer the question of why financial volatility coincides with the forecasting ranking of the SW and SWFF models found in Del Negro and Schorfheide (2012). This is done by comparing the two models in a data-rich environment and by utilizing misspecification error in DSGE-DFM estimation. The use of misspecification error allows me to incorporate an exogenous shock that can be thought of as the theoretical gap between what the DSGE model foresees for an economic variable and what the data series used to measure the economic series observes. The use of AR(1) persistence and independent misspecification error will allow inferences on which DSGE model better explains certain data series belonging to categorized economic series. If an economic series' dynamics are best explained by large independent misspecification error shocks, its dynamics are not incorporated inside the dynamics of the DSGE model. If however, a series' dynamics can be completely explained by a combination of the DSGE model's variables and structural shocks, then when the series becomes volatile, its dynamics can be integrated inside the DSGE model's transitional dynamics and structural parameters. Using the DSGE-DFM approach discussed in Chapter II, I will provide an historical overview of what sectors were well captured in each DSGE model.

I find empirical evidence that the share of variance decomposition attributed to exogenous misspecification error for financial and housing data series is higher, and in some cases significantly higher, in the SW model without financial frictions than in the model with financial frictions (SWFF). Further, historical decompositions show that the time periods that Del Negro and Schorfheide found that the financial frictions model outperformed the original SW model, corresponded to times when the misspecification error process for GDP is also largest in the SW model. Alternatively, historical decomposition of GDP for the SWFF model show that finance spread shocks (exclusive to the SWFF model) that contribute to fluctuations in GDP are largest around these same periods.

These results suggest that the SWFF model needs relatively smaller misspecification error shocks to explain many of the financial series than does the SW model. The existence of the financial accelerator and its corresponding financial spread shocks allows the SWFF model's endogenous variables and exogenous structural shocks to better explain many investment and financial series. However, if one compares the two models' variance decomposition share attributed to the misspecification error at capturing the dynamics of inflation and hours worked series, the SW model marginally outperforms the SWFF model. This suggests that the SW model does a relatively effective job of explaining output fluctuations as long as financial series are relatively less volatile.

In addition, many models have been altered or created to account for the short comings some of the original models faced in the presence and after-math of the financial crisis. Recent research has found that DSGE models that attempt to incorporate financial and/or housing markets inside the model can significantly out-forecast those that do not, since the beginning of the Great Recession. (Del Negro et al., 2014; Kolasa and Rubaszek, 2015) The development of additional models and estimation techniques has lent more credence to the idea of time-varying model averaging. Amisano and Geweke (2013) discuss how optimal weighting of a handful of model density forecasts can significantly increase the log predictive scores of density forecasts generated by just one model.

In the second part of this chapter, I examine the forecasting advantages DSGE-DFM estimation can bring and how the use of a high dimensional data vector in the estimation procedure of a DSGE model can mitigate some of the problems associated with DSGE model selection. I find that DSGE-DFM estimation significantly out performs DSGE-Reg estimation over the entire sample for all forecast horizons of GDP, investment and consumption growth. The use of the large data set makes the SWFF model's predictive performance more competitive when compared to the SW model over the first decade of the 21st century and especially in the 2008-2012 time period. I also find that DSGE-DFM estimation can mitigate some of the diffuse density forecasts that have been found when density forecasts of DSGE-Reg models have been evaluated.

Finally, I use the methodology laid out in Amisano and Geweke (2013) to construct optimized time-varying forecast weights for economic variables of interest using the two DSGE models estimated in a real-time data-rich environment (DSGE-DFM). The historical density forecasts for each forecasting model are used to construct the time-varying forecasting weights. I compare the individual DSGE-DFM models forecasting performance against each other as well as against non-DSGE model forecasts and forecasts that are generated by optimally assigning forecasting weights to a pool of forecasting models. I find that forecasts generated by real-time optimal pool (RTOP) model weighting out forecasts many models including vector autoregression models, a dynamic factor model and linearized DSGE models. Furthermore, RTOP model forecasting weighting tops the forecasting performance of equal weights in regard to predicting inflation and wage growth. This chapter hopes to link the DSGE model averaging literature (Wieand and Wolters, 2013) to the literature associated with the forecasting advantages of using high dimensional data vectors in one's forecasting model. (Stock and Watson, 2009, 2011)

The remaining structure of this chapter is as follows. Section III.2 discusses and examines the point forecasts of the four models of Chapter II that are generated by out-of-sample forecasting. Also included in this section are the unconditional variance decompositions of each financial data series and historical decompositions of GDP from both DSGE-DFM models. Section III.2.3 compares the macroeconomic forecasting performance of DSGE-DFM models to other reduced form macroeconomic forecasting models. Section III.3 lays out the RTOP weighting scheme and its point and density forecasting benefits. Lastly, Section III.4 summarizes the the results of this chapter and discusses potential extensions.

III.2 Evaluating Point Forecasts

In this section I compare and evaluate the out-of-sample point forecasts that are generated by the SW-Reg, SWFF-Reg, SW-DFM and SWFF-DFM models. In addition, I compare the point forecasts generated by DSGE-DFM estimation to other reduced form macroeconomic forecasting models. I examine the generated forecasts for quarter-to-quarter per capita GDP, investment, consumption and wage growth, as well as interest rates and inflation starting in 1998Q1 and ending in 2012Q1. Since the main objective of this chapter is to compare models and estimation techniques, all out-of-sample forecasting is generated by using final revised data sets. Since real time data are not used to calculate forecasts, predictive accuracy of the models cannot be compared to historical Greenbook or Blue Chip forecasts. Rolling Root Mean Square Errors (RMSEs) are compared across models and Diebold-Mariano (1995) tests are performed on the squared errors to determine if a model statistically out performs another in its forecasting performance.

III.2.1 Comparing the Point Forecasts of the Four DSGE Models

The first models I wish to discuss are the four DSGE models of Chapter II. Since the out-of-sample forecasting evaluation window includes time periods that the zero lower bound is in effect, I augment the SW-Reg and SWFF-Reg models starting in 2008Q4. Anticipated monetary policy shocks are introduced into both models identified by Federal Fund Rates market expectations, as measured by OIS rates, following the approach described in Section 3 of Del Negro et al. (2013). This augments both models exogenous structural shocks as well as their measurement equations. Throughout the rest of this chapter I will refer to these augmented models as the SW-ZLB-Reg and SWFF-ZLB-Reg models.[1]

The charts of Figure 14 show the rolling difference over time of the two models' RMSEs. Model comparisons for quarter-to-quarter output growth are located on the left while model differences for inflation are located on the right. Each point on the graph represents the rolling average of the previous eight quarters difference in RMSEs across models. For example, the top two charts illustrate the rolling difference between the RMSEs of SW-ZLB-Reg and the RMSEs of SWFF-ZLB-Reg for output growth and inflation.[2]

In evaluating the model forecasts, I find a similar result obtained by Del Negro and Schorfheide (2012), the SW-ZLB-Reg and the SWFF-ZLB-Reg models' forecast ranking for inflation and GDP growth are not stable over the past 15 years. Most notably, the SW-ZLB-Reg model has out forecasted the SWFF-ZLB-Reg model for the majority of the past 15 years with the two exceptions being the periods of 2000-2004 and 2008-2012. This can be observed by the first row of charts in Figure 14, both of which closely resemble the charts of Figure 14 in the Del Negro and Schorfheide (2012) paper. A few reasons why the charts are similar, but not identical, are likely due to a few differences. First, Del Negro and Schorfheide used unrevised data in their forecasting estimation.

[1] I, like Del Negro et al. (2013), assume a structural break in both models at 2008Q4, suggesting that the Fed begins to use forward guidance only after this date. This implies that the SW-Reg and SWFF-Reg models are identical to the SW-ZLB-Reg and SWFF-ZLB-Reg models until 2008Q4.

[2] $RMSE_t(M_i) = \frac{1}{8}\sum_{j=0}^{7}\sqrt{\left(y_{t-j} - \hat{y}_{t-j|t-j-h}\right)^2}$ where $\hat{y}_{t-j|t-j-h}$ is the h quarter ahead forecast of either output growth or inflation using model M_i, M_i ={SW-ZLB-Reg, SWFF-ZLB-Reg, SW-DFM, SWFF-DFM}. In Figure 14 $h = 2$ for growth forecasts and $h = 4$ for inflation forecasts.

Second, Del Negro and Schorfheide estimated the SWFF model with current information for the Federal Funds Rate and the Spread Rates. Third, Del Negro and Schorfheide used a linearly trending log productivity process in their models, where I use a stationary productivity process.

Conducting Diebold-Mariano tests on the squared forecast errors for various quarter ahead forecasts show that the SW-ZLB-Reg model statistically out forecasts the SWFF-ZLB-Reg model in its 2, 3 and 4 quarter ahead forecasts for the entire out-of-sample period for output growth. This outcome along with the previous discussed ranking observations is further evidence that SW-ZLB-Reg model out forecasts the SWFF-ZLB-Reg model in most periods except in times of financial volatility. The Diebold-Mariano tests reveal a similar story in regard to inflation forecasting, when the forecast errors of inflation are used. The SW-ZLB-Reg model significantly out-forecasts the SWFF-ZLB-Reg model for most forecast horizons of investment growth, inflation, wage growth and interest rates. All Diebold-Mariano test statistics are located in Table 6.

When I compare the SW-DFM and SWFF-DFM models 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 1998-2012 forecasting time frame. This is suggested by the second row of charts in Figure 14 and the Diebold-Mariano tests which are either inconclusive for most h period ahead forecasts, or in the cases of short-term output growth, and wage growth statistically significant in favor of the SWFF-DFM model.

The beneficial use of large data sets is best exemplified when the output growth forecasts for the SW-ZLB-Reg and SWFF-ZLB-Reg models are compared to the SW-DFM and SWFF-DFM forecasts. I see that the use of the extra data series substantially lowers the RMSEs for forecasting output growth as shown in the bottom left two charts of Figure 14. All Diebold-Mariano tests for 1, 2, 3 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.

In addition to the DSGE-DFM models outperforming the DSGE-Reg models throughout the forecast evaluation window (1998-2012), I also see that the "predictive performance enhancing" effects of large data sets used in DSGE-DFM estimation really start to amplify in the fourth quarter of 2007. Figure 15 shows the forecast of quarter to quarter GDP and consumption growth for all four previously mentioned models as well as a simple VAR(1) model. We can see that the DSGE-DFM estimation forecasts a more accurate growth path for output and consumption. Most notably the SWFF-DFM model and its 68% posterior forecast band actually foresees the depth of the negative output growth path on the eve of the financial crisis and splits the growth path of consumption as well.

However, when I examine the forecasts for inflation, I see that the regularly estimated models out predict the data-rich estimated models seen in both the bottom two charts on the right in Figure 14 and the significant Diebold-Mariano test statistics of Table 6. Recall that when the model is estimated in the data-rich environment, inflation is defined as a combination of the GDP Deflator, PCE and CPI indexes and when estimated in the regular environment inflation is observed using just the GDP Deflator. This along with the finding of a non-dominant forecasting model over time lends credence to the idea of real-time model averaging, a topic we will discuss in Section III.3

III.2.2 Comparing FEVD of the SW-DFM and SWFF-DFM Models

The set-up of the DSGE-DFM estimation allows me to calculate the unconditional forecast error variance decomposition (FEVD) share that is attributed to each of the eight structural shocks and the exogenous misspecification shock for the entire set of data series. This allows us to make some inferences of why the SW-ZLB-Reg model outperforms the SFFF-ZLB-Reg model, in most times, except those centered around time periods of high financial volatility. If a large portion of FEVD of a series or group of series is attributed to the misspecification shock, we can conclude that the series or group of series is not well incorporated inside the model. I find that some of the grouped series exhibit a smaller share of FEVD attributed to misspecification error in the SWFF-DFM model then in the SW-DFM model. These results are tabulated in Table 7. In particular, the finance and housing grouped series show a decline in the share of FEVD attributed to misspecification error between the two models.

Tables 8 and 9 look at the FEVD individual finance series for both models. The tables demonstrate that the FEVD share attributed to misspecification error is larger for stock price indexes, business loans and yield curve slopes in the SW-DFM model. The main driver of this result is the realization that FEVD attributed to the finance shock is much larger in the SWFF-DFM model compared to the FEVD contributed to the equity price shock of the SW-DFM model. This is because financial spread shocks still have a negative effect on the relative price of capital in the model, just as a negative equity price shock would have. However, financial spread shocks are more persistence since they have a negative effect on net worth which governs future interest rate spreads that will eventually affect real economic variables through the financial accelerator mechanism.

The above inferences are made only at the posterior means of the parameters. However, we can examine the confidence intervals of the FEVD share attributed to misspecification error by sampling parameter values from the posterior distributions. I find that for many of the core series the 90% confidence intervals of the share of FEVD attributed to misspecification error intersect each other across the two DSGE-DFM models. However, this is not the case if we look at the individual finance series, the intersection of the 90% confidence intervals for both models is empty for both the S&P 500 and Dow Industrial Average, as well as the spreads between the 1-year, and 6-month to 3-month T-bills. These confidence intervals for the core series and the finance series are graphically displayed in Figure 16.

Further, I find that historical decompositions show that the time periods[3] that Del Negro and Schorfheide (2012) found that the SWFF model out-forecasted the SW model correspond to times when the misspecification error process for GDP is largest in the SW-DFM model as illustrated in the bottom left graph of Figure 17. Alternatively, historical decomposition of GDP for the SWFF-DFM model shows that finance shocks that contribute to fluctuations in GDP are largest around these same periods as illustrated by the third plot on the left of Figure 18. Finally, if we examine the historical decomposition of the S&P 500 in the SW-DFM model plotted in Figure 19 we see that large shocks in the misspecification error process are needed to explain the declines in the index seen around 2002Q3, 2008Q1 and 2008Q3.

In summary, the SWFF-DFM uses less misspecification error to explain financial series then does the SW-DFM model. The presence of a financial sector built into the SWFF model allows its endogenous variables and exogenous structural shocks to better explain many economic and financial series. However, if one simply compares the series of inflation and output across both models, the SW-DFM model marginally explains the dynamics of these series with relatively less misspecification gap error than does the SWFF-DFM model. This suggests that the SW model does a relatively effective job of explaining output and inflation fluctuations as long as financial series are relatively less volatile. A finding I will utilize to our advantage when I introduce a weighting scheme that incorporates the sate of the financial markets in Section III.3.

[3] Recall, that Del Negro and Schorfheide find that these periods were 2000-2003 and 2008-2010

III.2.3 Evaluating DSGE-DFM Point Forecasts

The use of forward looking variables in the estimation process that DSGE-DFM estimation entails can give it an advantage in structural estimation when compared to models estimated with only a handful of data series. DSGE-DFM estimation provides a hybrid approach between reduced form and structural estimation. In the previous subsection, I performed Diebold-Mariano tests that compare the forecasting advantages of this approach compared to the standard estimation of other structural DSGE models. In this subsection, I compare the DSGE-DFM estimated models to reduced form forecasting models, including Vector Autoregression (VARs) of different lag lengths and dynamic factor models (DFM). The data sets used in estimating the parameters of the VAR are the same seven data series used to estimate the SW-Reg DSGE model; and the data series used in estimating the dynamic factor model is the same 97 series used in the estimating SW-DFM and SWFF-DFM models. This use of the same data sets allows us to compare these models on a level playing field.

Reduced Form Forecasting Models

Since Smets & Wouters influential 2003 paper the benchmark that all structural DSGE models are evaluated against is the vector autoregression. Del Negro and Schorfheide (2012) have found that forecasts generated by the SW-ZLB-Reg and SWFF-ZLB-Reg models hold their own when compared to forecasts generated by VARs and Bayesian VARs. During the great moderation, structural DSGE models were found to out-forecast Bayesian VARs in terms of short-term and medium term output, inflation and short term interest rates. (Edge and Gurkaynak, 2010) However, during the Great Recession this result seems to have only held for certain DSGE models, most notably the SWFF-ZLB-Reg model. (Del Negro et al. 2013)

Like the previous literature I choose to compare the two DSGE-DFM models to standard VARs of the form of III.2.1.

$$X_t^{VAR} = \sum_{i=1}^{n} \hat{\Lambda}_i X_{t-i}^{VAR} + \hat{e}_t \qquad \text{(III.2.1)}$$

where n is the number of lags and X_t^{VAR} encompasses the same seven data series used to estimate the SW-Reg model.

I also choose to add a DFM to the model evaluation pool because Stock and Watson (2012) have found that over the 3-6 month time horizon DFMs out perform many other simple and more complex forecasting models. The principle behind a DFM is that there exists a handful of latent factors f_t inside the economy that power the co-movements among macroeconomic variables. These latent factors are believed to be extractable using a large set of macroeconomic time series.

I use the DFM linear/Guassian state space set-up (III.2.2-III.2.3) outlined in Stock and Watson (2011) to estimate the parameters of the DFM model.

$$X_t^{DFM} = \hat{\lambda} f_t + \hat{e}_t \tag{III.2.2}$$

$$f_t = \Psi f_{t-1} + \omega_t \tag{III.2.3}$$

where N is the number of series used in estimation and q is the number of extracted latent factors and $\hat{\lambda}$ is a Nxq matrix of factor loadings. The qxq transition matrix, Ψ, oversees the VAR dynamics of the q latent factors.[4] There are two types of mean-zero idiosyncratic disturbances that govern the DFM model. There are the Nx1 vector of shocks ($\hat{e}_t$) which only affects the individual data series in X_t^{DFM} and there is the qxq vector of shocks (ω_t) which govern the dynamics of the latent factors. The i.i.d. shocks are distributed $N(0, R)$ and $N(0, Q)$ respectively.

The 97 series of X_t^{DFM} are identical to the series used in both the SW-DFM and SWFF-DFM models. As is common in the Dynamic Factor Model literature, all series sample standard deviations are normalized to 1. In addition, these series are either demeaned, linearly detrended log level or log first differenced and demeaned. The estimation window used for the DFM starts in 1984Q2. The number of factors, q, is selected using the criteria of Bai and Ng (2002, 2007) and that of Breitung and Pigorsch (BP) (2013) where the maximum number of factors is set to seven. The number of latent factors that the BP statistic calls for expands as the number t observations increase in the estimation sample.

Evaluating the Forecasts of all models

Diebold-Mariano tests are performed to compare the point forecasting performance of the SW-DFM and SWFF-DFM models compared to the VAR(1), VAR(2), and DFM reduced form models. We use the same forecast evaluation window of 1998-2012. The results of these tests are located in Table 10. A few patterns emerge, first, DSGE-DFM models hold their own in terms of short-term growth forecasting of output, consumption

[4] The estimated parameter values of Ψ are truncated to ensure that the eigenvalues of Ψ all lie inside the unit circle.

and investment. Although very few DM test statistics reject the null hypothesis of equal predictive accuracy at the 5% level, all test statistics are positive, implying that the DSGE-DFM models marginally out-forecast the VAR(1), VAR(2) and DFM models.

However, the same is not true when it comes to the point forecasting of inflation and wage growth. When we compared the DSGE-Reg models to the DSGE-DFM models recall that DSGE-Reg models held a slight advantage in terms of predictive accuracy of inflation and wage growth. When we compare the DSGE-DFM models in these two categories, the reduced form models significantly out-forecast them, as evidenced by the negative and large DM test statistics.

In summary, DSGE-DFM models that use large data sets have a better predictive performance when compared to their DSGE-Reg models for all growth forecasts. These DSGE-DFM models can hold their own against other reduced from macroeconomic forecasting models when it comes to predicting output, consumption and investment growth in the short-term. Further, the state of the world will affect which DSGE model forecasts better if estimated in the DSGE-Reg fashion. The use of additional data sets makes the state of the world less influential on predictive performance. I see that during times of high economic volatility, DSGE-DFM estimation may be even more beneficial, as exemplified by the predictive performance enhancement of using this method to forecast output, consumption, and investment growth begins to amplify during the start of the Great Recession. Yet, this is not the case if one is more interested in inflation or wage growth forecasting, as it appears that the DSGE-Reg, VAR and DFM models all outperform the DSGE-DFM models.

III.3 Model Pooling: Designs and Evaluation

This section discuses different weighting methodologies in order to evaluate the performance of macroeconomic models in prediction and to discuss the best weights an econometrician might select and weigh predictive distributions generated by a medium sized model pool. With the exception of one technique, all of these methods have previously been discussed in the forecasting literature.

III.3.1 Model Averaging Designs

In the previous section we compared the point forecasts generated by the seven different macroeconomic models. This section concentrates on examining the point and density forecasts when the econometrician weighs each one of the seven models included in the model pool. The benchmark model-weighting method is referred to as equal weights (EW), as it name suggests, the econometrician equally weighs the forecasts of all models in the model pool. Wolters (2012), has found that equally weighted forecasts of several standard DSGE-Reg models tend to be more accurate than forecasts generated by more sophisticated means or forecasts generated by just a single DSGE model.

The second weighting method I examine is referred to as real-time optimal pool (RTOP) model weighting. This method generates an optimal weights vector (w^*_{t-1}) that solves the following problem:

$$\underset{w_{t-1}}{\operatorname{argmax}} \sum_{s=2}^{t-1} log \left[\sum_{i=1}^{n} \omega_{t-1,i} P\left(y_s | y_{1:s-1}, M_i\right) \right] \tag{III.3.1}$$

where n is the number of models in the model pool and w_{t-1} is a weighting vector of positive elements (ω_i) that sum up to one. $P\left(y_s | y_{1:s-1}, M_i\right)$ is the scoring criterion of Model i calculated using the models' density forecasts. The optimal weights are then used to weigh each model in the pool to come up with aggregate forecasts of $y_{t+1:t+h}$.

The results of Section III.2.3 and Figure 20 suggest that the SWFF model is better at forecasting the path of output than is the SW model when the economy is in a volatile financial state. Coupling this with the results of Section III.2.2 that illustrated that the FEVD of financial series was better explained inside the SWFF-DFM model than inside the SW-DFM model, one might think that the FEVD of certain sectors can be a useful metric in model selection or model weighing. Previous research has used equal priors for all models in the prediction pool, but I introduce a hierarchical prior that accounts for financial volatility at the time. For example, one can amend equation III.3.1 by adding a model probability prior that is independent of the scoring criterion of Model i.

$$\underset{w_{t-1}}{\operatorname{argmax}} \sum_{s=2}^{t-1} log \left[\sum_{i=1}^{n} \omega_{t-1,i} P\left(y_s | y_{1:s-1}, M_i\right) \right] + log \left[\sum_{i=1}^{n} P(\omega_{t-1,i} | S_{j|s-1}) \right] \tag{III.3.2}$$

where $P(\omega_{t-1,i}|S_j)$ is the prior probability of the weight assigned to Model i conditional on the state of the world j in time $s-1$.

States of the world (SOW) are determined by what grouping of economic series in the data vector is relatively most volatile. For example, the DSGE-DFM model that internally best explains the financial data series (SWFF) is given a higher prescribed model prior in times of relative financial volatility. I utilize Figure 20, this figure plots the relative volatility of the financial markets compared to the expenditure markets to assign a current state of a world. For example, if the average normalized standard deviation of all output components is greater than the average normalized standard deviation of all financial series in time t a *Beta* prior with a mean of 0.14 and a standard deviation of 0.2 is put on each element of the ω_{t-1} vector. If however, the opposite is true and the average normalized standard deviation of all the financial series is relatively greater at time t a *Beta* prior with a mean of 0.7 and a standard deviation of 0.1 is put on the element of the ω_{t-1} vector that is associated with the SWFF-DFM model and a *Beta* prior with a mean of 0.05 and a standard deviation of 0.1 is put on all the other elements of the ω_{t-1}. This third weighting scheme and its use of a "state of the world hierarchical prior" is referred to as RTOP-SOW weighting and is the third weighting scheme I examine.

III.3.2 Evaluating the Point Forecasts of the Different Weighting Techniques

The forecasting performance of all three model weighting techniques outlined above are discussed here. First, the RTOP weighting technique significantly out-forecasts the equal weighting technique for inflation and wage growth. In regard to output, consumption, and investment growth the RTOP technique outperforms EW for many forecasting horizons, but only significantly on a few occasions as evident by the negative DM test statistics of Table 11. Compared to individual models, we see that the RTOP technique significantly out-forecasts both DSGE-Reg models in all categories except short-term interest rates. Further, the RTOP technique holds its own in forecasting all macroeconomic variables against the forecasting models of a VAR(1), VAR(2) and a DFM, as evidenced by the sparse amount of positive DM test statistics of Table 11 and the absence of any significantly positive DM test statistics.

RTOP weights are constructed for all periods as described in the previous subsection. These weights provide useful summaries of the interaction between models over particular time periods. Figure 21 plots the RTOP weights for all six variables of interest throughout the forecast evaluation window and Table 12 averages the RTOP weight assignment for the entire sample, pre 2008, and post 2008 for all six variables of interest. First, in terms of forecasting GDP, the weight assigned to the SWFF-DFM model begins to rise and the weight assigned to the VAR models begin to decline around the Great Recession. In terms of of consumption and investment growth the DSGE-DFM models' weight is also largest around the Great Recession. Consumption Growth and the Federal Funds Rate are the only two macroeconomic variables that the weight assigned to the DSGE-Reg models are significant before and after the Great Recession.

In particular the addition of the anticipated monetary shocks and the use of the OIS interest rates give a significant boost to the SW-ZLB-Reg model in comparison to the VAR and DSGE-DFM models after 2008.

The plotted RTOP weights of Figure 21 also demonstrate how relatively poor all the DSGE models do in forecasting inflation and wage growth. We see that throughout the forecast evaluation window the weights assigned to the VAR models and the DFM model are large and the weights assigned to the other four DSGE models are negligible. This Suggests that both the SW and SWFF models need improvement in the structural set-up of how prices and wages progress in the model.

In some cases the forecasting gains of the RTOP technique can be further improved upon by the RTOP-SOW weighting method. Recall, that this method put a prior on the assigned model weight depending on the relative volatility of financial markets. The forecasting gains of this method are greatest in terms of predicting output, consumption and investment growth. The SWFF models do the best job of predicting these variables in and around the Great Recession, thus the use of a model prior attached to relative financial volatility assures that they receive greater weight in this period. However, in terms of forecasting inflation and wage growth, the model prior actually causes the RTOP-SOW technique to perform worse than the standard RTOP technique. This is because the SWFF-DFM model does a relatively sub-par job in forecasting these two particular variables, thus the extra weight assigned to the SWFF-DFM model by the state of the world prior is counter productive. Table 13 reports all DM test statistics that compare the RTOP weighting technique to the RTOP-SOW weighting technique.

III.3.3 Density Forecast Examination

Thus far, I have only inspected point forecast, but I can also identify some patterns when I look at the density forecasts produced by all the models. In this subsection I construct and compare the density forecasts of all the DSGE models and the density forecasts created by the different weighting techniques by splitting them into probability bins comprising 20% of the probability mass and assigning the observed data realization into the corresponding probability bin. Previous work using probability integral transformations (PITs) by Gerard and Nimark (2008), Wolters (2012) and Herbst and Schorfheide (2012) has shown that DSGE models estimated using regular techniques tend to have diffuse forecast distributions for many variables; Implying that forecast uncertainty is overestimated by DSGE-Reg models. Figures 22-23 show the PITs created for each model when examining the density forecasts of output growth and inflation.

I see that the PIT distributions do not appear to be much different across estimation techniques. Many of these PIT histograms are also not centered around the middle forecast percentiles, as was found in previous literature. This is mainly due to the fact that the observed data for inflation and output growth have fallen into the tails of the forecast distribution with much more frequency over the past several years.

If I examine the Goodness-of-Fit χ^2 test statistics, which test the null hypothesis of a uniform PIT distribution, I observe that DSGE-Reg estimation does create significantly non-uniform PIT distributions for output growth and inflation at various quarter ahead forecasts as shown in the aforementioned literature. DSGE-DFM estimation create a mixed collection of PIT distributions that are both significantly different and indifferent from a uniform distribution. Most notably, the SW-DFM model creates PIT distributions for 1, 3 and 4 quarters ahead Inflation that are not significantly non-uniform. However, DSGE-DFM estimation is still plagued by the problem of generating non-uniform PITs. All χ^2 test statistics are presented in Table 14.

However, when we examine the PIT distribution of output growth and inflation for the density forecasts created by equal weighting all the models and RTOP weighting the different models, we see that these approaches create more uniform looking PIT distributions. These PIT histograms for inflation and output growth are plotted in Figure 24. In order to create a density forecast from any model weighting scheme, I calculate the weight vector first and then draw from the density forecasts created by each of the models. Each draw is then weighted appropriately and the aggregate point forecast is then placed into the weighting schemes forecast distribution.

The χ^2 test statistics in Table 14 also show that many of these PIT distributions created by weighing the different models' density forecasts do not reject the null of a uniform distribution at the 5% level. For the most part the χ^2 test statistics are all lower on the PIT distributions created by the different weighting schemes than the PIT distributions created solely using a DSGE-DFM or DSGE-Reg model for 2, 3 and 4 quarter ahead forecasts. It appears that that the use of different weighting schemes can mitigate some of the uncertainty associated when forecasting with DSGE-DFM and DSGE-Reg models.

III.4 Conclusion

The results of this chapter support the finding of Bekiros and Paccagnini (2014) for both the SW and SWFF models of the previous chapter. I find that forecasting performance of both DSGE-DFM models outperform the forecasting of DSGE-Reg estimated models as DSGE-DFM estimation incorporates the inclusion of many forward leading indicators. The forecasting advantage of DSGE-DFM estimation has most notably increased in the recent past. A comparison of the forecasting performance of the SWFF-DFM and SW-DFM models is also performed to see if the results of Del Negro and Schorfheide (2012) still exist when Bayesian estimation is performed in a data-rich environment. I find that the inclusion of the larger data vector does not indicate an intuitive forecasting advantage pattern between SW-DFM and SWFF-DFM models as is the case for the SW-ZLB-Reg and SWFF-ZLB-Reg models. The out-of-sample forecasting conducted in this chapter indicates that theoretical model selection in DSGE-Reg forecasting is likely determined by the state of the economy in the short-run, but the incorporation of higher dimensional data vectors can offset this effect, and will produce more accurate forecasts over the long-run.

Finally, the main conclusion of this chapter is that forecasts are best formed from weighting the density forecasts of several macroeconomic models from a model pool. The use of current information regarding the relative volatility of the financial markets in the model weighting process can further improve upon the forecasting performance generated by weighting models from a medium sized model pool. Furthermore, model weighting may diffuse the large forecast distributions and over uncertainty that is associated with DSGE estimation.

CHAPTER IV

EFFECTS OF PROFESSIONAL FORECAST DISSEMINATION ON MACROECONOMIC VOLATILITY

IV.1 Introduction

It has long been believed that beliefs about the future paths of economic variables play a critical role in explaining macroeconomic fluctuations. Expectation formation continues to be studied and modeled in macroeconomics under a broad range of different assumptions and specifications. Expectation formation has real consequences on the optimality of public policy decisions, economic growth and macroeconomic volatility. Some forms of expectation formation can lead to multiple equilibriums that can be associated with periods of deep recessions and deflation (Evans, Guse and Honkapohja 2008) or long periods of high inflation and little economic growth (Hommes and Zhu, 2014). It is for these reasons the continuing study of expectation formation is needed and examined in the following chapter.

Commonly macroeconomic agents are assumed to be completely rational. Complete rationality implies that agents have available to them comprehensive knowledge about the modeled economy, including the values of the structural parameters and exogenous processes which drive the dynamics of the modeled economy. Yet, in a world with ever-evolving information and an ever-evolving amount of sources in which consumers, producers, and financiers can retrieve both accurate and inaccurate information; rational expectations may be too strong of an assumption about expectation formation. The assumption of complete rationality can be relaxed by incorporating the procedure of adaptive learning outlined by Evans and Honkapohja (2001).

Adaptive learning assumes agents do not know the structural parameters that underline the macroeconomy but instead they must learn them overtime through simple recursive econometric methods. Previous empirical research (Milani, 2005, 2007) in adaptive learning has shown that various learning rules embedded in stylized DSGE models can better explain fluctuations in macroeconomic variables when compared to the same DSGE models which assume agents form beliefs about future variables using rational expectations.

These results and other like results regarding boundedly rational modeled agents attracted Ireland (2003) to call for work in “irrational expectations econometrics” to better understand what guides the expectation formation process of agents. Carroll (2003) did just this in his influential paper regarding the household expectation formation of inflation. Carroll found that households use some linear combination of their previously held beliefs about inflation and the Survey of Professional Forecasters (SPF) mean forecast of the future inflation level when forming future and current inflation expectation beliefs. Carroll found that SPF forecasts had the greatest impact on expectation formations when it was most frequently reported in the media.

This chapter builds on the work of Slobodyan and Wouters (2012b) who estimate an adaptive learning stylized DSGE model under the assumption that agents form expectations using and weighting a handful of simple underspecified linear forecasting models and Rychalovska (2013) who does the same but augments the DSGE model with a financial accelerator. For this chapter I allow modeled agents inside a stylized DSGE model with a financial accelerator to form expectations about future variables in a closely related way to Carroll (2003). Carroll's expectation formation has been found to be plausible and empirically sound for expectation formation regarding inflation and the unemployment rate. By introducing the Carroll method it allows future expectations of all forward looking variables in the model to incorporate a public forecast announcement in addition to previously observed values of the endogenous economic variable.

I first estimate the linearized DSGE model under the assumption of both rational expectations and expectation formation under adaptive learning. In the adaptive learning estimation agents are allowed to use three different underspecified linear forecasting models in the expectation formation of forward variables that appear in the model. All parameters in the forecasting models are updated recursively using constant gain learning. The first forecasting model or perceived law of motion (PLM) is a simple AR(1) process of each forward variable and does not incorporate any public announcement. The third forecasting model incorporates both the lagged value of the variable it is trying to forecast and the public announcement. It is this PLM that most closely follows the expectation formation outlined by Carroll (2003).[1] For the estimation I use the real time SPF mean forecast to act as the public announcement of future and present values

[1] More detail about each model can be found in section IV.2.2

of certain economic variables.[2] I estimate the model under different assumptions about how the agents choose or weigh each forecast model when deriving the agent's aggregate PLM.

After I have estimated the model over the time period of 1984Q2-2011Q2, I calibrate the structural parameters to the median of the posterior estimates and run simulations of the economy over the next 500 quarters. Each simulation starts in 2011Q3 and with initial beliefs about the forecasting parameters to be equal to where they were at the end of the estimation window. This allows all simulations to start at the same initial beliefs and under the same structural parameters.[3] However, in each simulated period I must create a public announcement that is comparable to the SPF. In the simulated economy I use a dynamic factor model (DFM) to proxy for the SPF. The DFM model has been estimated over the period of 1968Q1-2011Q2 and uses its estimated parameters to generate the publicly announced forecasts of the future variables. I find that the out-of-sample forecast of the DFM model for inflation, output growth and the unemployment rate are all highly correlated with the SPF of each variable respectively over the time period of the estimation window.

Results: Most notably, I find evidence that the inclusion of accurate and noise free public signals about the values of future economic variables, when incorporated with the agents' own private signals, can significantly lower macroeconomic volatility when it comes to inflation, hours worked and output growth. If agents "rationally" weigh the past performance of the public announcement macroeconomic volatility is lowered when compared to just using their private AR(1) signal, but is still higher than when agents always use the noise free public signal in their expectation formation.

If agents are given the public signal with some proportionally scaled shock (noise) attached to each of the forecast announcements we see that agents will be less inclined to use the public signal and more inclined to revert back to their private signal associated with higher macroeconomic volatility. If the variance of the noise shock around the public announcement is large, I find that agents may be inclined to enter into a cascade and accept the incorrect public signal due to its past performance history and ignore their own private signal. This behavior which I refer to as a "coordinated volatility cascade" can actually raise the level of macroeconomic volatility above the levels calculated when

[2] For certain forecasted variables that are not released by the SPF, I use a forecast generated by a dynamic factor model (DFM) to proxy for the SPF. This DFM is the same one used to proxy for the public announcement in the simulation results.

[3] The zero lower bound is respected in each simulation by the process described by Holden (2012).

agents are not given any public forecast announcement. Finally, I examine the simulated macroeconomic volatility when the public signal is consistently "manipulated" either upwardly or downwardly and I find that macroeconomic volatility is not brought down by the addition of the public signal and the average growth rate or inflation rate is not affected by the upward or downward biased noise shock. Agents simply learn that the public signal is biased and adjust their forecast parameters appropriately or ignore the announcement all together in their expectation formation procedure. In addition to the above results, I find further evidence supporting the findings of Milani (2005, 2007) and Slobodyan and Wouters (2012a, b) that the marginal likelihoods of the adaptive learning models are much greater than the marginal likelihood of the model with rational expectations.

All of these results give credence to the importance of accurate and noise free forecast announcements provided by the public sector. The findings suggest that the policy implications of an accurate, credible, and well-communicated forecasts of future economic variables to the economic public at-large have the ability to lower macroeconomic volatility and thus increase overall economic welfare.

The rest of the chapter is structured as follows: in Section IV.2, I present the linearized model and explain the expectation formation process used by the agents. In Section IV.3, I outline the Bayesian estimation technique and contrasts how the results can change across different expectation formation assumptions. Section IV.4 outlines and discusses the dynamic factor model that is used as a proxy for the Survey of Professional Forecasters in the simulations that occur in the proceeding section. Section IV.5 discusses the results of the DSGE model simulations and compares the macroeconomic volatility across different expectation formations. It also explains how public announcement noise and/or bias are introduced in the simulations. Finally, Section IV.6 summarizes and concludes.

IV.2 The Model

The 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, Gertler and Gilchrist (1999). It includes many of the features of Christiano, Motto and Rostagno (2010). This section continues as follows, I first outline the agents of the DSGE model and I present the linearized equations of the model around the steady state that are used to produce my results. I then proceed to explain how adaptive learning and public signals are introduced into the linearized

DSGE model. For more detail on the model including its micro-foundations I point the reader to Chapter II.

IV.2.1 General Outline of the Model and Its Linearized Equations

The model involves a number of exogenous shocks, economic agents, and market frictions. The agents include households, firms, banks, entrepreneurs, capital producers and government agencies.

Households supply household-specific labor to employment agencies. Households maximize a CRRA utility function over an infinite horizon with additively separable utility in consumption, leisure and money. Utility from consumption includes habit persistence measure. Households are subject to an exogenous preference shock that can be viewed as a shock in the consumer's consumption and savings decisions.

Firms come in two forms, intermediate good producing firms and final good producing firms. There is a continuum of intermediate good firms, who supply intermediate goods in a monopolistically competitive market. Intermediate firms produce differentiated goods, decide on labor and capital inputs, and set prices in a Calvo (1983) manner. As with wages, those firms unable to change their prices, are able to partially index them to past inflation rates. Intermediate firms face two exogenous shocks, the first is a productivity shock that affects their production ability and the second is a price mark-up shock. The price mark-up shock captures the degree of competitiveness in the intermediate goods market. Final goods use intermediate goods in production and are produced in perfect competition.

Capital Producers control the creation of new capital (Investment), a process that requires both the newly bought consumption output and the previous stock of capital in the economy. The investment procedure is subject to adjustment costs and capital producers are subject to investment shocks that affect the marginal efficiency of investment as in Justiniano et al. (2011).

Financial Sector centers around two economic agents, banks and entrepreneurs. Entrepreneurs must use their net worth and an agreed upon loan from the bank to buy capital from the capital producers. Once the capital is bought they are subject to idiosyncratic risk shock that can decrease or increase their overall level of capital just purchased. The entrepreneur must optimize its utilization rate of the new level of capital and rent it out to the intermediate firms. Once the capital has been used in the production process the remaining capital stock is purchased by the capital producers. If entrepreneurs received enough revenue they pay back the agreed upon loan with interest to the bank. Banks incorporate the risk of default by charging entrepreneurs an interest rate higher than the deposit rate payed to households. This risk premium that entrepreneurs must pay creates a financial friction resulting in real and exogenous fluctuations to the capital stock and thus output.

Government Agencies are composed of a monetary authority and a fiscal authority. The short term nominal interest rate is determined by the monetary authority, which is assumed to follow a generalized Taylor Rule and are subject to monetary policy shocks. The fiscal authority sets fiscal policy and is subject to exogenous government spending shocks.

Log Linear Equations

The model is linearized around the non-stochastic steady state and 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 model is reduced to 12 equations and eight exogenous shocks all of which are listed in this section.

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

$$\hat{\bar{K}}_t = (1-\tau)\hat{\bar{K}}_{t-1} + \tau \hat{I}_t + \tau(1+\beta)S''\hat{\varepsilon}_t^I \tag{IV.2.1}$$

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

$$\hat{L}_t = -\hat{w}_t + (1+\tfrac{1}{\psi})\hat{r}_t^k + \hat{\bar{K}}_{t-1} \tag{IV.2.2}$$

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:

$$\hat{Y}_t = C_y\hat{C}_t + I_y\hat{I}_t + \frac{r^k\bar{k}_y}{\psi}\hat{r}_t^k + \mathcal{M}_t + \hat{\varepsilon}_t^G \tag{IV.2.3}$$

$$\hat{Y}_t = \phi\hat{\varepsilon}_t^a + \phi\alpha\hat{\bar{K}}_{t-1} + \frac{\phi\alpha}{\psi}\hat{r}_t^k + \phi(1-\alpha)\hat{L}_t \tag{IV.2.4}$$

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

$$\hat{R}_t = \rho\hat{R}_{t-1} + (1-\rho)\left[r_{\pi_1}\hat{\pi}_t + r_{y_1}\hat{Y}_t + r_{\pi_2}\hat{\pi}_{t-1} + r_{y_2}\hat{Y}_{t-1}\right] + \hat{\varepsilon}_t^r \tag{IV.2.5}$$

The consumption and investment transition equations are

$$\hat{C}_t = \frac{h}{1+h}\hat{C}_{t-1} + \frac{1}{1+h}E_t[\hat{C}_{t+1}] - \frac{1-h}{(1+h)\sigma_c}\left(\hat{R}_t - E_t[\hat{\pi}_{t+1}]\right) + \hat{\varepsilon}_t^b \tag{IV.2.6}$$

$$\hat{I}_t = \frac{1}{1+\beta}\hat{I}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{I}_{t+1}] + \frac{1}{(1+\beta)S''}\hat{q}_t + \hat{\varepsilon}_t^I \tag{IV.2.7}$$

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

$$E_t[\hat{\hat{R}}_{t+1}^k - R_t] - E_t[\hat{\pi}_{t+1}] = \frac{1-\tau}{1-\tau+r^k}[\hat{q}_{t+1}] + \frac{r^k}{1-\tau+r^k}E_t[\hat{r}_{t+1}^k] - \hat{q}_t - R_t \tag{IV.2.8}$$

The model yields a phillips curve equal to:

$$\hat{\pi}_t = \frac{\beta}{1+\beta\iota_p}E_t[\hat{\pi}_{t+1}] + \frac{\iota_p}{1+\beta\iota_p}\hat{\pi}_{t-1} + \frac{(1-\beta\xi_p)(1-\xi_p)}{(1+\beta\iota_p)\xi_p}\left(\alpha\hat{r}_t^k + (1-\alpha)\hat{w}_t - \hat{\varepsilon}_t^a\right) + \hat{\varepsilon}_t^p \tag{IV.2.9}$$

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:

$$\begin{aligned}\hat{w}_t = {} & \frac{\beta}{1+\beta}E_t[\hat{w}_{t+1}] + \frac{1}{1+\beta}\hat{w}_{t-1} + \frac{\beta}{1+\beta}E_t[\hat{\pi}_{t+1}] - \frac{1+\beta\iota_w}{1+\beta}\hat{\pi}_t + \frac{\iota_w}{1+\beta}\hat{\pi}_{t-1} \\ & - \frac{(1-\beta\xi_w)(1-\xi_w)}{(1+\beta)\left(1+\nu_l\frac{1+\lambda_w}{\lambda_w}\right)\xi_w}\left(\hat{w}_t - \nu_l\hat{L}_t - \frac{\sigma_c}{1-h}(\hat{C}_t - h\hat{C}_{t-1})\right) + \hat{\varepsilon}_t^w\end{aligned} \tag{IV.2.10}$$

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:

$$\hat{S}_t \equiv E_t \left[\hat{\tilde{R}}^k_{t+1} - \hat{R}_t\right] = \chi \left(\hat{q}_t + \hat{\bar{K}}_t - \hat{n}_t\right) + \hat{\varepsilon}^F_t \tag{IV.2.11}$$

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 affects 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:

$$\hat{n}_t = \delta_{\tilde{R}^k}(\hat{\tilde{R}}^k_t - \hat{\pi}_t) - \delta_R(\hat{R}_{t-1} - \hat{\pi}_t) + \delta_{qK}(\hat{q}_{t-1} + \hat{\bar{K}}_{t-1}) + \delta_n \hat{n}_{t-1} - \delta_\sigma \hat{\varepsilon}^F_{t-1} \tag{IV.2.12}$$

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, 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, the value of χ will determine the values of the δ coefficients.[4]

In all, the SWFF model has eight exogenous shocks, six of which are AR(1) processes, the two lone exceptions being the monetary policy shock which is simply white noise and the price-mark-up shock which is assumed to follow an ARMA(1,1) process. All processes are assumed to be i.i.d. with mean zero and standard deviation σ_i and autocorrelation parameters ρ_i, where $i = \{a, b, G, r, I, F, p, w\}$

IV.2.2 Expectation Formation and Adaptive Learning

The linearized equations of the SWFF model can be represented in the following form:

$$A\left[Y_t\right] = B\left[Y_{t-1}\right] + CE^*_t\left[Y_{t+1}\right] + D\left[v_t\right] \tag{IV.2.13}$$

[4]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.

where the vector Y_t includes all of the time t endogenous variables and all of the exogenous structural processes in the model. If we assume agents are aware of the values of A, B, C, and D and use rational expectation formation the rational expectation equilibrium (REE) solution to (IV.2.13) can be given by:

$$\begin{bmatrix} Y_t \end{bmatrix} = \mu_{RE} + G_{RE} \begin{bmatrix} Y_{t-1} \end{bmatrix} + H_{RE} \begin{bmatrix} v_t \end{bmatrix} \tag{IV.2.14}$$

Alternatively, one can assume agents do not have complete knowledge about the values of the structural parameters, model structure and/or information about the exogenous processes. The exclusion of any of these from the agent's information set makes it impossible to produce model consistent predictions of the path of forward-looking variables since the true dynamics of the model are unknown to the agents. This chapter follows Evans and Honkapohja (2001) and assumes agents do not have a complete information set available to them and instead use simple linear autoregressive forecasting rules estimated on past observed observations in the economy to form expectations E_t^*.

I assume agents believe the economy follows one of the following laws of motions (PLM):

$$y_t^f = a_{1,t} + b_{1,t} y_{t-1}^f + e_{1,t} \tag{IV.2.15}$$

$$y_t^f = a_{2,t} + c_{2,t} Y_{t|t-1}^* + e_{2,t} \tag{IV.2.16}$$

$$y_t^f = a_{3,t} + b_{3,t} y_{t-1}^f + c_{3,t} Y_{t|t-1}^* + e_{3,t} \tag{IV.2.17}$$

The vector y_t^f contains the five forward looking endogenous variables in the model which include investment, consumption, inflation, wages, and capital prices. Further, y_t^f is a subset of Y_t implying that there exists some selection matrix Φ to assure $y_t^f = \Phi Y_t$. The matrices $b_{1,t}$ and $b_{3,t}$ are square matrices whose off diagonal elements are equal to zero. This implies that equation (IV.2.15) perceives all forward-looking variables to follow an AR(1) process with an intercept.

Equations (IV.2.16) and (IV.2.17) are where I introduce professional public forecasts of future variables derived by large datasets into the DSGE model with the inclusion of Y^*. The vector Y^* is announced in the economy to the agents and provides expected values of the forward variables using time $t-1$ information available in the economy. Matrices $c_{2,t}$ and $c_{3,t}$ are square matrices whose off diagonal elements are equal to zero.The third PLM is most closely aligned to how Carroll (2003) assumed households updated inflation expectations, however, I assume agents use quarterly forecasts of variables to update their beliefs rather than yearly forecasts as Carroll does.

All non-zero coefficients in the three PLM's are calculated using constant gain learning and Recursive Least Squares (RLS). Every period, agents are updating their PLM coefficients in a constant gain RLS step:

$$\hat{\phi}_t = \hat{\phi}_{t-1} + \gamma \Re_t^{-1} Z_{t-1}(y_t^f - \hat{\phi}_{t-1}' Z_{t-1})' \tag{IV.2.18}$$

$$\Re_t = \Re_{t-1} + \gamma(Z_{t-1}Z_{t-1}' - \Re_{t-1}) \tag{IV.2.19}$$

Notation wise the non-zero coefficient values of $a_{i,t}, b_{i,t}, c_{i,t}$ for PLM i (IV.2.15-IV.2.17) are in the vector $\hat{\phi}_t$ and the data vector[5] denoted Z_t is equal to $(1, y_{t-1}^f, Y_{t-1|t-2}^*)'$

Agents are uncertain about which PLM best describes the actual economy and wheather or not to use the public forecast announcement. Thus agents use Bayesian weights to calculate the aggregate PLM. These Bayesian weights are derived by previous realizations of each PLM's forecasting residuals and incorporate a forecasting model specific degree of freedom penalty.

$$B_{i,t} = t \cdot ln\ det \left(\frac{1}{t} \sum_{\tau=1}^{t} e_{i,\tau} e_{i,\tau}' \right) + \kappa_i \cdot ln(t) \tag{IV.2.20}$$

If a model has produced large residuals over the recent past observations it will receive a lesser weight used in averaging across all PLMs.[6] Given $B_{i,t}$ the weight of a forecasting model is proportional to $exp(-\frac{1}{2}B_{i,t})$ These weights are used to form an aggregate PLM of:

$$y_t^f = a_{agg,t} + b_{agg,t} y_{t-1}^f + c_{agg,t} Y_{t|t-1}^* + e_{agg,t} \tag{IV.2.21}$$

The inclusion of Bayesian weighting allows agents to choose between and weigh private signals derived from AR(1) processes (IV.2.15), completely using the public signal (IV.2.16) and using both the public signal and the private signal (IV.2.17) when calculating their aggregate PLM.

Agents use their aggregate PLM (IV.2.21) to form expectations about the future

[5]The data vector Z_t does not include $Y_{t-1|t-2}^*$ for PLM(1) and y_{t-1}^f for PLM(2)

[6]I use a rolling window of 15 residuals for each model to calculate $B_{i,t}$ to allow for agents to more easily switch PLMs if the short-term forecasting performance of one became dominant. The results of this chapter are robust to a rolling residual window of 5-25

paths of the endogenous variables in the vector y_t^f.

$$E_t^* Y_{t+1} = E_t^* y_{t+1}^f \tag{IV.2.22}$$

Since it assumed at time t that agents only know the values of all endogenous variables up to $t-1$, equation (IV.2.22) can be rewritten as

$$E_t^* Y_{t+1} = a_{agg,t} + a_{agg,t} b_{agg,t} + b_{agg,t}^2 \Phi Y_{t-1} + b_{agg,t} c_{agg,t} Y_{t|t-1}^* + c_{agg,t} Y_{t+1|t-1}^* \tag{IV.2.23}$$

Plugging the above equation into the structural form of the modeled economy equation (IV.2.13) gives us the actual law of motion (ALM) of:

$$\begin{bmatrix} Y_t \end{bmatrix} = \mu_t + G_t \begin{bmatrix} Y_{t-1} \end{bmatrix} + H \begin{bmatrix} v_t \end{bmatrix} \tag{IV.2.24}$$

where G_t is a time dependent transition matrix that is a function of A, B, C and b_{agg}. The coefficient vector of μ_t is a time dependent function of A, a_{agg}, b_{agg}, c_{agg} and Y^*. The matrix H is not time dependent as agents are unaware of any properties of the exogenous processes including any past realizations of them. This means agents cannot and do not use the exogenous processes in any of their PLMs and RLS updating. As a result the elements of H are only a function of A and D.

In summary, agents form expectations and the economy evolves according to the following algorithm:

1. Agents observe $t-1$ values of all endogenous values.
2. Public forecasts are announced to the agents about time t variables (y_t^f) and time $t+1$ variables (y_{t+1}^f)
3. Agents use all $t-1$ information and the public forecasts previously announced to update the coefficients on each of their PLMs(IV.2.15-IV.2.17) using constant gain RLS (IV.2.18-IV.2.19).
4. Agents use the past residuals for each PLM and equation (IV.2.20) to apply weights that are used to compute the aggregate PLM (IV.2.21) of the economy.
5. The aggregate PLM is used to forecast future levels of each forward-looking variable in the model and is plugged into the reduced structural form of the model (IV.2.13) to produce an ALM (IV.2.24).

6. Time t exogenous shocks occur and all time t economic variables (Y_t) are then realized in the economy.

IV.3 Bayesian Estimation of The Models

This section presents the steps needed to generate Bayesian estimates of the models' parameters of the linearized model of the previous section under different expectation formation assumptions. First, the priors for the models' structural parameters are shown. The data sets used in estimation and their respected transformations are outlined as well as the calibration process of initial learning parameter beliefs $\Re_0$ and $\hat{\phi}_0$. When conducting Bayesian estimation I use the standard Random Walk Metropolis-Hasting algorithm where the Kalman filter is used to construct the likelihood of the different linearized models. The estimated structural parameters and estimated marginal likelihoods for each expectation formation model are examined and discussed in this section.

IV.3.1 Initial Set-Up

Parameter Priors

The structural parameter priors are in accordance to the Slobodyan and Wouters (2012a) 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. The steady state default rate is set to .0075 which corresponds to Bernanke, Gertler, Gilchrist (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 bill 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 and steady states can be found in Table 15.

The distribution of the prior along with its mean, standard deviation and description of each estimated parameter are laid out in Table 16. The parameter priors include normal, beta, gamma, and inverse gamma distributions. All coefficients whose values lie within the unit interval are drawn from beta distributions, while all standard deviations of the structural shocks are drawn from inverse gamma distributions. The priors on the autocorrelation coefficients of the structural shock ensure that shocks will be persistent in the model economy. The joint prior is given by the products of the marginals and is truncated to parameter values that guarantee a determinate and unique model equilibrium. The structural parameter priors and calibrated priors are identical for both the model estimated under rational expectations and the model estimated under adaptive learning.

Data for Estimation and Public Forecast Announcement

The DSGE model is estimated using eight Macroeconomic time series at the quarterly level over the period of 1984Q2 to 2011Q2. These series include real per capita GDP, the GDP price deflator, per capita consumption and private investment expenditures, real average hourly wage, hours worked, the annualized federal funds rate and the spread between BAA corporate bond yields to the 10 year Treasury bill yield. All per capita variables are calculated using the adult population of 16 years and older. These series are either demeaned, linearly detrended at the log level or log first differenced and demeaned. A complete list and transformation rubric of each of these series along with their corresponding Fred-II database code is found in Appendix C.

I use the historical SPF forecast announcements on the GDP price deflator, real consumption and real investment levels to proxy for the modeled public announcements $Y^*_{t|t-1}$ and $Y^*_{t+1|t-1}$ which can be used in the agent's perceived law of motion. Since the Survey of Professional Forecasters reports the mean forecasted value of inflation, GDP, investment and consumption in levels and the model is estimated using percent deviations away from steady state I must transform the SPF data. I do this by assuming the SPF forecasters slowly learn the steady state by recalculating the mean or detrending the data before the beginning of each quarter. This means that as the sample gets closer to 2011Q2 the public announcements in the modeled economy are also getting closer to using the calibrated steady state levels of inflation, GDP, consumption, investment and wage growth used in the initial transformation of the measurement data when the historical SPF level data is transformed to percent deviation from steady state.

Initial Beliefs and Projection Facility

In addition to the structural parameters, I must calibrate the agent's initial beliefs when estimating the model under adaptive learning. These initial beliefs ($\Re_0$ and $\hat{\phi}_0$) for each PLM are calibrated using a training sample from 1978Q3-1984Q1. This training sample time period was selected to start at the 3rd quarter of 1978 because this is the first quarter in which the relevant endogenous variables are first forecasted by the survey of professional forecasters (SPF). To generate the appropriate initial beliefs for equations (IV.2.18-IV.2.19) the following equations over the time span of the training sample window must be used for each forward looking variable y^f for each PLM.

$$\hat{\phi}_0 = (Z'Z)^{-1}Z'y^f \tag{IV.3.1}$$

$$\Re_0 = t^{-1}Z'Z \tag{IV.3.2}$$

When Bayesian weighting is used the initial forecast weights assigned to each PLM is assumed to be equal and is updated with each additional residual observed by the agents.

Given that Clarida et al. (2000) have shown that the stability of monetary policy of the form of equation (IV.2.5) did not occur until the early 1980's and Lubik and Schorfheide (2004) assert that it was not until the early 1980's that monetary policy of this form was consistent with a determinate equilibrium. For these reasons I assume a structural break in the steady state level of inflation. During the estimation window I assume the steady state level of annual inflation is 2.2% while during the training sample window I assume that the steady state level of annual inflation is 6.5% both of which correspond with the mean level of inflation calculated from the GDP deflator for 1984-2011 and 1975-1984 respectively.

There are two forward looking endogenous variables that are not reported or forecasted by the SPF. These are wages and capital prices. To provide a public forecast announcement of these variables I use the Dynamic Factor model (DFM) explained in detail in Section IV.4 to construct forecasts for wages. DFM can be used to provide forecasts for wages since it is an included data set in my DFM. Since there is no corresponding data set for capital prices as it is presented in the DSGE model I do not provide a public announcement of it in my estimation procedure. Instead I use the estimated percentage deviation of capital prices derived by the Kalman filter during the estimation window as the only means available in forecasting future capital prices. Since there is no public announcement, agents are left with only the AR(1) PLM of equation (IV.2.15) to forecast capital prices. As a result I do not allow the forecasted residuals of capital prices to play a role in assigning weights to each PLM in equation (IV.2.20). Further, the lack of a resembling data set to generate the initial parameter beliefs of the perceived law of motion of capital prices leaves us with a quandary. I opt to use the data set which divides the value of stocks by corporate net worth as a proxy data set for capital prices during the training sample window.

Moreover, a projection facility is used in both the estimation and simulation procedures of the DSGE model under adaptive learning. If the recursive parameter estimates on the aggregate PLM cause one or more of the eigenvalues of the matrix G_t in equation (IV.2.24) to lie outside the unit circle agents ignore the updated coefficients and instead rely on the previous period's parameter estimates to forecast forward looking endogenous variables. This ensures that the ALM does not allow any economic variables to explode. The use of the projection facility in the estimation procedure is very small. In fact the number of periods with unstable eigenvalues does not exceed five during the estimation procedure and at its median posterior parameter values when the aggregate PLM is formed using Bayesian weights the projection facility is only used in one quarter throughout the estimated sample window. However, the use of the projection facility becomes more frequent in the simulation procedures and is discussed with more detail in Section IV.5.

IV.3.2 Estimation Procedure

I Bayesian estimate the described DSGE model under a variety of expectation formations. These include rational expectations and adaptive learning. Under adaptive learning I estimate 5 different model assumptions. These include only allowing agents to use one PLM for the entire sample period, putting equal weights on each of the PLM's throughout the sample period and assigning Bayesian weights on each PLM using equation (IV.2.20) throughout the sample period. All of these modeling assumptions are Bayesian estimated using a Metropolist-Hastings algorithm using a state-space representation.

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

$$Y_t = G(\theta)Y_{t-1} + H(\theta)v_t \tag{IV.3.3}$$

and the measurement equation:

$$\begin{bmatrix} \text{RGDP} \\ \text{PGDP} \\ \text{RCONS} \\ \text{RINV} \\ \text{RWAGE} \\ \text{HOURS} \\ \text{FedFunds} \\ \text{SFYBAAC} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4 & \dots & 0 \end{bmatrix} \begin{bmatrix} y_t \\ \pi_t \\ c_t \\ I_t \\ w_t \\ L_t \\ R_t \\ S_t \\ \vdots \end{bmatrix} \tag{IV.3.4}$$

$$X_t = \Lambda \quad Y_t \tag{IV.3.5}$$

Here X_t are the macroeconomic time series and Λ is a matrix matching the observed data to the definitions of the model's state Y_t. The vector Y_t also includes an intercept term when estimating the adaptive learning models. The matrices $G(\theta)$ and $H(\theta)$ are functions of the model's structural parameters and v_t is a vector of the i.i.d. components of the model's exogenous processes $\hat{\varepsilon}_t$. Depending on whether or not I am estimating under the assumption of adaptive learning or rational expectations the matrix $G(\theta)$ may or may not be time specific.

With the model set up in state-space form and all stochastic processes being distributed normally and independently the Kalman Filter is used to calculate the likelihood of a certain set of θ. Using the given priors found in Tables 15 and 16, a Random-Walk Metropolis-Hastings[7] algorithm is then used to obtain the posterior distribution of the model's parameters $P(\theta|X)$. The applied algorithm is based on 500,000 draws using two parallel chains of 250,000 draws discarding the initial burn-in period of 100,000 iterations.

IV.3.3 Results of Empirical Procedure

Described and analyzed below are the empirical findings of Bayesian estimation conduction on the New Keynesian model with financial frictions in which expectations of future variables were derived by both rational expectations and adaptive learning as perviously outlined. The marginal likelihood of all the adaptive learning models was much greater than the marginal likelihood of the model with rational expectations. This result is in concurrence with the findings of Slobodyan and Wouters (2012a, b) and Milani (2005, 2007). Table 17 gives the marginal likelihoods calculated using the

[7]For more detail on this and other Bayesian DSGE estimation techniques please see An and Schorfheide (2007)

modified harmonic mean estimator and the Bayes' posterior odds for the estimated DSGE model under different expectation formation assumptions. As is evident in Table 17 the posterior odds are much greater for the adaptive learning models which use some combination of the different PLM's.

The empirical evidence suggests that households are likely to be using both equations (IV.2.15) and (IV.2.17) in their aggregate PLM. However the marginal likelihoods suggests that the exclusive use of the PLM's which include the public signal for the entire estimation window is not likely. However, a closer examination of the endogenous weights assigned to each PLM when the Bayesian weights (BW) model is estimated reveals that the weight given to the third PLM (IV.2.17) is usually low except around business cycle turning points.[8] In fact the weight on third PLM (IV.2.17) increases and peaks around both the financial crisis and the stock market volatility of the late 1990's and early 2000's. Figure 25 shows the estimated BW weight of the third PLM at the median posterior parameter values.

I believe the mechanism behind this observation is that more professionally complex forecasts can identify and forecast future economic fluctuations faster than simple AR(1) forecasts. The set up of the adaptive learning model allocates the effect of the public announcement to be entirely incorporated in the perceived steady state value of the economy. This allows agents' constant coefficient term on their aggregate PLM to fluctuate more quickly while still assuming a relatively low but empirically supported constant gain learning parameter. As a result there is less fluctuation in the AR(1) PLM coefficients over time but more fluctuation in the constant PLM coefficient term over time. Intuitively, public forecast announcements can alter or create short term structural breaks in the "agent perceived" steady state of the modeled economy.

As a result these public announcements can play a role in the volatility of economic business cycles. If it is assumed that professional forecasts may be better in deducing additional information about the structure of the economy or the unobserved shocks occurring in the economy it is reasonable to infer that when these shocks are largest the professionally generated public forecast may be able to significantly out perform the forecast generated by the agents who have no information about the exogenous shock process. As a result the professional forecasts become most beneficial to the agents in times of macroeconomic volatility.

A closer look at the parameter estimates for the models reveals a few patterns that

[8]Further examination of the weights reveal that the second PLM has little to no weight throughout the estimation window when endogenous Bayesian weights are used to calculate the aggregate PLM.

arise when comparing the model estimated under rational expectations and the models estimated under adaptive learning. First, I find that nominal rigidities including wage and price stickiness as well as habit formation were all lower in the adaptive learning model as was found in Milani (2007). However, the estimates of nominal frictions in the adaptive learning model do not disappear as Milani (2007) found in his less stylized New Keynesian model but are more inline with the estimates found by Slobodyan and Wouters (2012a) in their DSGE model without any financial accelerator. Yet, unlike both papers previously mentioned, I find that high levels of price and wage indexation are needed in the adaptive learning model.

The structural exogenous shocks were less persistent but came from a much more dispersed normal distribution in adaptive learning models when compared to the rational expectations model. Most notably the mean estimate for the standard deviation on investment increases from 0.89 under rational expectations to 3.09 under adaptive learning while the persistence parameter on investments shocks decreases from 0.72 under rational expectations to 0.52 under adaptive learning. In fact the standard deviation on investment, price and wage markup shocks are all three to four times larger in the adaptive learning models when compared to the estimated model under rational expectations.

Inspection of the constant gain learning parameter (γ) used by the agents in updating their beliefs shows that it is estimated to be between 0.015-0.02. This estimate is in line with other recursive least square constant gain estimates for other New Keynesian DSGE models estimated under adaptive learning including Orphanides and Williams (2005), Milani (2005, 2007), and Slobodyan and Wouters (2012a). The median gain estimate of 0.017 implies that the weight assigned to each new data point has a half life of about 9 years. A complete listing of all the posterior parameter estimates for both the model with rational expectations and the model with adaptive learning in which agents form their aggregate PLM using Bayesian weights can be found in Table 18.

IV.4 Dynamic Factor Model Forecasting vs. SPF

Using the historically estimated parameters calculated in the previous section, I will study the effects that professional forecast announcements have in the macroeconomy under the empirically likely expectation formation modeling assumption of adaptive learning. However, in order to perform these simulation exercises I must find some advanced forecasting instrument to proxy for the mean SPF forecast announcement. I opt to use a dynamic factor model (DFM) estimated using 98 real-time macroeconomic time series to forecast the forward endogenous variables in the DSGE model.

I choose to use a DFM as a stand-in for the SPF for various reasons. First, Stock and Watson (2012) have found that over the 3-6 month time horizon DFMs out perform many other simple and more complex forecasting models. Since time t public forecast announcements are announced for time t and $t+1$ quarterly variables it seems that a forecast generated by a DFM will be the most sound forecast performer. Additionally, if we compare the out-of-sample 1-2 quarter ahead forecasts generated by the DFM over time and compare them to the 1-2 quarter ahead forecasted economic variables in the SPF, we observe that there is a significant correlation between the two.

Before, further comparing forecasts generated by the DFM to SPF forecasts, let's first outline the basic structure of the DFM model used in this chapter. The principle behind a DFM is that there exists a handful of latent factors f_t inside the economy that power the comovements among macroeconomic variables. These latent factors are believed to be extractable using a large set of macroeconomic time series.

I use the DFM linear/Guassian state space set-up (IV.4.1-IV.4.2) outlined in Stock and Watson (2011) to estimate the parameters of the DFM model.

$$X_t^{DFM} = \hat{\lambda} f_t + \hat{e}_t \tag{IV.4.1}$$

$$f_t = \Psi f_{t-1} + \omega_t \tag{IV.4.2}$$

where N is the number of series used in estimation and q is the number of extracted latent factors and $\hat{\lambda}$ is a Nxq matrix of factor loadings. The qxq transition matrix, Ψ, oversees the VAR dynamics of the q latent factors.[9] There are two types of mean-zero idiosyncratic disturbances that govern the DFM model. There are the Nx1 vector of shocks ($\hat{e}_t$) which only affects the individual data series in X_t^{DFM} and there is the qxq vector of shocks (ω_t) which govern the dynamics of the latent factors. The i.i.d. shocks are distributed $N(0, R)$ and $N(0, Q)$ respectively.

The 98 series of X_t^{DFM} are grouped into multiple categories. The first category is labeled *Core Components* which is a set of variables that are used or could be used in the empirical estimation of the DSGE model. For example, Real GDP and Real GDI are both categorized here and either could be used in measuring production ($\hat{Y}_t$) in the DSGE model. The *Output Components* category includes series that explain deviations

[9]The estimated parameter values of Ψ are truncated to ensure that the eigenvalues of Ψ all lie inside the unit circle.

from per capita linear trends of different GDP and production output components. The *Labor Market* category includes series of employment by sector as well as different types of unemployment rates and durations. The *Housing Market* group includes regional housing starts and residential investment series. The *Financial Market* classification includes a number of different interest rates, loan and credit quantities and asset prices. The *Investment* grouping includes inventory indexes and other investment series and the *Price and Wage* category includes a number of pricing indexes, wage indexes and commodity prices.

As is common in the Dynamic Factor Model literature, all series sample standard deviations are 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 series used in the DFM estimation along with their corresponding Fred-II database code can be found in Appendix C.

The structural parameter values ($\Gamma = \hat{\lambda}, \Psi, f_t, R, Q$) of the DFM model of (IV.4.1-IV.4.2) are Bayesian estimated using the linear/Gaussian DFM Gibbs sampler first implemented by Otrok and Whiteman (1998). The priors and the identification strategy of the model are identical to those used in the Bernanke, Boivin, and Eliasz (2005) paper. The estimation window used for the DFM is 1968Q1 to 2011Q2. The number of factors, q, is selected using the criteria of Bai and Ng (2002, 2007) and that of Breitung and Pigorsch (BP) (2013) where the maximum number of factors is set to seven. The number of latent factors that the BP statistic calls for expands as the number t observations increase in the estimation sample. The number of latent factors the BP statistic selects to extract form X^{DFM} for the full DFM estimation window is five.

To compare how the DFM forecasts would compare to those of the SPF over the time period of 1978-2011, I perform out-of-sampling one and two quarter forecasts for the DFM over that time period and compare them to those provided by the SPF and used in the estimation procedure of Section IV.3. Over the course of the out-of-sample DFM estimates the number of latent factors selected by the BP statistic changes as more and more observations are realized. Table 19 reports the correlation between the generated forecasts of the DFM and those reported by the SPF for the inflation level, real output growth, real consumption growth, real non-residential investment growth and the unemployment rate. The two quarters ahead forecasts for both the DFM and the SPF are highly correlated for all five series. However, the one quarter ahead forecasts of real consumption and investment growth are not highly correlated with each other.

This is likely do to the fact that the SPF forecast is usually released in the second month of a given quarter so it has the advantage of using updated data in its information set to generate a forecast while the DFM forecast does not have such a luxury. Figures 26 and 27 show how similar the forecasts for output growth and inflation are between the DFM and SPF over 1978-2011. It is believed that the high correlation between these two generated forecasts as well as the theoretical advantages of using large data sets to forecast justifies the use of forecasts generated by a DFM to proxy for the SPF forecasts in the simulation exercises.

IV.5 Simulation Exercises: Public Forecasts and Economic Volatility

In order to empirically show the effects of clear and accurate public forecasts can have on business cycle fluctuations, I conduct simulations under numerous expectation formation assumptions and calculate the volatility of output growth, inflation and other macroeconomic variables over time. I find that if the public forecast is provided and transmitted to the agents without any noise, agents will use the public announcement in forecasting future variables and macroeconomic volatility declines. Yet, if the public signal is transmitted to the agents with some sort of random noise it seems that macroeconomic volatility can increase. In fact, we see that if the noise around the announcement is large enough, macroeconomic volatility can be larger when compared to an economy where no public forecast is provided whatsoever.

I start each simulation where the estimated DSGE model ended and use the same structural parameters for each simulation exercise. I use forecasts generated by the DFM of Section IV.4 as a proxy for the SPF. This allows the DSGE model to continue through time while still keeping the relationship of its endogenous variables and the public forecast that were calibrated in the sample period of the Bayesian estimation explained in Section IV.3. Below, the initialization of the simulated process is given and I present the simulated moments for each model.

IV.5.1 Simulated Procedures

The first step in the simulation exercise is to estimate the posterior structural parameters (Γ) of the DFM using the DFM dataset form 1968Q1 to 2011Q2. These estimated parameter distributions are used throughout the simulated path of the economy.[10] It is

[10]This assumes that there is no structural change or break in how the latent factors govern the macroeconomy throughout the 450 simulated quarters

these posterior distributions that are used for all future public forecast announcements in the simulated economy. Of course many of the time series used in the DFM have little to no direct connection inside the DSGE model. However, we can think of these datasets as providing noisy information about past and future exogenous shocks in the DSGE model, in which professional forecasters inside the model try and extract as much possible information about the past and future transitional path of the economy.

Further, to continue the real world connection of the public forecast and the SPF forecasts, I start each simulation in 2011Q3 and calibrate all the structural parameters (θ) equal to their median estimate of the **BW** model estimation of Section IV.3.[11]. In addition, all learning parameters ($\hat{\phi}_t, \Re_t$) are assumed to be equal to where they were last estimated in 2011Q2. This assures that any difference in macroeconomic volatility is not attributed to different structural parameters or initial learning beliefs. Each model discussed is simulated 5000 times for 450 quarters.

For all simulations, after each τ period of the DSGE model, I take the 8 observable time τ variables just generated in the DSGE model that are also in the dataset of the DFM and randomly pick k of them. Next, the vector of $\hat{e^g}_\tau$ shocks is generated from the $N(0, R^g)$ distribution and the number of k time τ factors, f^g_τ are solved using the measurement equation (IV.4.1). The transition equation (IV.4.2), the f^g_τ latent factors and the other Γ^g posterior distributions draws are used to forecast the $f^g_{\tau+1}$ and $f^g_{\tau+2}$ latent factors. Finally the $f^g_{\tau+1}$ and $f^g_{\tau+2}$ latent factors are put back into the measurement equations and the future variables $X^{DFM(g)}_{\tau+1}$ and $X^{DFM(g)}_{\tau+2}$ are found and announced in the economy.[12] All public forecasts are point forecasts generated using the average of $X^{DFM(g)}_{\tau+1}$ and $X^{DFM(g)}_{\tau+2}$ that result from sampling the posterior distributions of Γ. In the simulation 1000 g draws of Γ are used in obtaining the public point forecast.

In each simulation the zero lower bound is protected using shadow monetary policy shocks using an algorithm outlined by Holden and Paetz (2012). If the structural shocks do not call for a negative interest rate the monetary shadow shock is equal to zero. If however, the set of structural shocks calls for the interest rate to be negative the corresponding monetary shadow shock is solved for in order to assure that the nominal interest rate is zero percent.

As was used in the estimation procedure, a projection facility is used in all of the simulations. During the simulated window the projection facility is more likely to be

[11]This includes all the calibrated parameters of Table 15

[12]Before being announced in the economy $X^{DFM(g)}$ must be unnormalized and transformed back to percent deviation from steady state as this is what is used in the agents PLM.

used (implemented in about 7-10% of the periods) than it was in the estimation window. Fortunately, the projection facility is not used in a particular model more than another. Therefore, we can assume that the differences in macroeconomic volatility across modeling assumptions are not being produced by the ad-hoc assumption of a projection facility.

IV.5.2 Simulated Results

For the first exercise I compare the simulated macroeconomic volatility of three different modeling assumptions. The first model I look at is referred to as **PLM(1)** assumes agents only use the first PLM (IV.2.15) to forecast future variables in the economy. We can think of this model as the private information model as agents only use privately observed endogenous variables in an AR(1) model. The second model I examine is refered to as **BW** and uses equation (IV.2.20) to "rationally" weigh each PLM (IV.2.15-IV.2.17) based on the recent past forecasting performance of each. This model allows agents to decipher between using only private information, only public information, or some combination of both private and public information in their expectation formation of future variables. Finally, the third model is referred to as **PLM(3)** which assumes agents always use PLM (IV.2.17) to forecast future variables. In this model agents are always using both their private information and the public forecast announcement in forming future variable expectations. For all three of these models I assume that the public forecast is disseminated to the agents without any noise. In other words all agents receive the actual forecasts generated by the DFM at the beginning of each period.

Using the simulated procedures described in IV.5.1 I simulate each to the three models discussed above. The average standard deviations and autocorrelations for Inflation, Interest Rate, hours worked, output, consumption, investment and wage growth are reported in Table 20. I drop any obvious outliers from the 5000 simulated sample when computing the average standard deviations of each variable for each model.[13]

A few main results of the simulated procedure can be seen in the first column of Table 20. First, the standard deviations of all macroeconomic variables decline when agents use the public forecast announcement in some way. The standard deviations for **PLM(1)** model are always higher than the standard deviations for the **BW** and **PLM(3)** models which do use the public forecast announcement. When agents always

[13] I use the threshold that any simulated sample standard deviation that is four times above the median simulated standard deviation is not included in the simulated sample mean calculation. Out of the 5000 simulations of each model the greatest number of dropped outliers was 63. Most of the time fewer than 10 simulations out of 5000 were not used in the mean calculations for each simulated model.

use the public forecast as they do in the **PLM(3)** model, economic volatility is lower than when they have the option to not use it and rely more heavily on the first PLM as they are able to in the **BW** model. We can see this in the top right graph of Figure 28 which plots the weight given to the third PLM in one of the simulations in the **BW** model. At certain quarters the weight on the public forecast PLM is low causing agents to apply more wight on the first PLM that does not use the public forecast and is associated with more economic volatility.[14]

The change in volatility from different modeling assumptions is much greater for certain macroeconomic variables. The volatility of inflation falls over 25% when agents always incorporate the public forecast in their PLM. A similar result occurs for hours worked and the nominal interest rate as the volatility of both fell by 9% and 16% respectively between the **PLM(1)** model and the **PLM(3)** model. The volatility of the different growth variables was not greatly dissimilar across expectation formation assumptions. However, the standard deviations and autocorrelations for all them were lowest in the **PLM(3)** model. For some it may seem that the change in volatility between models is minor, yet it is important to remember that the *only* mechanism that differs between the models is the use of the public forecast. In fact, if the public forecast is deemed to be not useful in forecasting the future path of the economy agents can endogenously ignore it. It is for these reasons that I deem any change in macroeconomic volatility across the models significant.

These results suggest that the existence of a professional forecast generated by a more complex forecasting model can bring down economic volatility, most notably the volatility of inflation. Intuitively, in the absence of professional forecasts economic households must solely rely on more simplistic forecasting techniques that do not see business cycle fluctuations as fast as more complexed forecasting models do. As a result it will take households a while to adjust to the new economic climate which can result in prolonging the business cycle and increasing economic volatility and economic autocorrelation.

Adding Noise and Bias to the Public Signal

The next simulated exercise centers around the dissemination of the public forecast to the agents. I take the **BW** model set up but add an independent shock term for each

[14]Recall that equation (IV.2.20) not only relies on past forecasting residuals but also on a degree of freedom penalty. This means that PLM that excludes the public forecast and has less degrees of freedom does not have to be out performing the third PLM that has more degrees of freedom.

forecasted variable. The resulting PLM's for these models take the form of

$$y_t^f = a_{1,t} + b_{1,t}y_{t-1}^f + e_{1,t} \tag{IV.5.1}$$

$$y_t^f = a_{2,t} + c_{2,t}(Y_{t|t-1}^* + \eta_t^f) + e_{2,t} \tag{IV.5.2}$$

$$y_t^f = a_{3,t} + b_{3,t}y_{t-1}^f + c_{3,t}(Y_{t|t-1}^* + \eta_t^f) + e_{3,t} \tag{IV.5.3}$$

where η_t^f is normally distributed with a mean of $\mu\, std(y^f)$ and a standard deviation of $\sigma std(y^f)$

These added noise terms to the second and third PLM's can be interpreted in a few ways. One way to interpret η_t is to think of a world where agents hear many forecasts and proclamations about the future path of the economy. In this world η_t can be thought of as the surrounding noise that these other public forecasts create around the true public forecast generated by the DFM model.[15] The higher σ is the less likely it is that agents receive the actual forecasts of the professional forecast model.

The second column of Table 20 adds noise to the dissemination process of the public forecast by setting μ equal to zero and σ equal to one in the **BW Low Noise** model and μ equal to zero and σ equal to three in the **BW High Noise** model. We can see that economic volatility for most variables ascends back to the volatility associated when agents do not use any public forecast in their expectation formation process whatsoever. However, we can see that if the noise around the public signal is high, volatility for the growth variables can actually be higher than if no public forecast was provided at all. In fact for many of the simulations in the **BW High Noise** model economic volatility is quite larger than that of the **PLM(1)** model. I refer to this occurrence as a "coordinated volatility cascades".

These cascades occur because agents perceive the public forecast to be accurate as a result of its past forecasting performance due to a sequence of small noise shocks. Yet, when large noise shocks begin to materialize, agents are unaware that the public announcement has been disseminated to them inaccurately. As a result, this causes large swings in the perceived structural steady state of the DSGE model. As the information cascades literature suggests, agents would be better off ignoring the noisy public signal and trusting their private signal, but rationally choose not to because of the past performance of the public signal. I find that "coordinated volatility cascades" are larger and more likely to occur when σ is increased and/or the rolling window (t) of forecasting

[15] Alternately, η_t can be thought of as a judgement or exuberance shock as outlined in Bullard, Evans, and Honkapohja (2008)

residuals in equation (IV.2.20) is decreased.

The final simulated exercise involves manipulation of the public forecast by the public forecaster. This is analogous to the public sector trying to promote economic exuberance by announcing overly positive forecasts to the agents. To implement this experiment I take the PLM's of (IV.5.1-IV.5.3) and set μ equal to one for the **BW Biased Up** model and set μ equal to negative one for the **BW Biased Down** model. For both of these models σ is set to 0.25. The third column of Table 20 shows that the simulated standard deviations of both of these models are very similar to the simulated standard deviations for the macroeconomic variables in the **BW** model. This implies that public forecast manipulated for one reason or another has little to no effect on economic volatility. Agents simply learn over time that the public forecast announcement is biased and adjust their learning parameters accordingly.

IV.6 Conclusion

In this chapter I have estimated and simulated the FRBNY New Keynesian DSGE model under different expectation formation assumptions. I find that the adaptive learning models fit the data better when compared to the rational expectation model. I then take those parameter estimates and simulate the model with and without a proxy for the Survey of Professional Forecasters' forecasts generated by a Dynamic Factor Model. I conclude that macroeconomic volatility, and in particular the volatility around inflation can decrease when agents are provided with and accurately communicated a professional forecast. If however, the forecast dissemination process is muddled, the public forecast has the potential to actually increase economic volatility.

The results highlight the policy importance of providing an accurate public forecasting signal to the private sector. In particular, it is important to minimize the noise around such announcements. This suggests that a policy that attempts to mask potentially inaccurate forecasts through numerous media appearances that disseminate the sound professional forecasts to the public, has the potential to decrease economic volatility. In the future I hope to introduce monetary policy rules that incorporate both private sector expectations and professional forecasts into the interest rate setting rule. The use of such forward looking interest rate rules may yield further declines in economic volatility. Suggesting that professional forecast can be further welfare-improving when the monetary authority knows in what ways they are used by the private sector.

Outside of the rational inattention literature, the expectation formation literature has not fully addressed the ever increasing amount of information and data available to the public at-large. This chapter tries to do just that by incorporating public forecasts generated in a data-rich environment that agents can decide to use or not use depending on their past performance. This chapter tries to take a small but significant step in incorporating a large amount of data series into the expectation formation literature as I only allow agents in the models to use such series indirectly. The exploration of how to incorporate a large amount of different time series into the agents' information set used in constructing expectations about the future should remain an ongoing frontier of macroeconomic research.

APPENDIX A
FIRST ORDER CONDITIONS AND OPTIMIZATION PROBLEMS

A.1 Households and Employment Agencies

Notice that household indexation is dropped because of the existence of state-contingent securities.

- FOC for Consumption

$$b_t(C_t - hC_{t-1})^{-\sigma_c} = P_t\lambda_t = \Lambda_t \tag{A.1}$$

- FOC for Money

$$b_t\left(\frac{M_t}{P_t}\right)^{-1} = \Lambda_t - \beta E_t[\Lambda_{t+1}\pi_{t+1}^{-1}] \tag{A.2}$$

- FOC for Bonds

$$\Lambda_t = \beta R_t E_t[\Lambda_{t+1}\pi_{t+1}^{-1}] \tag{A.3}$$

- Profit maximization problem for the Employment Agency

$$\max_{L_t(j)} \quad W_t\left(\int_0^1 L_t(j)^{\frac{1}{1+\lambda_{w,t}}}\,dj\right)^{1+\lambda_{w,t}} - \int_0^1 W_t(j)L_t(j)dj \tag{A.4}$$

- Zero Profit condition for Employment Agencies

$$W_tL_t = \int_0^1 W_t(j)L_t(j)dj \tag{A.5}$$

- FOC for Wage Maximization Problem

$$\begin{aligned}E_t\sum_{s=1}^{\infty}(\xi_w\beta)^s\Lambda_{t+s}\tilde{L}_{t+s}&\left[(1+\lambda_{w,t+s})\frac{b_{t+s}(L_{t+s})^{\nu_l}}{\Lambda_{t+s}} - \prod_{k=1}^{s}\left(\pi_{t+k-1}^{\iota_w}\pi^{1-\iota_w}\right)W_t^*\right]\\ &+ \Lambda_t\tilde{L}_t\left[(1+\lambda_{w,t})\frac{b_tL_t}{\Lambda_t} - W_t^*\right] = 0\end{aligned} \tag{A.6}$$

- Combining equation (II.2.4) with the zero profit condition (A.5) gives a definition for the aggregate wage:

$$W_t = \left(\int_0^1 W_t(j)^{\frac{1}{\lambda_{w,t}}}\,dj\right)^{\lambda_{w,t}} \tag{A.7}$$

- Using equation (A.7) and dropping the household indexation, the aggregate wage index is governed by:

$$W_t = \left[(1-\xi_w)(W_t^*)^{\frac{1}{\lambda_{w,t}}} + \xi_w \left(\pi_{t-1}^{\iota_w}\pi^{1-\iota_w}W_{t-1}\right)^{\frac{1}{\lambda_{w,t}}}\right]^{\lambda_{w,t}} \tag{A.8}$$

A.2 Final Good Producers and Intermediate Good Producers

- Profit maximization problem for the Final Good Sector

$$\max_{Y_t(i)} \quad P_t \left(\int_0^1 Y_t(i)^{\frac{1}{1+\lambda_{f,t}}}\, dj\right)^{1+\lambda_{f,t}} - \int_0^1 P_t(i)Y_t(i)di \tag{A.9}$$

- Zero Profit condition for the Final Good Sector

$$P_tY_t = \int_0^1 P_t(i)Y_t(i)di \tag{A.10}$$

- Combining equation (II.2.9) with the zero profit condition (A.10) gives a definition for the aggregate price for the composite good:

$$P_t = \left(\int_0^1 P_t(i)^{-\frac{1}{\lambda_{f,t}}}\, dj\right)^{-\lambda_{f,t}} \tag{A.11}$$

- Intermediate Firm Cost Minimization with respect to Labor

$$W_t = (1-\alpha)\varepsilon_t^a K_t(i)^\alpha L_t(i)^{-\alpha} \tag{A.12}$$

- Intermediate Firm Cost Minimization with respect to Capital

$$R_t^k = \alpha\varepsilon_t^a K_t(i)^{\alpha-1} L_t(i)^{1-\alpha} \tag{A.13}$$

- Using ((A.12) & (A.13)) there is a relationship between aggregate labor and capital:

$$K_t = \frac{\alpha}{1-\alpha}\frac{W_t}{R_t^k}L_t \tag{A.14}$$

- Variable Costs and Marginal Costs, where marginal cost uses (A.14)

$$\begin{aligned} VC_t &= \left(W_t + R_t^k \tfrac{K_t(i)}{L_t(i)}\right) L_t(i) \\ VC_t &= \left(W_t + R_t^k \tfrac{K_t(i)}{L_t(i)}\right) \tilde{Y}_t(i)(\varepsilon_t^a)^{-1} \left(\tfrac{K_t(i)}{L_t(i)}\right)^{-\alpha} \end{aligned} \tag{A.15}$$

$$MC_t = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}(W_t)^{1-\alpha}(R_t^k)^\alpha(\varepsilon_t^a)^{-1} \tag{A.16}$$

- FOC for Price Optimization

$$\begin{aligned} E_t \sum_{s=1}^{\infty}(\xi_p\beta)^s \Lambda_{t+s}\tilde{Y}_{t+s}&\left[\prod_{k=1}^{s}\left(\pi_{t+k-1}^{\iota_p}\pi^{1-\iota_p}\right)P_t^* - (1+\lambda_{f,t+s})MC_{t+s}\right] \\ &+ \Lambda_t\tilde{Y}_t\left[P_t^* - (1+\lambda_{f,t})MC_t\right] = 0 \end{aligned} \tag{A.17}$$

- The aggregate price index is governed by:

$$P_t = \left[(1-\xi_p)(P_t^*)^{\frac{1}{\lambda_{f,t}}} + \xi_p \left(\pi_{t-1}^{\iota_p} \pi^{1-\iota_p} P_{t-1}\right)^{\frac{1}{\lambda_{f,t}}} \right]^{\lambda_{f,t}} \tag{A.18}$$

A.3 Capital Producers

- Profit function

$$\Pi_t^k = Q_t(\bar{K}_t - (1-\tau)\bar{K}_{t-1}) - P_t I_t \tag{A.19}$$

- Profit maximization problem for the Capital Producers

$$\max_{I_t} \quad E_t \sum_{s=0}^{\infty} \beta^s \Lambda_{t+s} \left(\frac{Q_{t+s}}{P_{t+s}} \mu_{t+s} \left[1 - S\left(\frac{I_{t+s}}{I_{t+s-1}} \right) \right] I_{t+s} - I_{t+s} \right) \tag{A.20}$$

- Capital Producer's FOC

$$\begin{aligned} \Lambda_t = {} & \frac{\Lambda_t Q_t \mu_t}{P_t} \left[1 - S\left(\frac{I_t}{I_{t-1}} \right) - S'\left(\frac{I_t}{I_{t-1}} \right) \frac{I_t}{I_{t-1}} \right] \\ & + \beta E_t \left[\frac{\Lambda_{t+1} Q_{t+1} \mu_{t+1}}{P_{t+1}} S'\left(\frac{I_{t+1}}{I_t} \right) \left(\frac{I_{t+1}}{I_t} \right)^2 \right] \end{aligned} \tag{A.21}$$

A.4 Entrepreneur and Banking Sector

- FOC of Entrepreneur profit

$$R_t^k = P_t a'(u_t(e)) \tag{A.22}$$

- Definition of utilized capital

$$K_t = u_t \bar{K}_{t-1} \tag{A.23}$$

- Fraction of net capital that banks receives $\Gamma_{t-1}(\bar{w}_t)$

$$\Gamma_{t-1}(\bar{w}_t) = \bar{w}[1 - F_{t-1}(\bar{w}_t)] + G_{t-1}(\bar{w}_t) \tag{A.24}$$

$$G_{t-1}(\bar{w}_t) = \int_0^{\bar{w}_t} w dF_{t-1}(w) \tag{A.25}$$

- Expected entrepreneur profits before the realization of productivity shock

$$\int_{\bar{w}_t(e)}^{\infty} \left[w_t(e) \tilde{R}_t^k Q_{t-1} \bar{K}_{t-1}(e) - R_t^c(e) B_{t-1}^b(e) \right] dF_{t-1}(w_t(e)) \tag{A.26}$$

- Rewriting banks zero profit condition using equations (A.24) and (A.25)

$$[\Gamma_{t-1}(\bar{w}_t(e)) - \mu G_{t-1}(\bar{w}_t(e))] \frac{\tilde{R}_t^k}{R_{t-1}} Q_{t-1} \bar{K}_{t-1}(e) = Q_{t-1} \bar{K}_{t-1}(e) - N_{t-1}(e) \tag{A.27}$$

- Optimal Contract Maximization Problem

$$\max_{\{\bar{w}_t(e),\bar{K}_{t-1}(e)\}} E_{t-1}\Bigg\{[1-\Gamma_{t-1}(\bar{w}_t(e))]\tilde{R}_t^k Q_{t-1}\bar{K}_{t-1}(e)$$
$$+\eta_t\left[[\Gamma_{t-1}(\bar{w}_t(e))-\mu G_{t-1}(\bar{w}_t(e))]\frac{\tilde{R}_t^k}{R_{t-1}}Q_{t-1}\bar{K}_{t-1}(e)-Q_{t-1}\bar{K}_{t-1}(e)-N_{t-1}(e)\right]\Bigg\} \tag{A.28}$$

- FOC for Capital

$$E_{t-1}\left\{[1-\Gamma_{t-1}(\bar{w}_t(e))]\tilde{R}_t^k+\eta_t\left[[\Gamma_{t-1}(\bar{w}_t(e))-\mu G_{t-1}(\bar{w}_t(e))]\frac{\tilde{R}_t^k}{R_{t-1}}-1\right]\right\}=0 \tag{A.29}$$

- FOC for $\bar{w}_t$

$$\eta_t=\frac{\Gamma'_{t-1}(\bar{w}_t(e))}{\Gamma'_{t-1}(\bar{w}_t(e))-\mu G'_{t-1}(\bar{w}_t(e))}R_{t-1} \tag{A.30}$$

- Combining FOC's

$$E_{t-1}\Bigg\{[1-\Gamma_{t-1}(\bar{w}_t)]\frac{\tilde{R}_t^k}{R_{t-1}}+\frac{\Gamma'_{t-1}(\bar{w}_t)}{\Gamma'_{t-1}(\bar{w}_t)-\mu G'_{t-1}(\bar{w}_t)}$$
$$\times\left[[\Gamma_{t-1}(\bar{w}_t)-\mu G_{t-1}(\bar{w}_t)]\frac{\tilde{R}_t^k}{R_{t-1}}-1\right]\Bigg\}=0 \tag{A.31}$$

  and dropping indexation because equations (A.22), (A.29) & (A.30) only depend on aggregate variables

- Definition of Transfer Payments to the Household

$$Trans_t=(1-\gamma)V_t-W_t^e \tag{A.32}$$

- Credit Market Clearing Equilibrium

$$D_t=B_t=B_t^b=Q_t\bar{K}_t-N_t \tag{A.33}$$

A.5 SW Model

- FOC for Capital

$$\Lambda_t q_t=\beta E_t[\Lambda_{t+1}\left(r_{t+1}^k-a(u_{t+1})+(1-\tau)q_{t+1}\right)] \tag{A.34}$$

A.6 Log Linearizations

$$w_t=\frac{W_t}{P_t},\quad r_t^k=\frac{R_t^k}{P_t},\quad m_t=\frac{M_t}{P_t},\quad p_t^*=\frac{P_t^*}{P_t},\quad w_t^*=\frac{W_t^*}{P_t}\quad mc_t=\frac{MC_t}{P_t}\quad q_t=\frac{Q_t}{P_t}$$
$$n_t=\frac{N_t}{P_t},\quad v_t=\frac{V_t}{P_t},\quad w_t^e=\frac{W_t^e}{P_t}$$

- Capital Accumulation (II.2.25)
  Equation (II.2.14) delivers the steady state relationship $I/K = \tau$ and results in

$$\hat{\bar{K}}_t = (1-\tau)\hat{\bar{K}}_{t-1} + \tau\hat{I}_t + \tau\hat{\mu}_t \tag{A.35}$$

  where using (A.73) results in equation (II.2.25)

- Labor Demand (II.2.26)
  Linearizing equations (A.14), (A.22) & (A.23) results in

$$\hat{K}_t = w_t - \hat{r}_t^k + \hat{L}_t \tag{A.36}$$

$$\hat{K}_t = \hat{u}_t + \hat{\bar{K}}_{t-1} \tag{A.37}$$

$$r^k\hat{r}_t^k = a''(u)\hat{u}_t \tag{A.38}$$

$$\implies \hat{K}_t = \frac{r^k}{a''(u)}\hat{r}_t^k + \hat{\bar{K}}_{t-1} \tag{A.39}$$

  where substitution and using (A.74) results in equation (II.2.26)

- Resource Contraint (II.2.27)
  Taking the household's budget constraint and subbing in the Government's budget constraint yields:

$$C_t + D_t + G_t = R_{t-1}^d D_{t-1} + w_t L_t + \Pi_t + Trans_t$$

  Using the definition of firms' profits $\Pi_t = Y_t - w_t L_t - r_t^k \bar{K}_{t-1}$ and equation (A.32)

$$C_t + D_t + G_t - R_{t-1}^d D_{t-1} + r_t^k u_t \bar{K}_{t-1} - ((1-\gamma)v_t - w_t^e) = Y_t$$

  Substituting the credit clearing condition (A.33), the definition of net worth yields (II.2.22) & (II.2.15) yields

$$C_t + G_t + q_t\bar{K}_t - v_t - R_{t-1}^d D_{t-1} + r_t^k u_t \bar{K}_{t-1} = Y_t$$

  Substituting (II.2.19) into the zero profit equation (II.2.20) and (A.26) for v_t yields

$$C_t + G_t + q_t\bar{K}_t - \tilde{R}_t^k q_{t-1}\bar{K}_{t-1} + \mathcal{M}_t + r_t^k u_t \bar{K}_{t-1} = Y_t$$

  Using equation (II.2.18) and the fact that $q_t\bar{K}_t - q_t(1-\tau)\bar{K}_{t-1} = I_t$ yields the resource constraint:

$$C_t + G_t + I_t + a(u_t)\bar{K}_{t-1} + \mathcal{M}_t = Y_t$$

  Log linearizing and using (A.75) results in equation (II.2.27)

- Production Function (II.2.28)
  Log Linearizing equation (II.2.10), substituting in (A.39) yields

$$\hat{Y}_t = \frac{y+f}{y}\hat{\varepsilon}_t^a + \frac{y+f}{y}\alpha\hat{\bar{K}}_{t-1} + \frac{y+f}{y}\frac{r^k}{a''(u)}\alpha\hat{r}_t^k + \frac{y+f}{y}(1-\alpha)\hat{L}_t \tag{A.40}$$

  using (A.74) & (A.76) and results in equation (II.2.28)

- Taylor Rule (II.2.29)
  Taking the log of (II.2.23) results in equation (II.2.29)

- Consumption Transition (II.2.30)
  Linearizing (A.1) and (A.3):

$$\hat{b}_t - \frac{\sigma_c}{1-h}\hat{C}_t + \frac{h\sigma_c}{1-h}\hat{C}_{t-1} = \hat{\Lambda}_t \tag{A.41}$$

$$\hat{\Lambda}_t = \hat{R}_t + E_t[\hat{\Lambda}_{t+1}] - E_t[\hat{\pi}_{t+1}] \tag{A.42}$$

  Taking the expectation of equation (A.41) yields:

$$E_t[\hat{\Lambda}_{t+1}] = \rho_b\hat{b}_t - \frac{\sigma_c}{1-h}E_t[\hat{C}_{t+1}] + \frac{h\sigma_c}{1-h}\hat{C}_t \tag{A.43}$$

  Subbing (A.42) and (A.43) into (A.41) and using (A.77) results in equation (II.2.30)

- Investment Transition (II.2.31)
  Equation (II.2.31) results from log-linearizing equation (A.21) abiding by the definition $S'(1) = 0$ and (A.73)

- Entrepreneur Return on Capital (II.2.32)
  Putting entrepreneurial return on capital (II.2.18) into real terms

$$\tilde{R}_t^k = \frac{r_t^k u_t + (1-\tau)q_t - a(u_t)}{q_{t-1}}\pi_t \tag{A.44}$$

  Equation (A.44) yields the steady state identity (where $q = 1$ and a(u)=0)

$$\tilde{R}^k = (r^k + (1-\tau))\pi \tag{A.45}$$

  Log Linearizing (A.44) and using (A.45) results in (II.2.32)

- New Keynesian Philips Curve (II.2.33)
  The Philips curve is derived from the following 3 equations:

$$mc_t = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}(w_t)^{1-\alpha}(r_t^k)^{\alpha}(\varepsilon_t^a)^{-1} \tag{A.46}$$

$$1 = \left[(1-\xi_p)(p_t^*)^{\frac{1}{\lambda_{f,t}}} + \xi_p\left(\pi_{t-1}^{\iota_p}\pi^{1-\iota_p}\pi_t^{-1}\right)^{\frac{1}{\lambda_{f,t}}}\right]^{\lambda_{f,t}} \tag{A.47}$$

$$E_t\sum_{s=0}^{\infty}(\xi_p\beta)^s\Lambda_{t+s}\tilde{Y}_{t+s}\left[\prod_{k=1}^{s}\left(\left(\frac{\pi_{t+k-1}}{\pi}\right)^{\iota_p}\left(\frac{\pi_{t+k}}{\pi}\right)^{-1}\right)p_t^* - (1+\lambda_{f,t+s})mc_{t+s}\right] = 0 \tag{A.48}$$

  Log-linearizing the above equations results in

$$\hat{mc}_t = (1-\alpha)\hat{w}_t + \alpha\hat{r}_t^k - \hat{\varepsilon}_t^a \tag{A.49}$$

$$\hat{p}_t^* = \frac{\xi_p}{1-\xi_p}(\hat{\pi}_t - \iota_p\hat{\pi}_{t-1}) \tag{A.50}$$

$$E_t\sum_{s=0}^{\infty}(\xi_p\beta)^s\left[\hat{p}_t^* + \hat{\Pi}_{t,t+s} - \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t+s} - \hat{mc}_{t+s}\right] = 0 \tag{A.51}$$

$$\hat{\Pi}_{t,t+s} = \sum_{k=1}^{s}\iota_p\hat{\pi}_{t+k-1} - \hat{\pi}_{t+k} \quad \text{when } s=0,\ \hat{\Pi}_{t,t+s} = 0 \tag{A.52}$$

Solving for $\hat{p}_t^*$ and eliminating the summation of (A.51)

$$\frac{1}{1-\xi_p\beta}\hat{p}_t^* = \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t} + \hat{mc}_{t+s} - \frac{\xi_p\beta}{1-\xi_p\beta}\hat{\Pi}_{t,t+1}$$

$$+ \xi_p\beta E_t\sum_{s=1}^{\infty}(\xi_p\beta)^{s-1}\left[-\hat{\Pi}_{t+1,t+s} + \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t+s} + \hat{mc}_{t+s}\right]$$

$$\frac{1}{1-\xi_p\beta}E_t\hat{p}_{t+1}^* = E_t\sum_{s=0}^{\infty}(\xi_p\beta)^s\left[-\hat{\Pi}_{t+1,t+1+s} + \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t+1+s} + \hat{mc}_{t+1+s}\right]$$

These equations imply

$$\frac{1}{1-\xi_p\beta}\hat{p}_t^* = \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t} + \hat{mc}_{t+s} + \frac{\xi_p\beta}{1-\xi_p\beta}E_t\left[\hat{p}_{t+1}^* - \hat{\Pi}_{t,t+1}\right]$$

Plugging in the forward expectations from equations (A.50) and (A.52)

$$\frac{1}{1-\xi_p\beta}\hat{p}_t^* = \frac{\lambda_f}{1+\lambda_f}\hat{\lambda}_{f,t} + \hat{mc}_{t+s} + \frac{(\xi_p\beta)}{(1-\xi_p\beta)(1-\xi_p)}E_t\left[\hat{\pi}_{t+1}\right] - \frac{(\xi_p\beta)}{(1-\xi_p)(1-\xi_p\beta)}\iota_p\hat{\pi}_t$$

Substituting (A.50) and (A.49) into the above equation solving for $\hat{\pi}_t$ and using (A.78) results in (II.2.33)

- New Keynesian Wage Philips Curve (II.2.34)
  The Wage Philips curve is derived from the following 4 equations:

$$b_t(C_t - hC_{t-1})^{-\sigma_c} = \Lambda_t \tag{A.53}$$

$$w_t = \left[(1-\xi_w)(w_t^*)^{\frac{1}{\lambda_{w,t}}} + \xi_w\left(\pi_{t-1}^{\iota_w}\pi^{1-\iota_w}\pi_t^{-1}w_{t-1}\right)^{\frac{1}{\lambda_{w,t}}}\right]^{\lambda_{w,t}} \tag{A.54}$$

(A.55)

$$E_t\sum_{s=0}^{\infty}(\xi_w\beta)^s\Lambda_{t+s}\tilde{L}_{t+s}\left[(1+\lambda_{w,t+s})\frac{b_{t+s}(L_{t+s})^{\nu_l}}{\Lambda_{t+s}} - \prod_{k=1}^{s}\left(\left(\frac{\pi_{t+k-1}}{\pi}\right)^{\iota_w}\left(\frac{\pi_{t+k}}{\pi}\right)^{-1}\right)w_t^*\right] = 0 \tag{A.56}$$

$$\tilde{L}_{t+s} = \left(\frac{\prod_{k=1}^{s}\left(\left(\frac{\pi_{t+k-1}}{\pi}\right)^{\iota_w}\left(\frac{\pi_{t+k}}{\pi}\right)^{-1}\right)w_{t+s}^*}{w_t}\right)^{-\frac{1+\lambda_{w,t+s}}{\lambda_{w,t+s}}} L_{t+s} \tag{A.57}$$

Log-linearizing the above equations results in

$$\hat{b}_t - \frac{\sigma_c}{1-h}\hat{C}_t + \frac{h\sigma_c}{1-h}\hat{C}_{t-1} = \hat{\Lambda}_t \tag{A.58}$$

$$\hat{w}^*_t = \frac{\xi_w}{1-\xi_w}(\hat{w}_t - \hat{w}_{t-1} + \hat{\pi}_t - \iota_p\hat{\pi}_{t-1}) \tag{A.59}$$

$$E_t\sum_{s=0}^{\infty}(\xi_p\beta)^s\left[\hat{w}^*_t + \hat{\Pi}^w_{t,t+s} - \frac{\lambda_w}{1+\lambda_w}\hat{\lambda}_{w,t+s} - \hat{b}_{t+s} - \nu_l\hat{\hat{L}}_{t+s} + \hat{\Lambda}_{t+s}\right] = 0 \tag{A.60}$$

$$\hat{\Pi}^w_{t,t+s} = \sum_{k=1}^{s}\iota_w\hat{\pi}_{t+k-1} - \hat{\pi}_{t+k} \quad \text{when } s=0,\ \hat{\Pi}^w_{t,t+s} = 0 \tag{A.61}$$

$$\hat{\hat{L}}_{t+s} = \hat{L}_{t+s} - \left(\tfrac{1+\lambda_w}{\lambda_w}\right)(\hat{w}^*_t + \hat{\Pi}^w_{t+s} - \hat{w}_{t+s}) \tag{A.62}$$

By plugging in the definition of marginal utility (A.58) and labor demand (A.62) into the wage setting FOC (A.60) and then using this equation with equations (A.59) and (A.79) one can obtain equation (II.2.34)

- Spread between the return on capital and the risk free rate (II.2.35)
  Linearizing the combined FOC of the optimal contract (A.31) and the banks' zero profit condition (A.27)

$$E_t\left[\hat{\tilde{R}}^k_{t+1} - \hat{R}_t\right] + \delta_{b,w}E_t[\hat{\bar{w}}_{t+1}] + \delta_{b,\sigma_w}\hat{\sigma}_{w,t} = 0 \tag{A.63}$$

$$\hat{\tilde{R}}^k_t - \hat{R}_{t-1} + \delta_{z,w}\hat{\bar{w}}_t + \delta_{z,\sigma_w}\hat{\sigma}_{w,t-1} = \frac{N}{K-N}(\hat{q}_{t-1} + \hat{\bar{K}}_{t-1} - \hat{n}_{t-1}) \tag{A.64}$$

  Solving the latter equation for $\hat{\bar{w}}_t$ and taking the forwarded expectation and plugging it into (A.63) and using (A.80) one obtains (II.2.35). Here the δ coefficients are functions of the steady state variables of the finance sector.

- Evolution of Aggregate Net Worth (II.2.36)
  Log-linearizing the evolution of equity (II.2.21) and plugging it into the log-linearized version of equation (II.2.22) one can obtain (II.2.36) where once again the δ coefficients are functions of the steady state variables in the finance sector.

- SW Model-Equity price evolution (II.2.38)
  Log Linearizing the FOC of capital (A.34) and minding the steady state relationships (A.70), (A.71), (A.72) yields:

$$\hat{q}_t + (\hat{\Lambda}_t - E_t[\hat{\Lambda}_{t+1}]) = \frac{1-\tau}{1-\tau+r^k}E_t[\hat{q}_{t+1}] + \frac{r^k}{1-\tau+r^k}E_t[\hat{r}^k_{t+1}] \tag{A.65}$$

  Subbing in equation (A.42) into the above equation and adding the equity price shock results in (II.2.38)

- Important Steady State Relationships SWFF Model

$$R = \beta^{-1} \tag{A.66}$$

$$r^k = SR - (1-\tau) \tag{A.67}$$

$$\tilde{R}^k R^{-1} = S \tag{A.68}$$

$$a'(u) = r^k \tag{A.69}$$

- Important Steady State Relationships SW Model

$$R = \beta^{-1} \tag{A.70}$$

$$r^k = \beta^{-1} - (1 - \tau) \tag{A.71}$$

$$a'(u) = r^k \tag{A.72}$$

- **Normalizations**

$$\hat{\varepsilon}_t^I = \frac{1}{(1+\beta)S''}\hat{\mu}_t \tag{A.73}$$

$$\psi = \left(\frac{r^k}{a''(u)}\right)^{-1} \tag{A.74}$$

$$\hat{\varepsilon}_t^G = \frac{G}{Y}\epsilon_t^G \tag{A.75}$$

$$\phi = \frac{y + f}{y} \tag{A.76}$$

$$\hat{\varepsilon}_t^b = \frac{(1-h)(1-\rho_b)}{(1+h)\sigma_c}\hat{b}_t \tag{A.77}$$

$$\hat{\varepsilon}_t^P = \frac{(1-\xi_p)(1-\xi_p\beta)\lambda_f}{\xi_p(1+\beta\iota_p)(1+\lambda_f)}\hat{\lambda}_{f,t} \tag{A.78}$$

$$\hat{\varepsilon}_t^W = \frac{(1-\xi_w)(1-\xi_w\beta)\lambda_w}{(1+\beta)\xi_p(1+\nu_l\frac{1+\lambda_w}{\lambda_w})(1+\lambda_w)}\hat{\lambda}_{w,t} \tag{A.79}$$

$$\hat{\varepsilon}_t^F = \frac{\frac{\delta_{b,w}}{\delta_{z,w}}\delta_{z,\sigma_w} - \delta_{b,\sigma_w}}{1 - \frac{\delta_{b,w}}{\delta_{z,w}}}\hat{\sigma}_{w,t} \tag{A.80}$$

APPENDIX B

DATA AND TRANSFORMATION FOR CHAPTER II

	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 Hours				
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 Rate 3 month	
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 Tbill	✓
17	SFYAAAC	AAA-GS10	0	Spread of AAA corporate yield to 10 year Tbill	
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 Tbill to 3 month Tbill
59	SFYGT10	GS10-TB3MS	0	Spread of 10 year Tbill to 3month 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
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	DNDGRA3Q086SBEA	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 Reg Estimation

The measurement equation (II.3.2) 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

DATA AND TRANSFORMATION FOR CHAPTER IV

	Kryshko Shorthand	FRED Code	Trans*	Long Description	Used in Reg Estimation
Used in Estimation					
	Measureables				
1	RGDP	GDPC1	2	Real GDP	✓
2	PGDP	GDPDEF	7	GDP Price deflator	✓
3	RCONS	PCECC96	2	Real Personal Consumption Expenditures	✓
4	RINV	GDPI	2	Real Private Domestic Investment	✓
5	RWAGE	AHETPI	4	Real Average Hourly wages:production:total private	✓
6	HOURS	HOANBS	2	Hours Worked (adjusted by multipling index by CE160V)	✓
7	FedFunds	FEDFUNDS	0	Federal Funds Rate (effective)	✓
8	SFYBAAC	BAA-GS10	6	Spread of BAA corporate yield to 10 year Tbill	✓
Used in DFM					
	Core Variables				
1	RWAGE	AHETPI	4	Real Average Hourly wages:production:total private	
2	PGDP	GDPDEF	3	GDP Price deflator	
3	RCONS	PCECC96	2	Real Personal Consumption Expenditures	
4	RINV	GDPI	2	Real Private Domestic Investment	
5	HOURS	HOANBS	2	Hours Worked (adjusted by multipling index by CE160V)	
6	FedFunds	FEDFUNDS	0	Federal Funds Rate (effective)	
7	SFYBAAC	BAA-GS10	0	Spread of BAA corporate yield to 10 year Tbill	
8	RGDP	GDPC1	2	Real GDP	
9	RGDI	A261RX1Q020SBEA	2	Real Domestic Income	
10	PCED	PCECTPI	3	PCE_ALL Price deflator	
11	CPI_ALL	CPIAUCSL	3	CPI_ALL Price index	
12	EMP_CES	PAYEMS+USGOVT	2	Employees:Total Nonfarm	
13	EMP_CPS	CE160V	2	Civilian Labor Force:Employed, Total	
14	Tbill_3m	TB3MS	0	Interest Rate U.S. Treasury Rate 3 month	
15	AAABond	AAA	0	Bond Yield: Moody's AAA corporate	
16	SFYAAAC	AAA-GS10	0	Spread of AAA corporate yield to 10 year Tbill	
17	IP_TOTAL	INDPRO	2	Industrial Production Index:total	
	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 Tbill to 3 month Tbill
59	SFYGT10	GS10-TB3MS	0	Spread of 10 year Tbill to 3month 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	EXR_US	TWEXMMTH	3	Trade Weighted U.S. Dollar Index: Major Currencies
65	EXR_SW	EXSZUS	3	Switzerland / U.S. Foreign Exchange Rate
66	EXR_JAN	EXJPUS	3	Japan / U.S. Foreign Exchange Rate
67	EXR_UK	EXUSUK	3	U.S. / U.K. Foreign Exchange Rate
68	EXR_CAN	EXCAUS	3	Canada / U.S. Foreign Exchange Rate
69	SP500	SP500	3	S&P 500 Stock Price Index
70	DJIA	DJIA	3	Dow Jones Industrial Average
	Investment			
71	NAPMI	NAPM	0	Purchasing Managers Index
72	NAPM_NEW_ORDERS	NAPMNOI	0	NAPM New Orders Index
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	DNDGRA3Q086SBEA	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
98	Q		HP	Value of Stocks/Corporate Net Worth

*Transformation codes are described in the data transformation ruberic

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
6	SFYBAAC-Steady State level of spread
7	Log() differenced-Steady State level of inflation

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

APPENDIX D
TABLES & FIGURES

Table 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 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 3: Priors for DSGE-DFM Γ Parameters

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

Note: The diagonal coefficients of the Ψ matrix are truncated to values inside the unit circle. The priors of the Λ elements whose rows correspond to the core data sets are explained in the data section of the paper. The diagonal element of R that corresponds to the Federal Funds rate is truncated to values less than 0.05

Table 4: 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

Table 5: 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

Figure 1: Economic Agents and Interactions

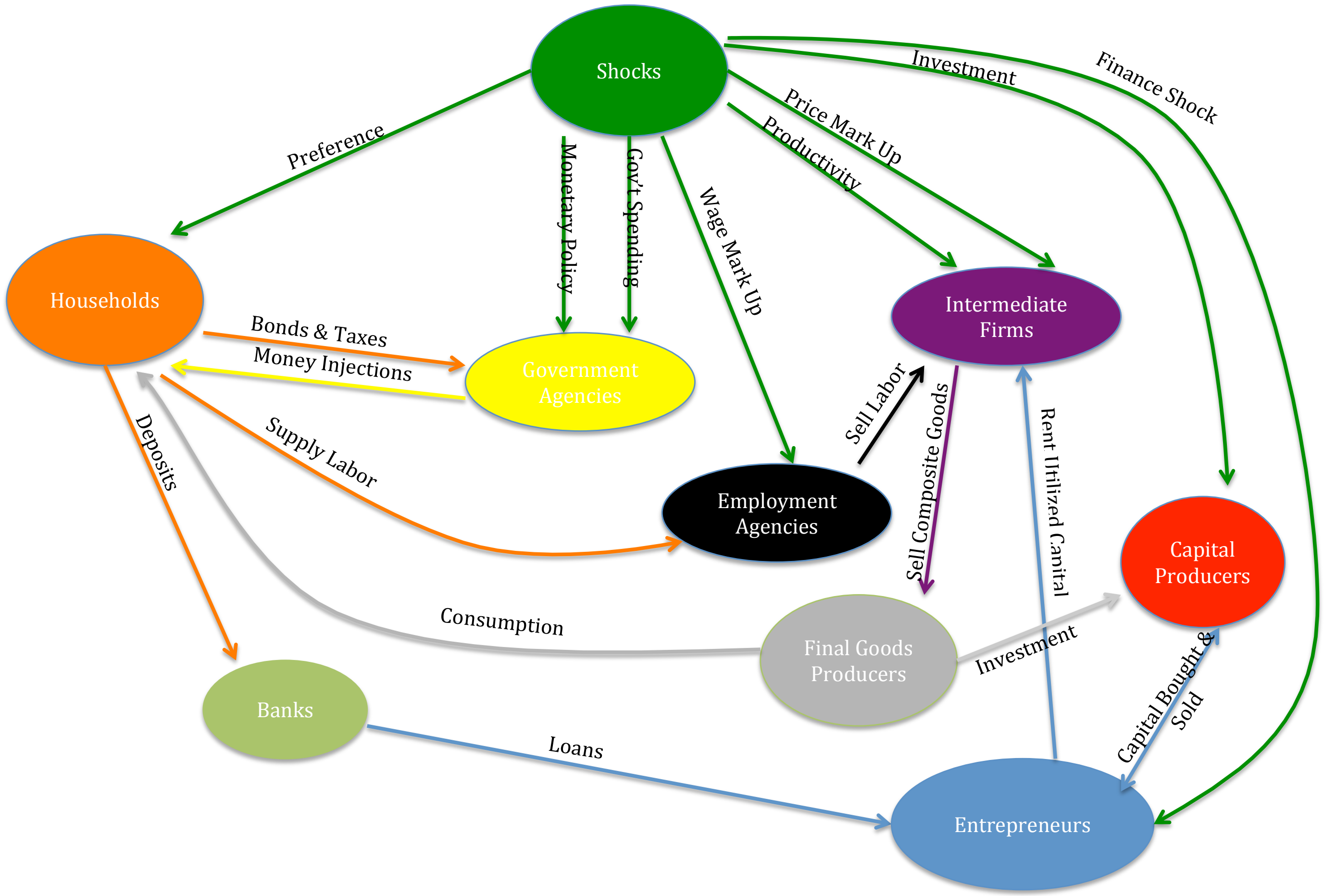


Figure 2: Sequence of Events between Agents in the Finance and Capital Sector of the Economy

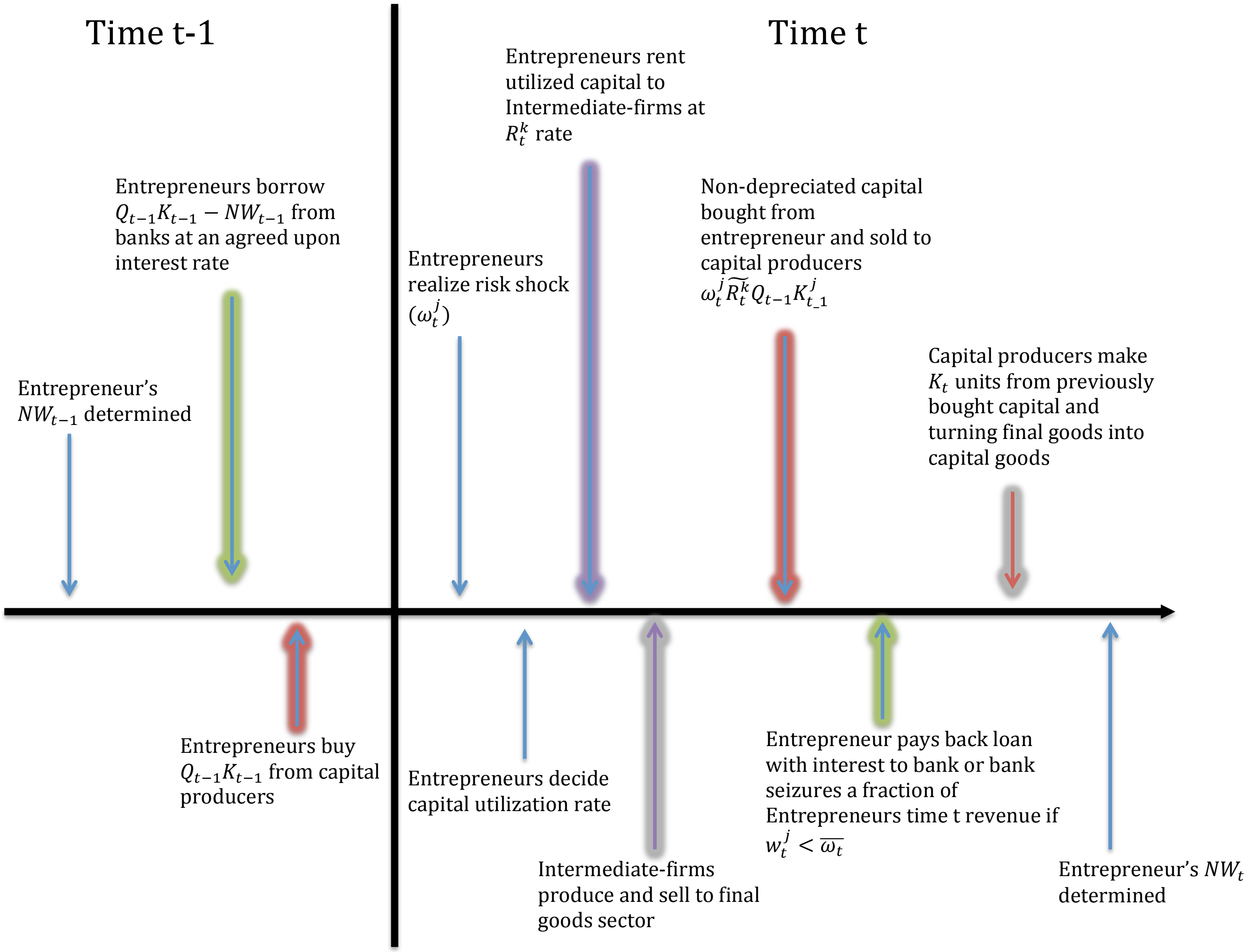


Figure 3: Posterior Distribution Estimates of Structural Parameters in SWFF

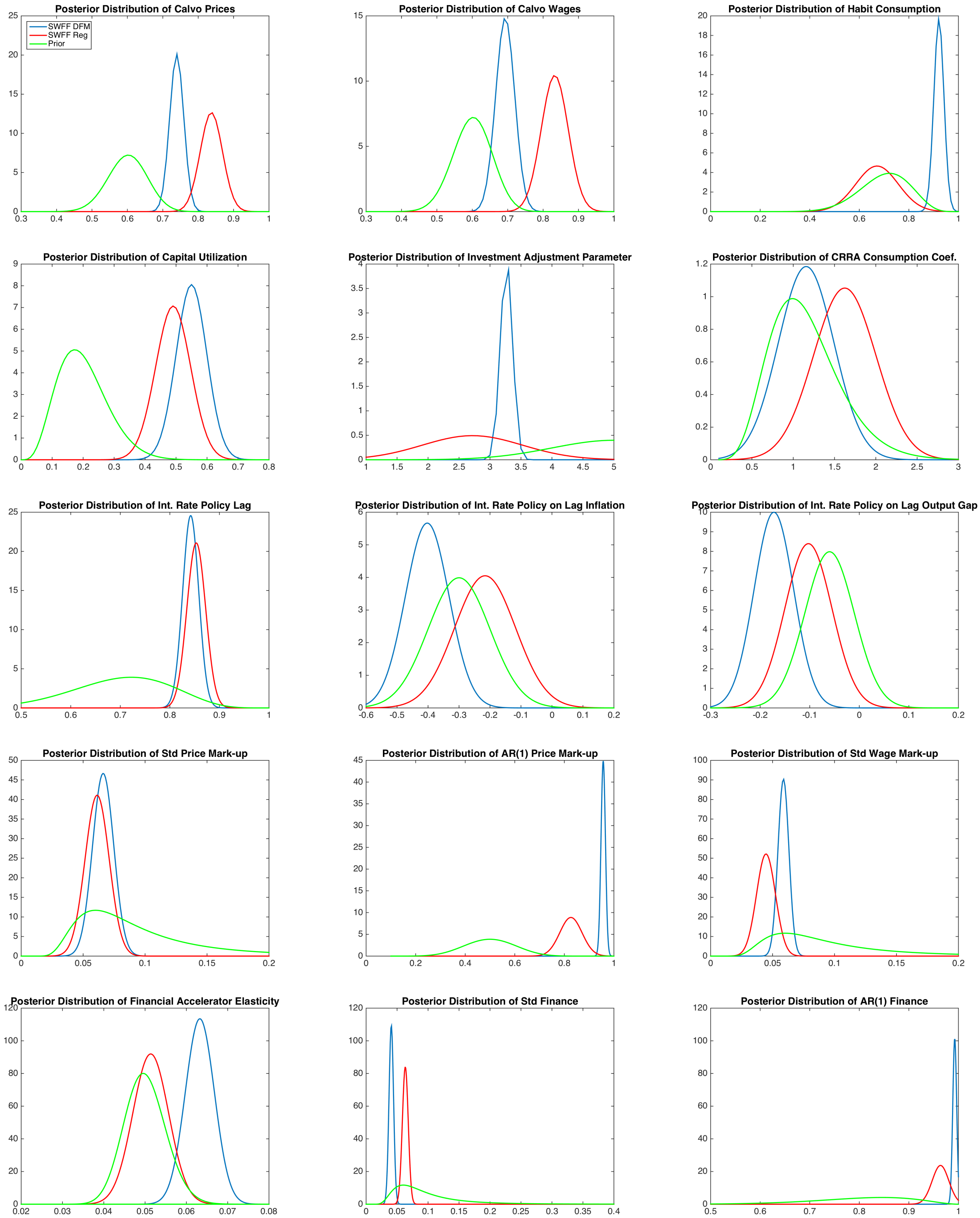
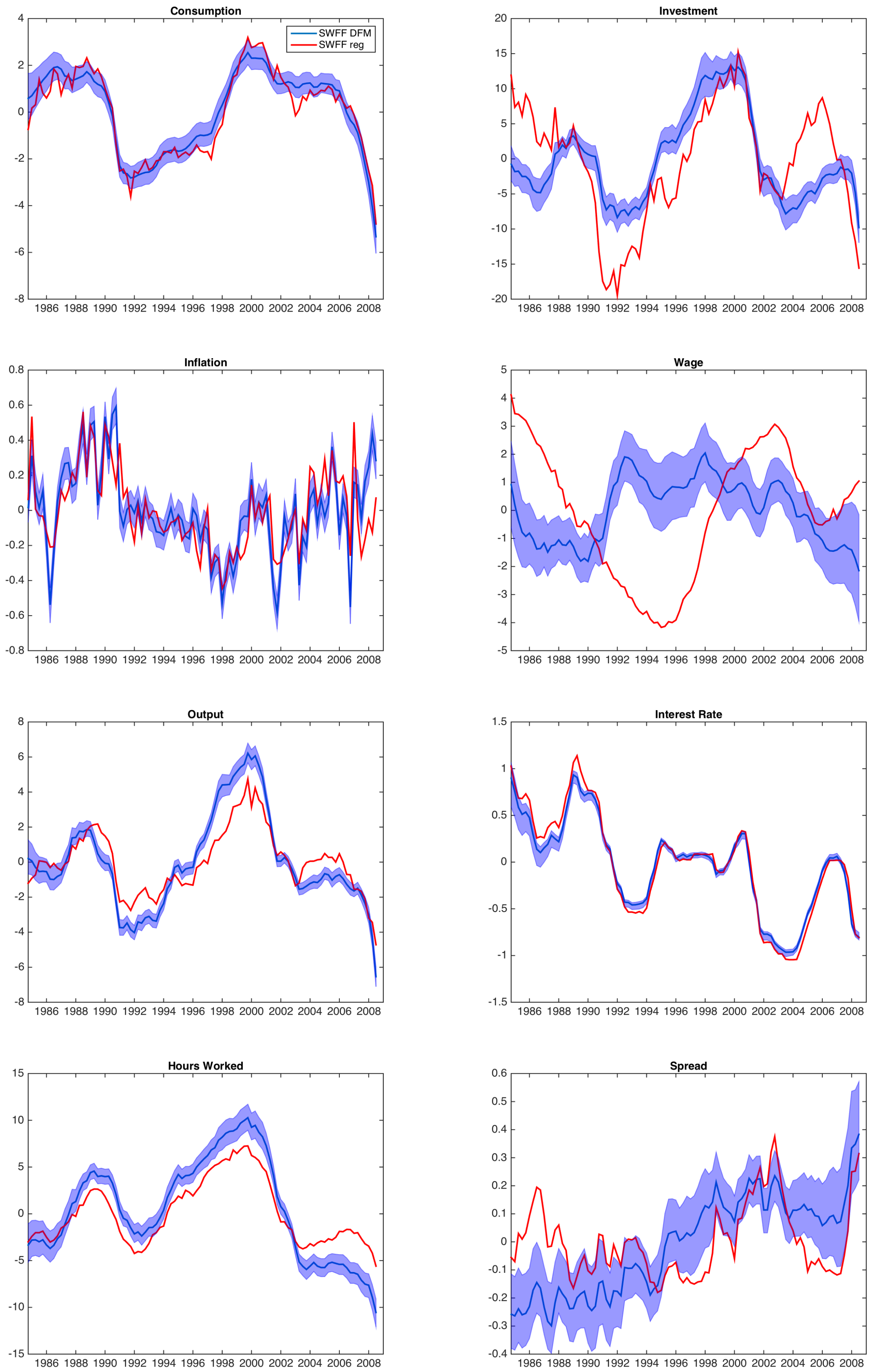
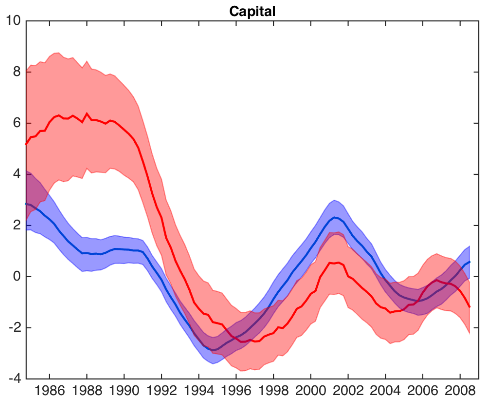
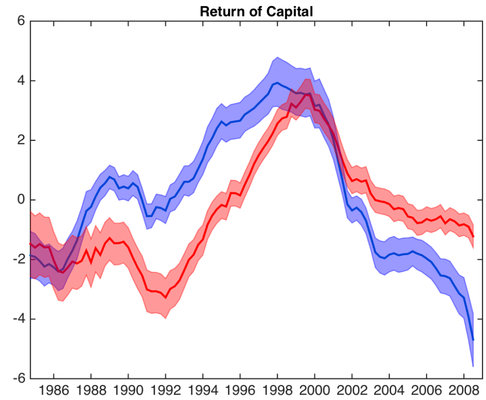
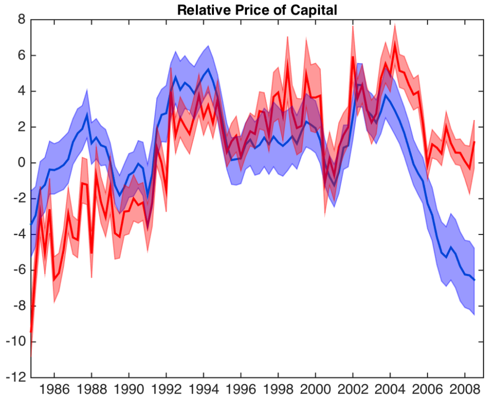


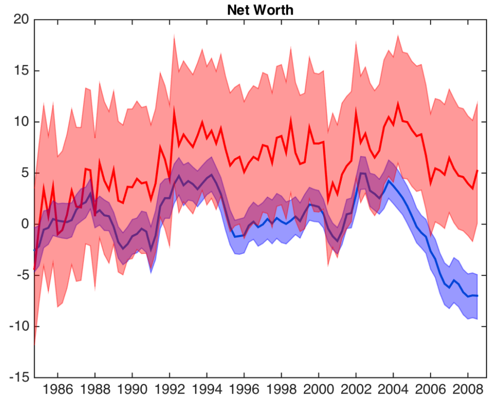
Figure 4: Simulated States of Endogenous Variables of SWFF




Capital
10
8
6
4
2
0
-2
-4
1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008


Return of Capital
6
4
2
0
-2
-4
-6
1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008


Relative Price of Capital
8
6
4
2
0
-2
-4
-6
-8
-10
-12
1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008


Net Worth
20
15
10
5
0
-5
-10
-15
1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008

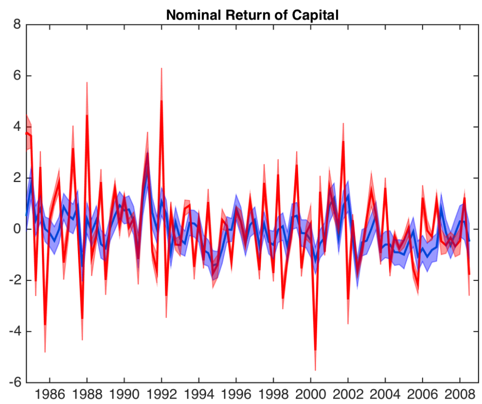

Nominal Return of Capital
8
6
4
2
0
-2
-4
-6
1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008

Figure 5: Simulated States of Exogenous Processes of SWFF

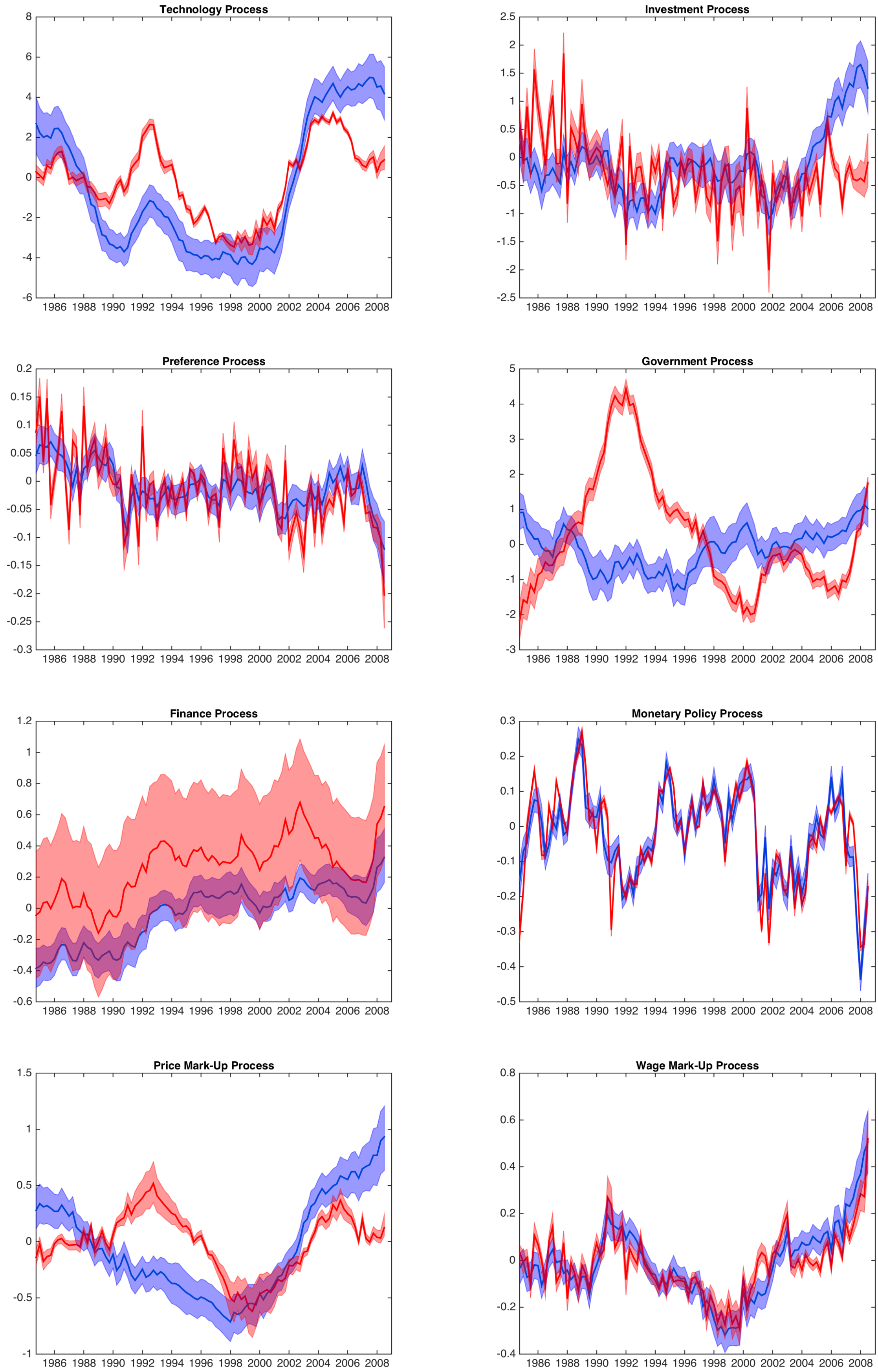


Figure 6: IRF's of Negative Finance Shock

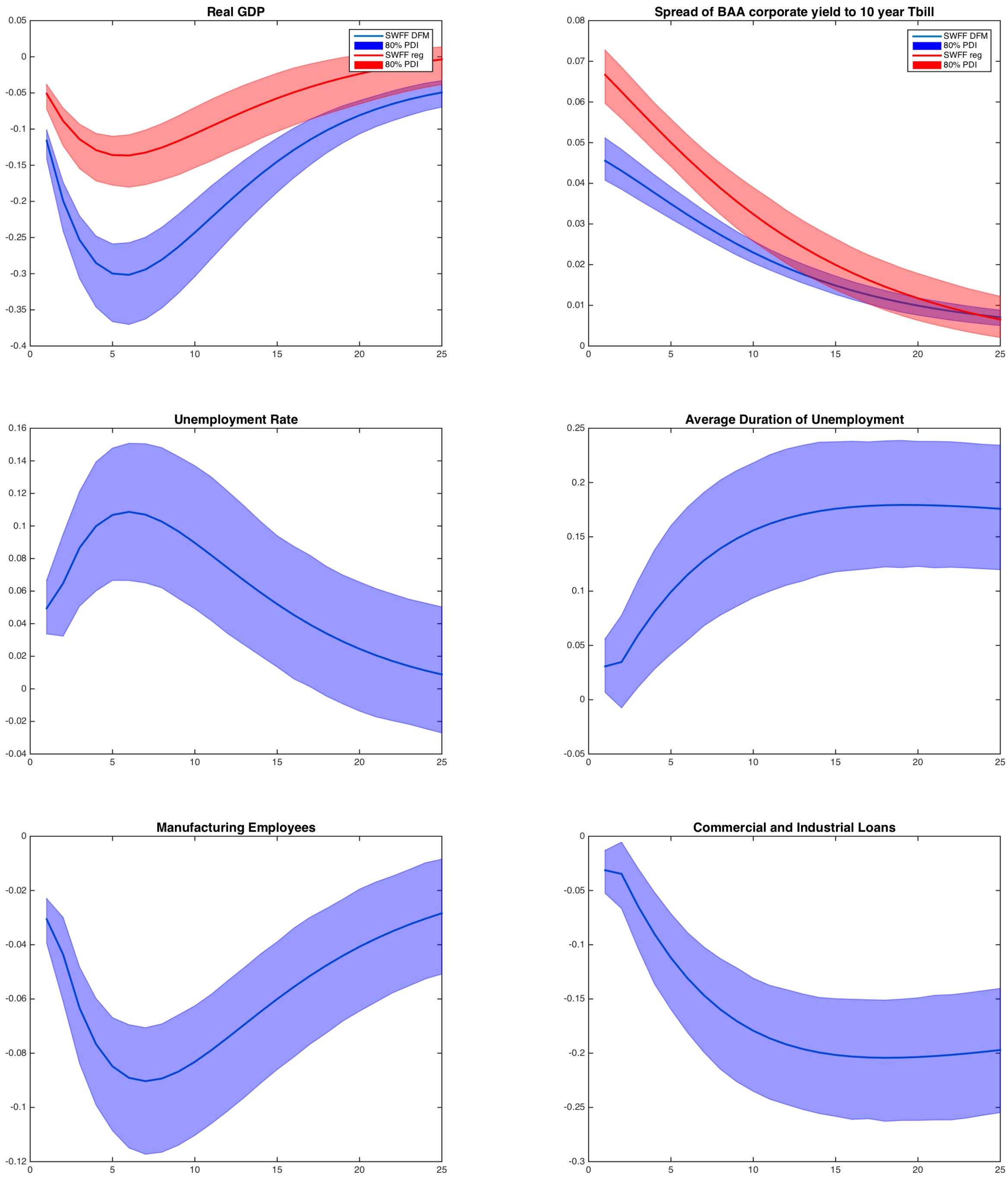


Figure 7: IRF's of Negative Productivity Shock

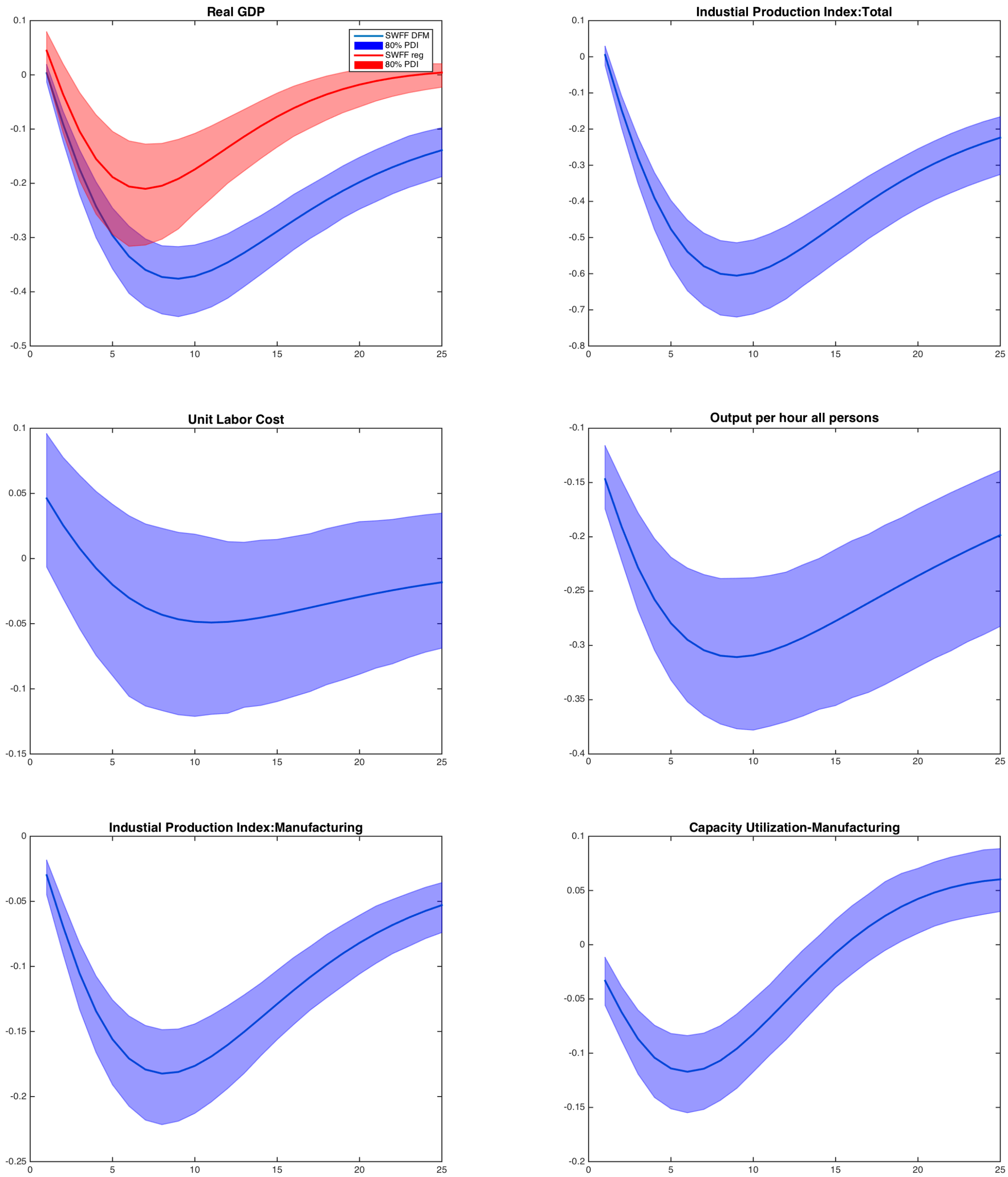


Figure 8: IRF's of Negative Investment Shock

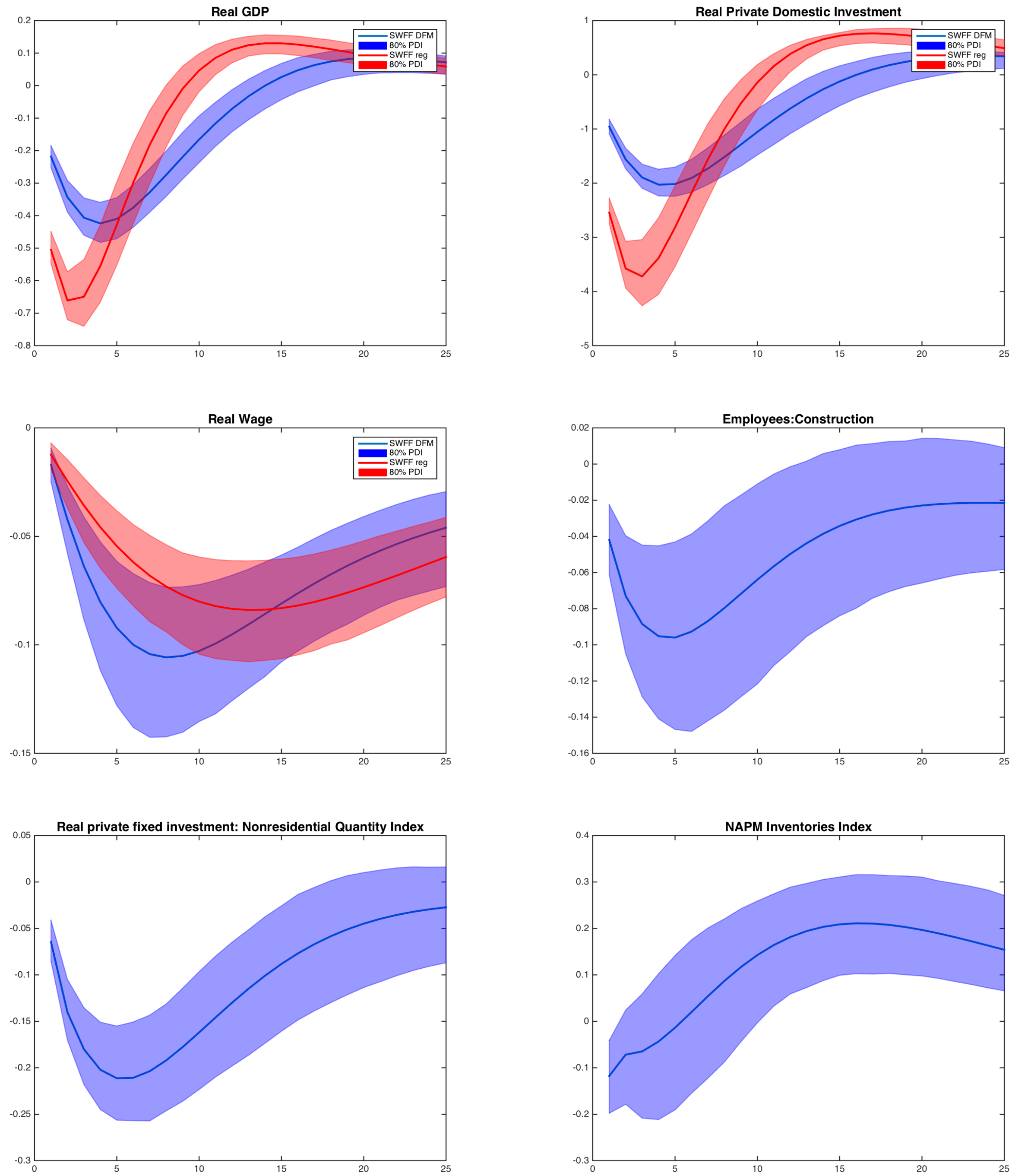


Figure 9: IRF's of Negative Preference Shock

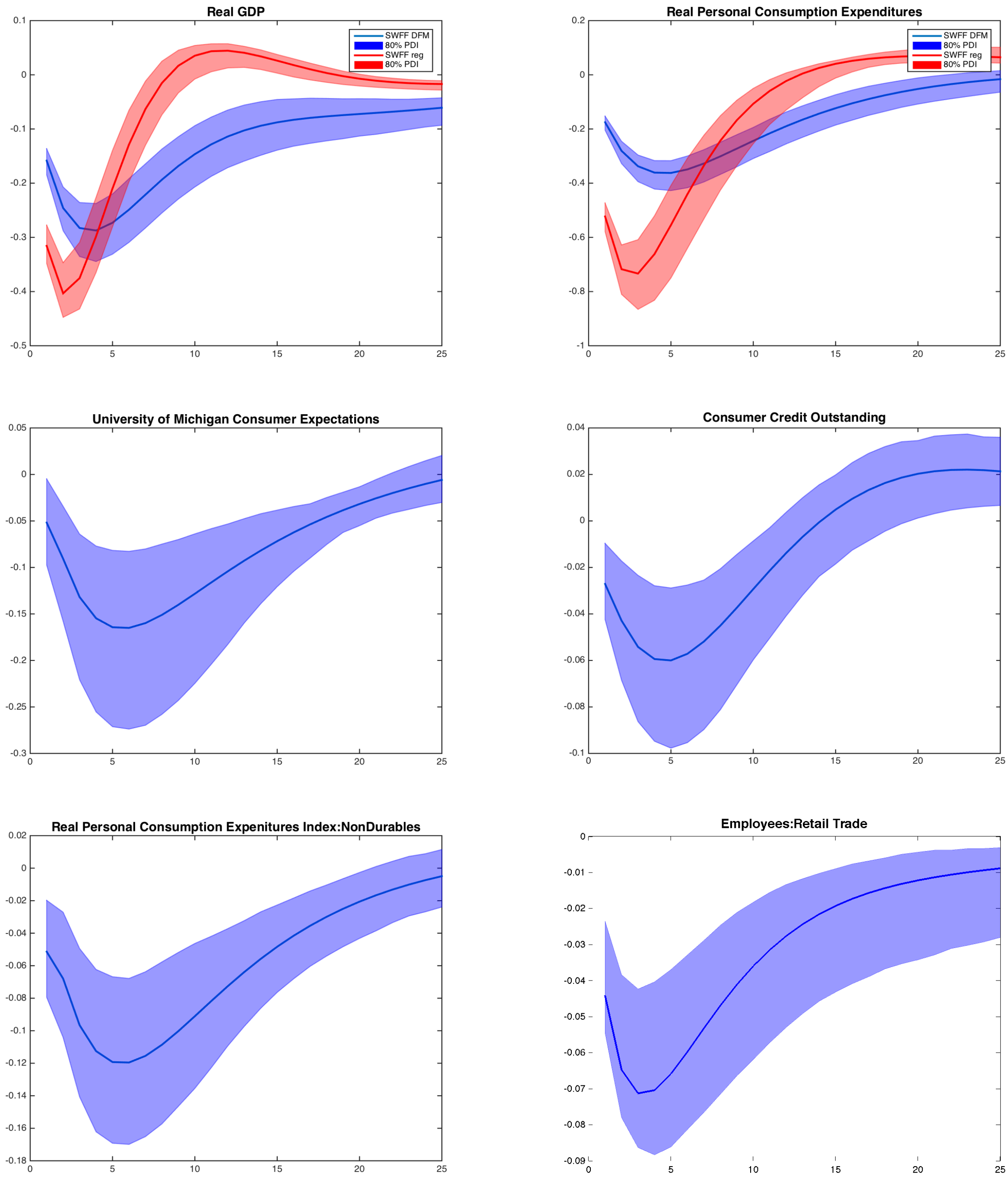


Figure 10: Comparing Normalized IRF's

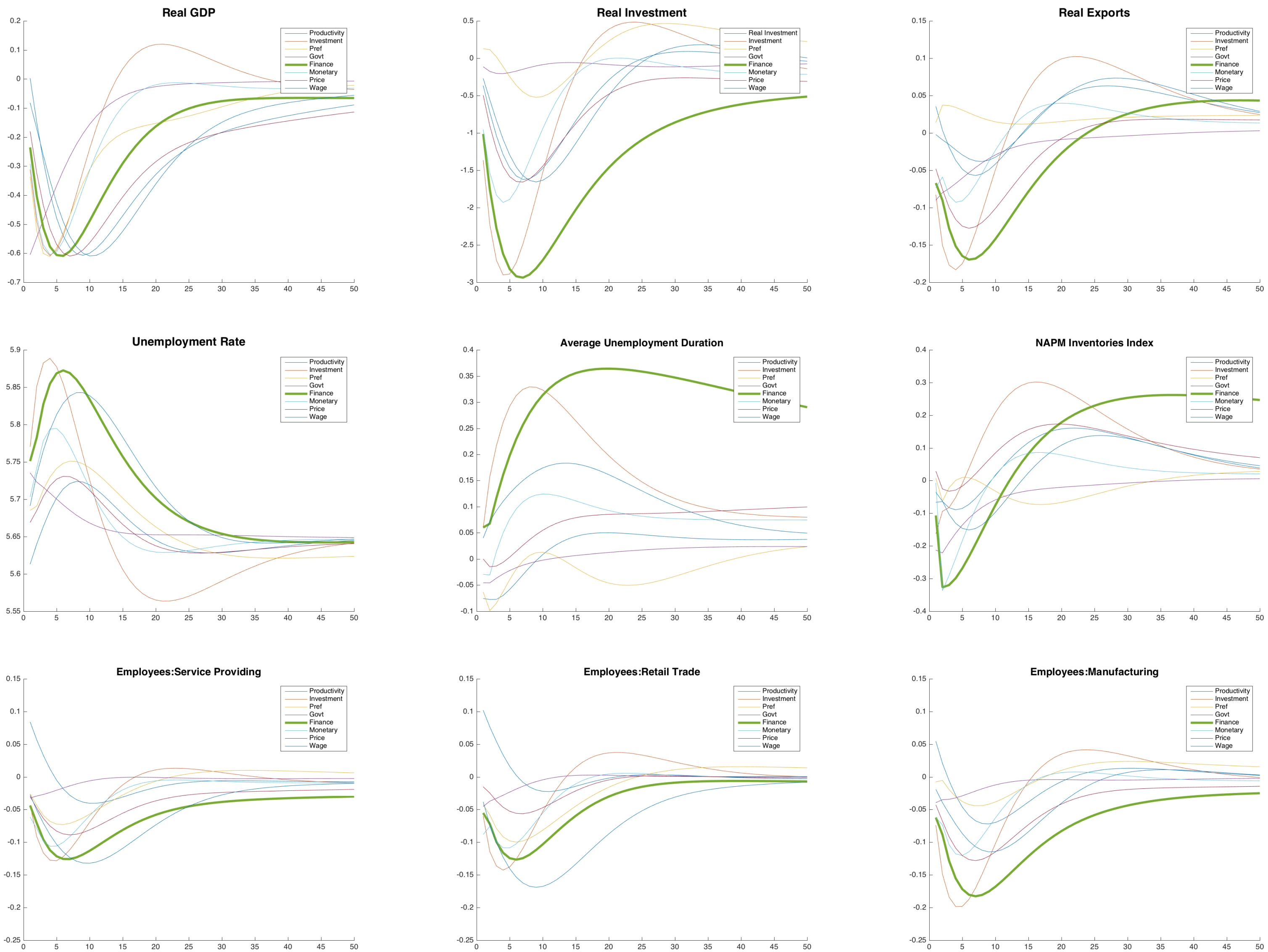


Figure 11: Forecasted Paths for Labor Market Metrics

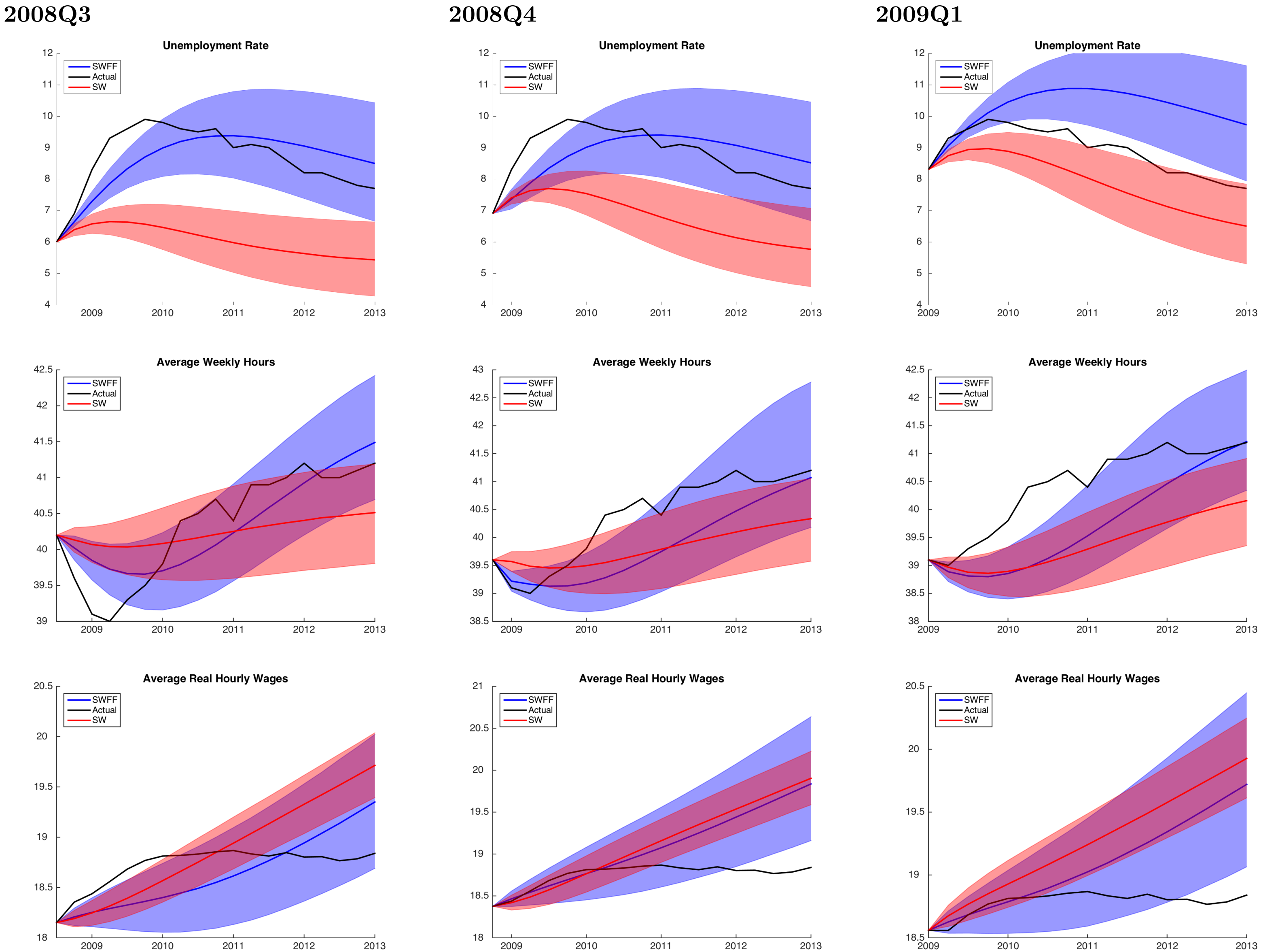
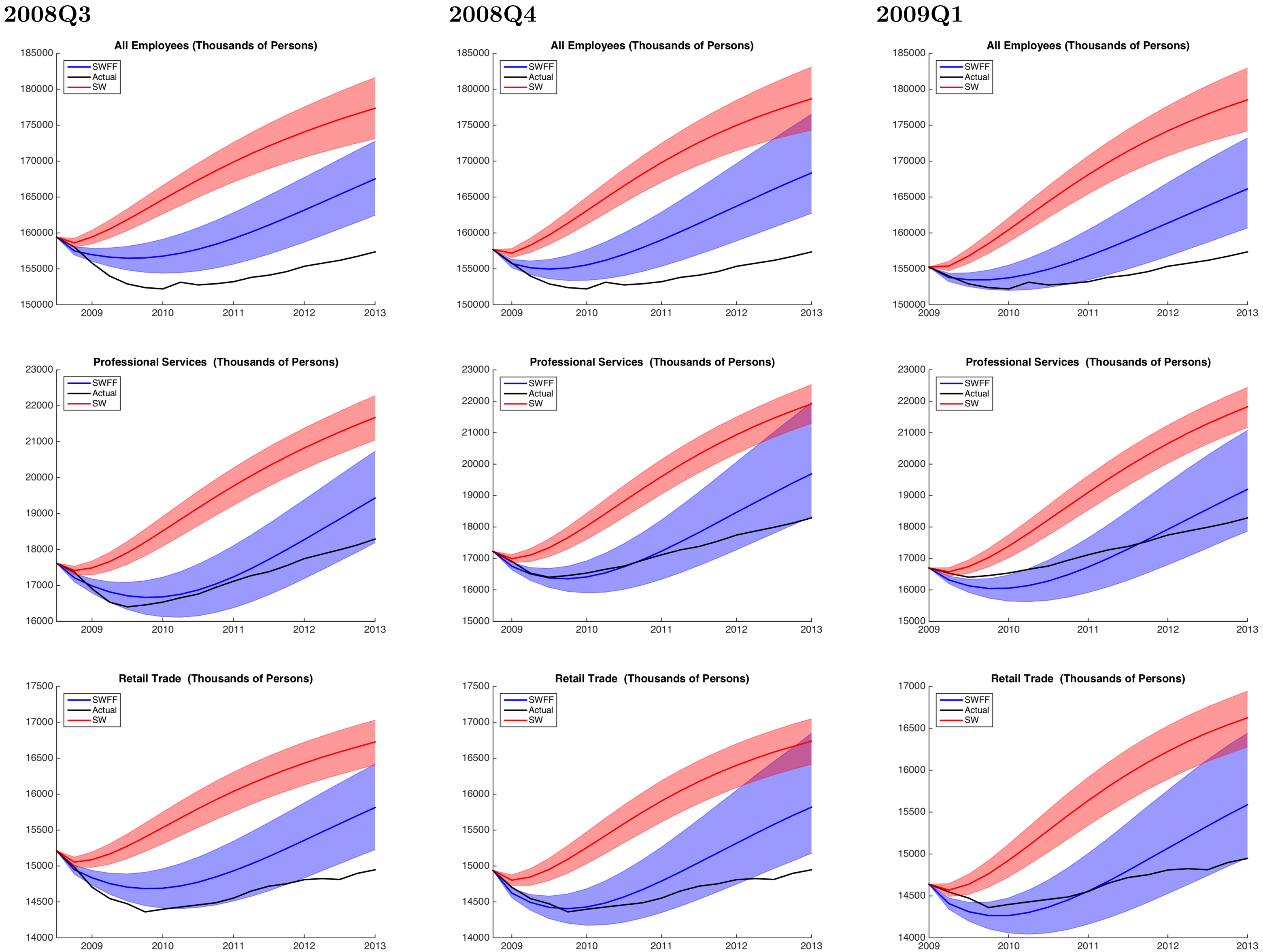


Figure 12: Forecasted Paths for Labor Market Sectors



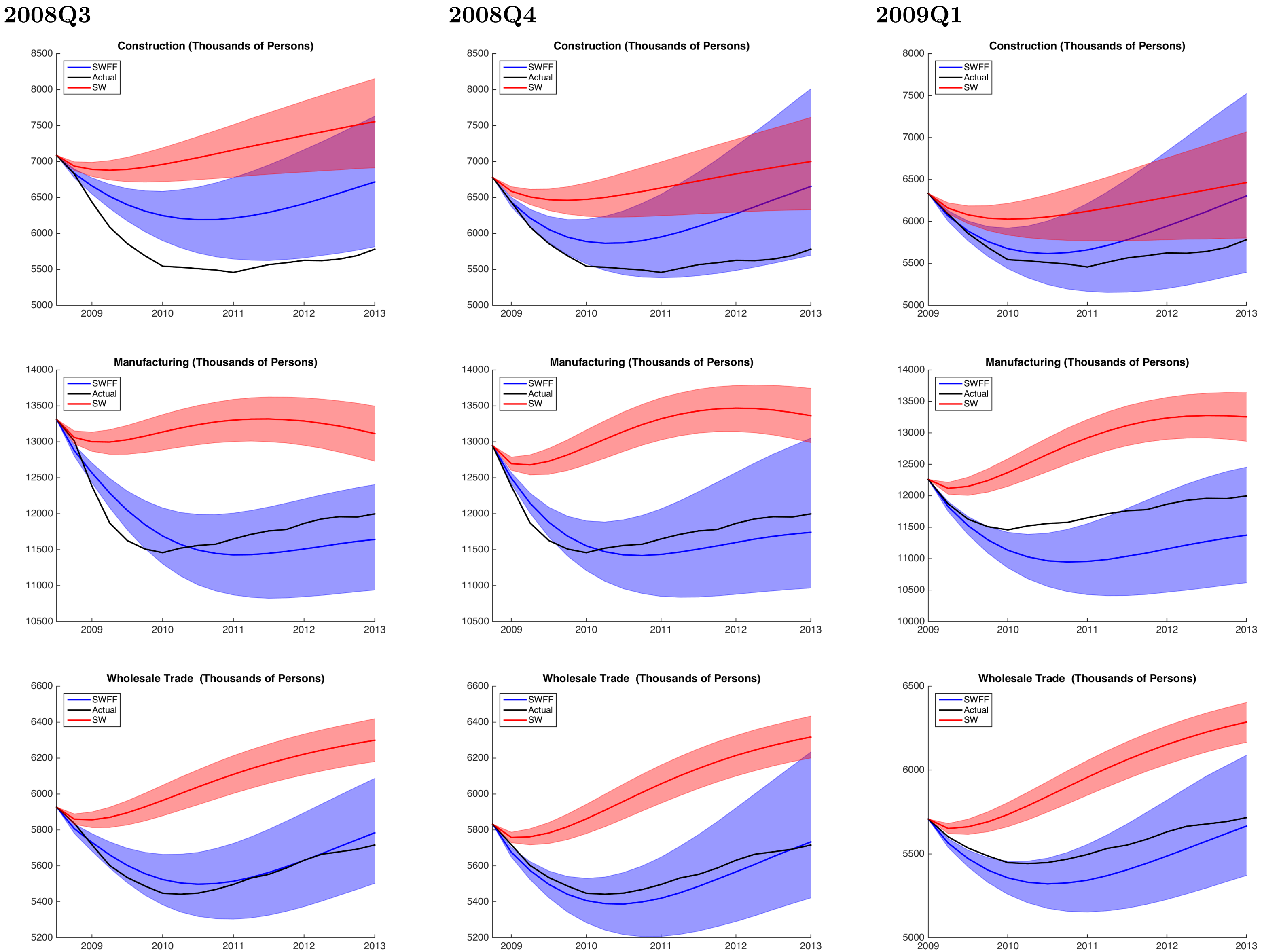

2008Q3
2008Q4
2009Q1
Construction (Thousands of Persons)
Manufacturing (Thousands of Persons)
Wholesale Trade (Thousands of Persons)
SWFF
Actual
SW

Figure 13: Forecasted Paths for Financial Metrics

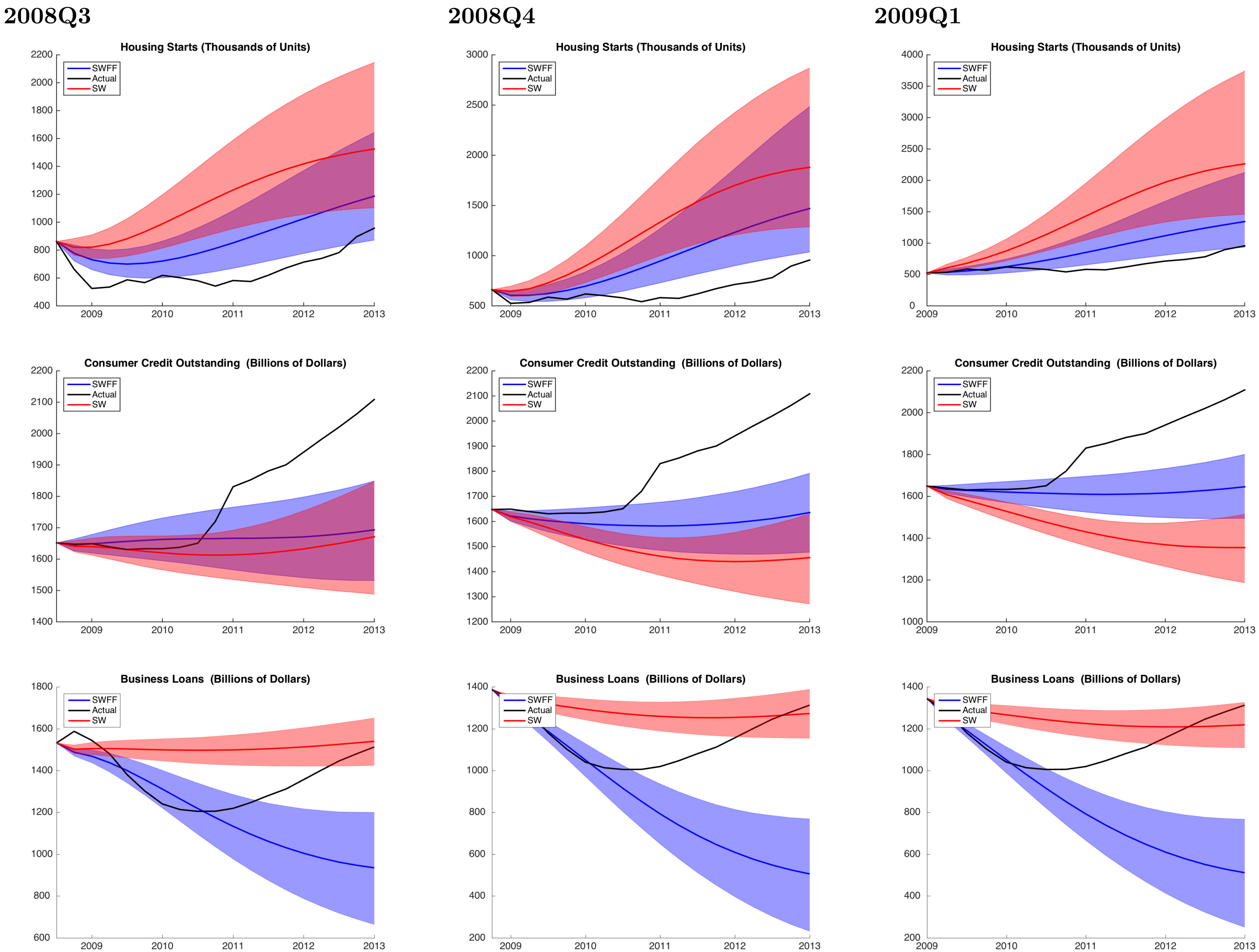


Table 6: Diebold-Mariano Test Statistics for DSGE Models

	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
	Output Growth				**Consumption Growth**			
SW-ZLB-Reg vs SWFF-ZLB-Reg	-0.61	-3.56*	-2.93*	-2.53*	2.32*	1.90*	2.20*	2.27*
SW-DFM vs SWFF-DFM	2.70*	1.00	0.88	0.73	0.23	0.44	0.14	-0.18
SW-ZLB-Reg vs SW-DFM	1.64*	1.98*	2.19*	2.14*	1.73*	2.60*	2.49*	2.41*
SWFF-ZLB-Reg vs SWFF-DFM	3.03*	2.43*	2.63*	2.38*	1.22	1.76*	1.57	1.48
	Investment Growth				**Inflation**			
SW-ZLB-Reg vs SWFF-ZLB-Reg	-0.13	-1.19	-2.30*	-2.31*	-2.68*	-2.17*	-1.62	-1.39
SW-DFM vs SWFF-DFM	-0.01	0.08	0.18	-0.17	-0.33	0.55	1.07	1.75*
SW-ZLB-Reg vs SW-DFM	2.96*	1.86*	0.64	1.23	-1.31	-1.11	-1.37	-1.79*
SWFF-ZLB-Reg vs SWFF-DFM	2.71*	1.30	1.16	1.35	-1.09	-1.57	-1.50	-1.40
	Wage Growth				**Interest Rate**			
SW-ZLB-Reg vs SWFF-ZLB-Reg	-4.48*	-2.96*	-2.38*	-1.59	-3.45*	-2.14*	-1.69*	-1.52
SW-DFM vs SWFF-DFM	3.64*	2.23*	1.84*	1.64*	-0.96	-0.63	-0.05	1.01
SW-ZLB-Reg vs SW-DFM	-3.28*	-1.76*	-1.31	-1.12	-2.24*	-1.45	-1.19	-1.12
SWFF-ZLB-Reg vs SWFF-DFM	1.60	1.57	1.54	1.44	-2.20*	-1.54	-1.10	-0.69

Note: * denotes a model specifications where the
null hypothesis of equal predictive accuracy is rejected at the 5% level

Table 7: Unconditional FEVD of Grouped Series

	SW-DFM Model		**SWFF-DFM Model**	
	Structural	Misspecification	Structural	Misspecification
Core Series	0.819	0.181	0.884	0.116
Real Output	0.757	0.243	0.956	0.044
Inflation	0.906	0.094	0.962	0.038
Consumption	0.941	0.059	0.986	0.014
Investment	0.939	0.061	0.944	0.056
Real Wage	0.442	0.558	0.731	0.269
Hours	0.818	0.182	0.800	0.200
Interest Rate	0.843	0.157	0.863	0.137
Spread	-	-	0.809	0.191
Non-Core Series	0.879	0.121	0.949	0.051
Output & Components	0.927	0.073	0.946	0.054
Labor Market	0.930	0.070	0.940	0.060
Housing	0.928	0.072	0.942	0.058
Finance	0.864	0.136	0.956	0.044
Exchange Rates	0.690	0.310	0.981	0.019
Investment & Orders	0.963	0.037	0.973	0.027
Prices & Wages	0.796	0.204	0.940	0.060
Other	0.908	0.092	0.967	0.033

Note: FEVD estimates in the table are calculated at posterior means of the structural and state-space parameters and are averaged for each group

Table 8: Unconditional FEVD of Finance Series in SW-DFM Model

	Productivity ε_a	Investment ε_I	Preference ε_b	Government ε_G	Equity ε_q	Monetary ε_R	Price ε_p	Wage ε_w	Misspecification e
SFYGM6	0.010	0.533	0.308	0.007	0.000	0.001	0.010	0.112	0.020
SFYGT1	0.037	0.520	0.258	0.009	0.002	0.001	0.018	0.121	0.034
SFYGT10	0.058	0.501	0.197	0.019	0.001	0.008	0.009	0.116	0.092
SFYBAAC	0.045	0.714	0.100	0.015	0.000	0.003	0.004	0.040	0.078
SFYAAAC	0.075	0.640	0.081	0.018	0.001	0.011	0.014	0.040	0.120
TOT_RES	0.092	0.635	0.086	0.013	0.000	0.003	0.006	0.051	0.114
TOT_RES_NB	0.080	0.066	0.216	0.059	0.000	0.005	0.005	0.048	0.522
BUS_LOANS	0.029	0.694	0.102	0.038	0.000	0.001	0.000	0.041	0.096
CONS_CREDIT	0.037	0.726	0.108	0.030	0.000	0.002	0.001	0.054	0.043
SP500	0.004	0.505	0.221	0.002	0.011	0.005	0.018	0.066	0.169
DJIA	0.001	0.513	0.252	0.001	0.006	0.003	0.017	0.070	0.136

Table 9: Unconditional FEVD of Finance Series in SWFF-DFM Model

	Productivity ε_a	Investment ε_I	Preference ε_b	Government ε_G	Finance ε_F	Monetary ε_R	Price ε_P	Wage ε_W	Misspecification e
SFYGM6	0.104	0.104	0.008	0.020	0.173	0.024	0.433	0.123	0.010
SFYGT1	0.112	0.115	0.007	0.019	0.152	0.025	0.435	0.126	0.009
SFYGT10	0.148	0.143	0.019	0.029	0.131	0.016	0.329	0.124	0.061
TOT_RES	0.095	0.086	0.008	0.002	0.127	0.033	0.448	0.167	0.034
TOT_RES_NB	0.054	0.114	0.078	0.003	0.109	0.044	0.344	0.134	0.119
BUS_LOANS	0.017	0.154	0.021	0.003	0.194	0.052	0.391	0.153	0.015
CONS_CREDIT	0.027	0.093	0.012	0.002	0.102	0.031	0.226	0.425	0.083
SP500	0.030	0.141	0.022	0.005	0.027	0.074	0.525	0.147	0.028
DJIA	0.035	0.141	0.021	0.007	0.022	0.072	0.518	0.142	0.040

Table 10: Diebold-Mariano Test Statistics for DSGE-DFM Models

	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
	Output Growth				**Consumption Growth**			
VAR(1) vs SW-DFM	0.39	0.15	0.48	0.83	1.52	0.46	0.96	0.78
VAR(1) vs SWFF-DFM	1.26	0.69	1.00	1.51	1.43	0.69	0.93	0.58
VAR(2) vs SW-DFM	1.28	0.68	1.14	1.11	1.44	1.15	1.90	1.24
VAR(2) vs SWFF-DFM	1.23	1.04	1.47	1.35	1.79*	1.31	1.69*	1.08
DFM vs SW-DFM	1.16	-0.02	0.43	0.71	2.87*	0.50	1.01	0.88
DFM vs SWFF-DFM	2.12*	0.39	0.67	0.87	2.70*	0.70	0.96	0.78
	Investment Growth				**Inflation**			
VAR(1) vs SW-DFM	1.31	2.03*	1.43	1.30	-2.62*	-1.75*	-1.77*	-2.21*
VAR(1) vs SWFF-DFM	1.37	1.20	1.05	1.40	-2.16*	-2.97*	-2.61*	-2.27*
VAR(2) vs SW-DFM	-0.13	1.73*	1.38	1.45	-2.55*	-1.72*	-1.80*	-2.23*
VAR(2) vs SWFF-DFM	-0.14	1.21	1.13	1.41	-2.04*	-2.77*	-2.68*	-2.35*
DFM vs SW-DFM	2.79*	1.02	0.51	0.92	-2.66*	-1.84*	-1.83*	-2.16*
DFM vs SWFF-DFM	2.50*	0.69	0.48	0.61	-2.16*	-3.06*	-2.68*	-2.21*
	Wage Growth				**Interest Rate**			
VAR(1) vs SW-DFM	-3.62*	-2.16*	-1.58	-1.04	-0.29	0.04	0.33	0.64
VAR(1) vs SWFF-DFM	-2.32*	-0.93	0.37	1.31	-0.49	-0.07	0.34	0.77
VAR(2) vs SW-DFM	-3.78*	-2.31*	-1.75*	-1.22	-0.91	-0.72	-0.42	-0.15
VAR(2) vs SWFF-DFM	-3.82*	-2.37*	-0.73	0.85	-1.04	-0.86	-0.46	-0.03
DFM vs SW-DFM	-3.29*	-2.23*	-1.71*	-1.38	2.77*	0.96	0.78	1.00
DFM vs SWFF-DFM	0.94	-1.72*	-0.42	0.62	2.68*	0.91	0.84	1.30

Note: * denotes a model specifications where the
null hypothesis of equal predictive accuracy is rejected at the 5% level

Table 11: Diebold-Mariano Test Statistics for RTOP Weights

	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
	Output Growth				**Consumption Growth**			
RTOP vs Equal Weights	-1.12	-0.68	-0.36	-0.30	-1.02	-1.91*	1.27	0.53
RTOP vs VAR(1)	-1.32	-0.97	-1.12	-1.16	-1.76*	-1.47	0.49	-0.03
RTOP vs VAR(2)	-0.60	-1.17	-1.32	-1.19	-1.32	-0.29	-1.29	-0.84
RTOP vs DFM	-2.10*	-0.41	-0.41	-0.51	-2.98*	0.64	-0.03	-0.52
RTOP vs SW-ZLB-Reg	-2.61*	-2.27*	-2.18*	-2.06*	-2.85*	-2.95*	-2.43*	-2.28*
RTOP vs SWFF-ZLB-Reg	-2.76*	-2.57*	-2.48*	-2.23*	-1.85*	-1.85*	-1.62	-1.59
RTOP vs SW-DFM	-1.66*	-0.66	0.15	0.38	0.39	1.13	1.45	0.97
RTOP vs SWFF-DFM	0.74	0.20	0.68	1.04	0.56	1.33	1.28	0.93
	Investment Growth				**Inflation**			
RTOP vs Equal Weights	-0.04	-0.91	-0.22	-0.29	-1.51	-1.66*	-2.18*	-2.30*
RTOP vs VAR(1)	-1.23	-3.04*	-1.83*	-1.39	-0.94	-0.04	-0.54	-2.49*
RTOP vs VAR(2)	0.59	-2.17*	-1.62	-1.54	-1.19	-1.00	-1.31	-1.29
RTOP vs DFM	-2.50 *	-1.07	-0.68	-0.85	0.96	-0.04	-0.36	-0.01
RTOP vs SW-ZLB-Reg	-2.39*	-1.97*	-0.82	-1.02	-2.42*	-2.99*	-2.17*	-1.53
RTOP vs SWFF-ZLB-Reg	-2.70*	-1.86*	-1.45	-1.79*	-2.52*	-3.28*	-2.57*	-1.82*
RTOP vs SW-DFM	0.76	-0.00	-0.57	0.57	-2.62*	-1.80*	-1.83*	-2.18*
RTOP vs SWFF-DFM	0.55	0.07	-0.08	0.13	-2.16*	-3.00*	-2.70*	-2.24*
	Wage Growth				**Interest Rate**			
RTOP vs Equal Weights	-3.76*	-2.39*	-2.01*	-1.60	0.94	0.24	0.13	-0.09
RTOP vs VAR(1)	0.13	0.14	-0.34	-0.16	-1.13	-0.87	-0.93	-1.13
RTOP vs VAR(2)	0.01	-0.33	-1.59	-1.75*	0.08	-0.05	-0.27	-0.51
RTOP vs DFM	-7.63*	-1.01	-1.29	-1.14	-3.88*	-1.93*	-1.79*	-2.15*
RTOP vs SW-ZLB-Reg	-1.35	-2.33*	-1.83*	-1.44	-0.58	-0.52	-0.66	-0.73
RTOP vs SWFF-ZLB-Reg	-0.99	-2.28*	-1.83*	-1.47	-1.27	-1.15	-1.22	-1.27
RTOP vs SW-DFM	-3.88*	-3.72*	-3.32*	-2.56*	-2.90*	-1.94*	-1.87*	-2.11*
RTOP vs SWFF-DFM	-4.72*	-3.42*	-2.62*	-2.24*	-3.27*	-2.36*	-2.36*	-2.76*

Note: * denotes a model specifications where the
null hypothesis of equal predictive accuracy is rejected at the 5% level

Table 12: RTOP Weights: Before and After the Financial Crisis

	Entire	Pre 2008	Post 2008	Entire	Pre 2008	Post 2008
	Output Growth			**Consumption Growth**		
DSGE-Reg Models	0.14	0.19	0.02	0.66	0.86	0.19
DSGE-DFM Models	0.23	0.05	0.65	0.23	0.03	0.71
VAR & DFM Models	0.63	0.76	0.33	0.11	0.12	0.10
	Investment Growth			**Inflation**		
DSGE-Reg Models	0.03	0.00	0.08	0.00	0.00	0.00
DSGE-DFM Models	0.70	0.69	0.73	0.00	0.00	0.00
VAR & DFM Models	0.27	0.31	0.19	1.00	1.00	1.00
	Wage Growth			**Interest Rate**		
DSGE-Reg Models	0.11	0.03	0.32	0.16	0.00	0.52
DSGE-DFM Models	0.04	0.06	0.00	0.63	0.81	0.20
VAR & DFM Models	0.84	0.91	0.68	0.21	0.19	0.28

Table 13: Diebold-Mariano Test Statistics for RTOP vs RTOP-SOW

	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
	Output Growth				**Consumption Growth**			
RTOP vs RTOP SOW	1.81*	1.64*	1.76*	1.65*	0.84	1.59	1.33	1.30
	Investment Growth				**Inflation**			
RTOP vs RTOP SOW	1.96*	1.06	0.97	0.62	-1.49	-2.04*	-2.02*	-1.65*
	Wage Growth				**Interest Rate**			
RTOP vs RTOP SOW	-1.32	-0.20	-0.25	-0.37	-1.56	-0.77	-0.54	-0.42

Note: * denotes a model specifications where the
null hypothesis of equal predictive accuracy is rejected at the 5% level

Table 14: χ^2 Goodness of Fit Test Statistics

	h=1	h=2	h=3	h=4
Output Forecasts				
SW-ZLB-Reg	13.61*	10.98*	9.40*	11.68*
SW-DFM	3.26	21.51*	24.67*	24.32*
SWFF-ZLB-Reg	18.70*	9.05	6.42	9.40
SWFF-DFM	15.02*	25.89*	22.91*	27.65*
Equal Wights	53.09*	2.91	3.26	2.91
RTOP	4.67	13.09*	12.91*	10.98*
Inflation Forecasts				
SW-ZLB-Reg	4.67	10.81*	6.25	8.18
SW-DFM	3.61	14.67*	5.02	3.61
SWFF-ZLB-Reg	5.19	6.77	4.67	6.25
SWFF-DFM	10.46*	5.54	7.12	4.49
Equal Weights	16.95*	7.30	9.93*	13.09*
RTOP	2.04	0.28	1.68	10.81*

Note: * denotes a model specifications where the null
hypothesis of a uniform PIT Distribution is rejected at the 5% level

Figure 14: Difference in Forecasting Accuracy over Time: Rolling RMSEs

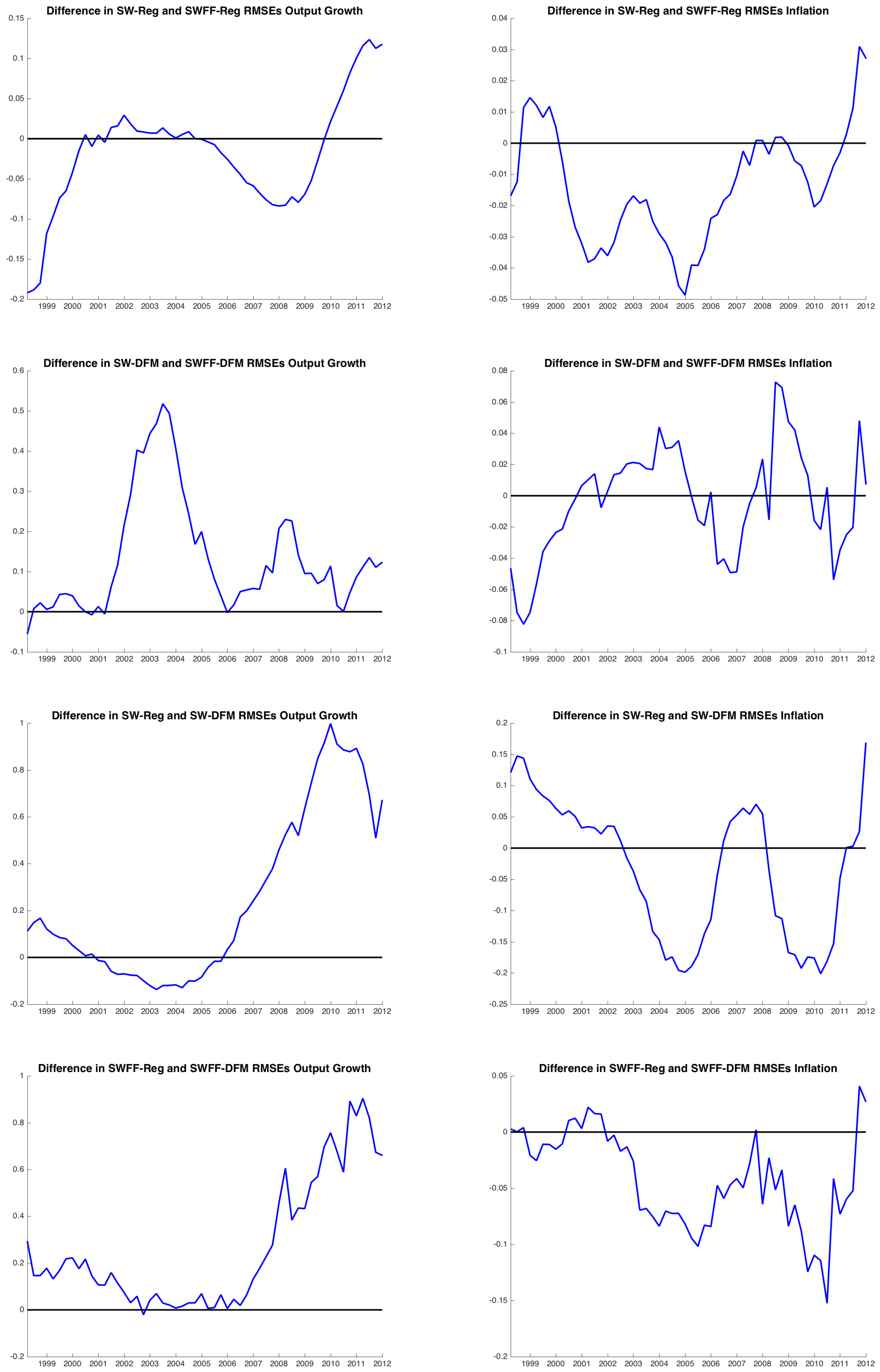
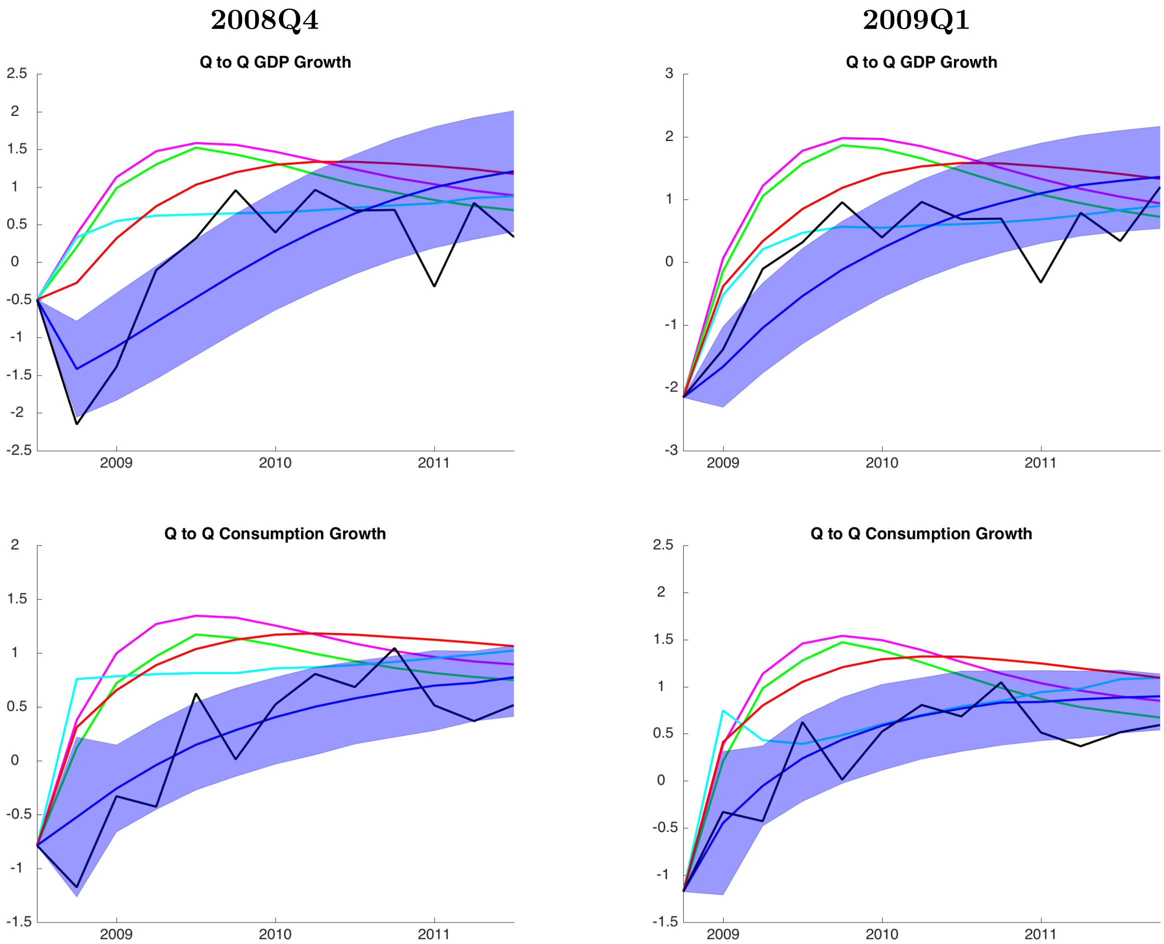
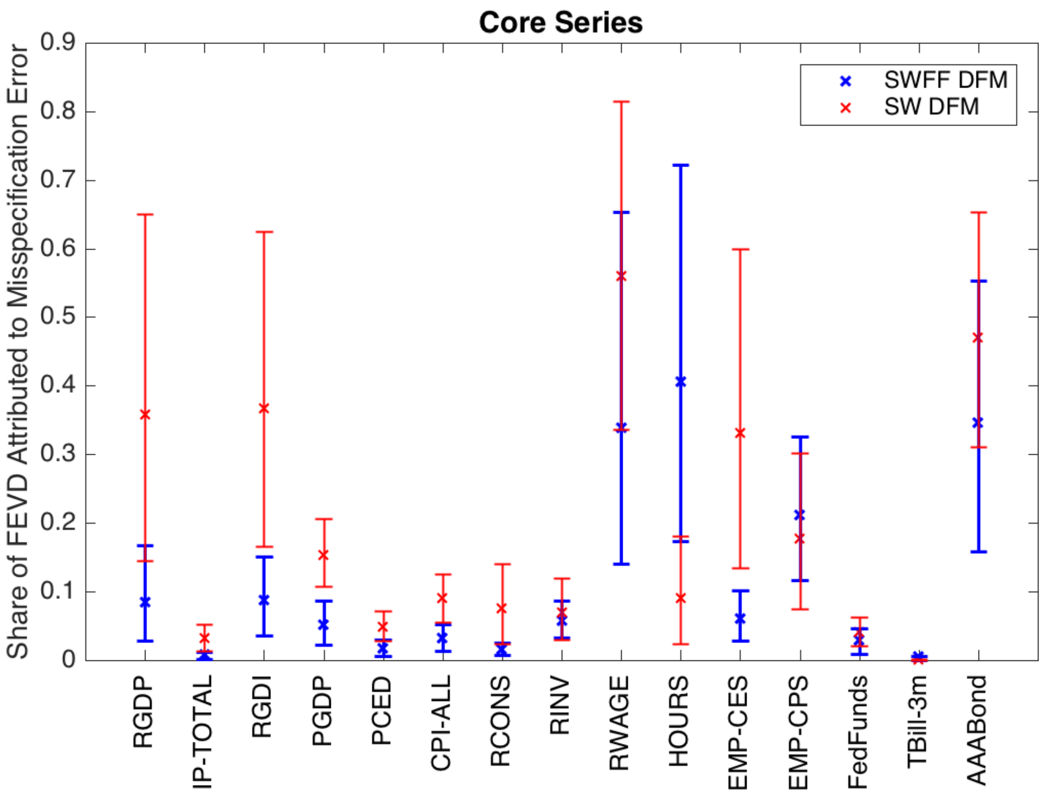


Figure 15: Forecasts of GDP and Consumption Growth around the Financial Crisis



This Figure plots the forecasts paths of SW-ZLB-Reg, SWFF-ZLB-Reg, VAR(1), SW-DFM and SWFF-DFM models for quarter to quarter GDP and consumption growth. The shaded blue area is the 68% posterior band around the SWFF-DFM forecast and the black line is the actual paths of GDP and consumption growth.

Figure 16: 90% Posterior Bands of FEVD Share Attributed to Misspecification Error



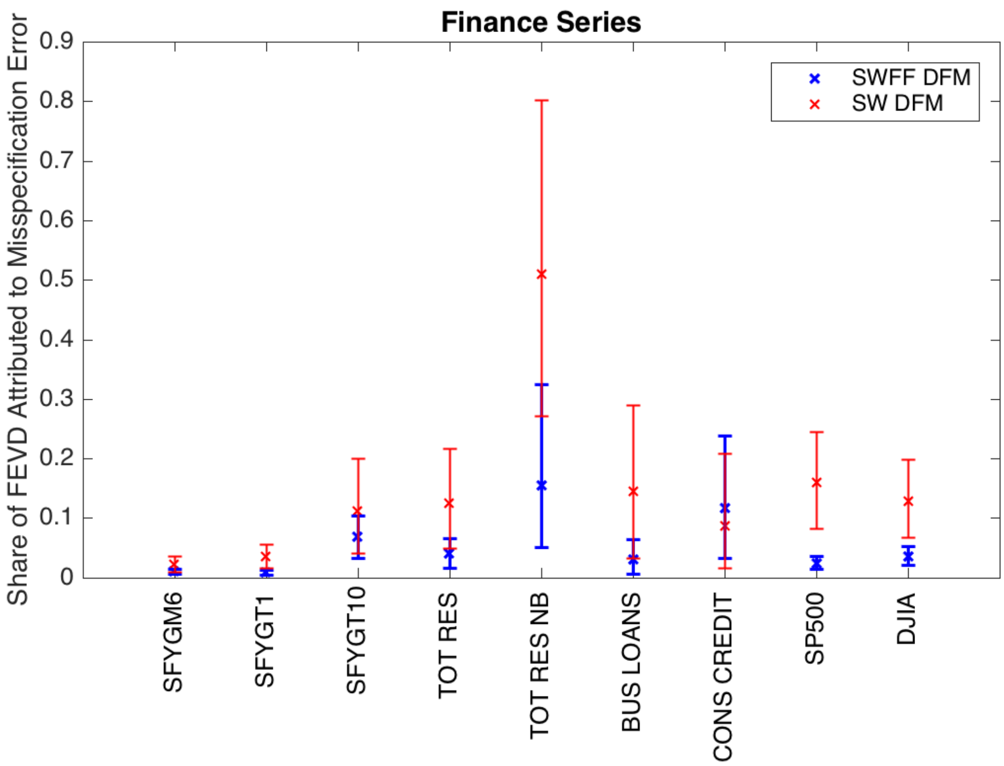


Figure 17: Historical Decomposition of GDP in SW-DFM

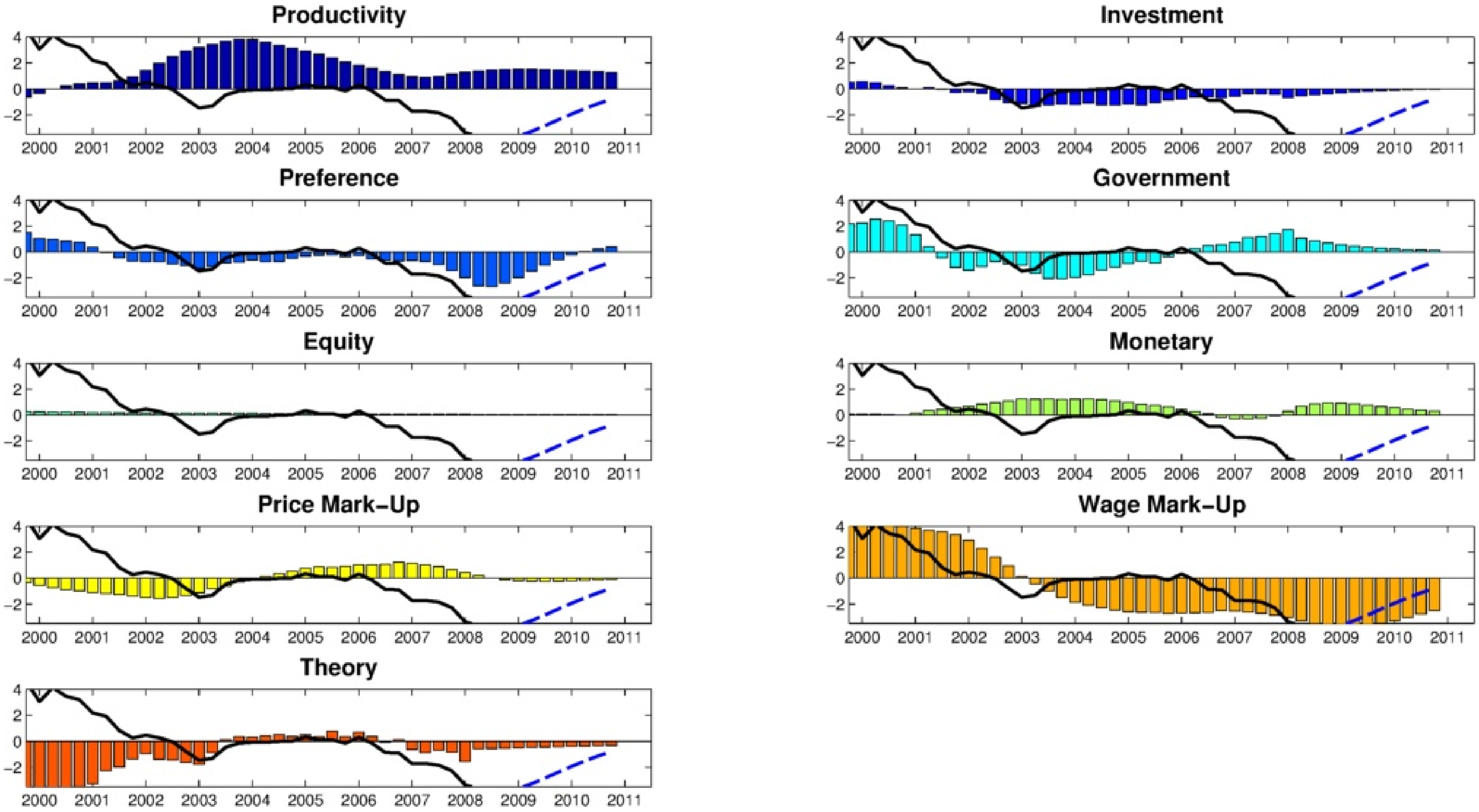


Figure 18: Historical Decomposition of GDP in SWFF-DFM

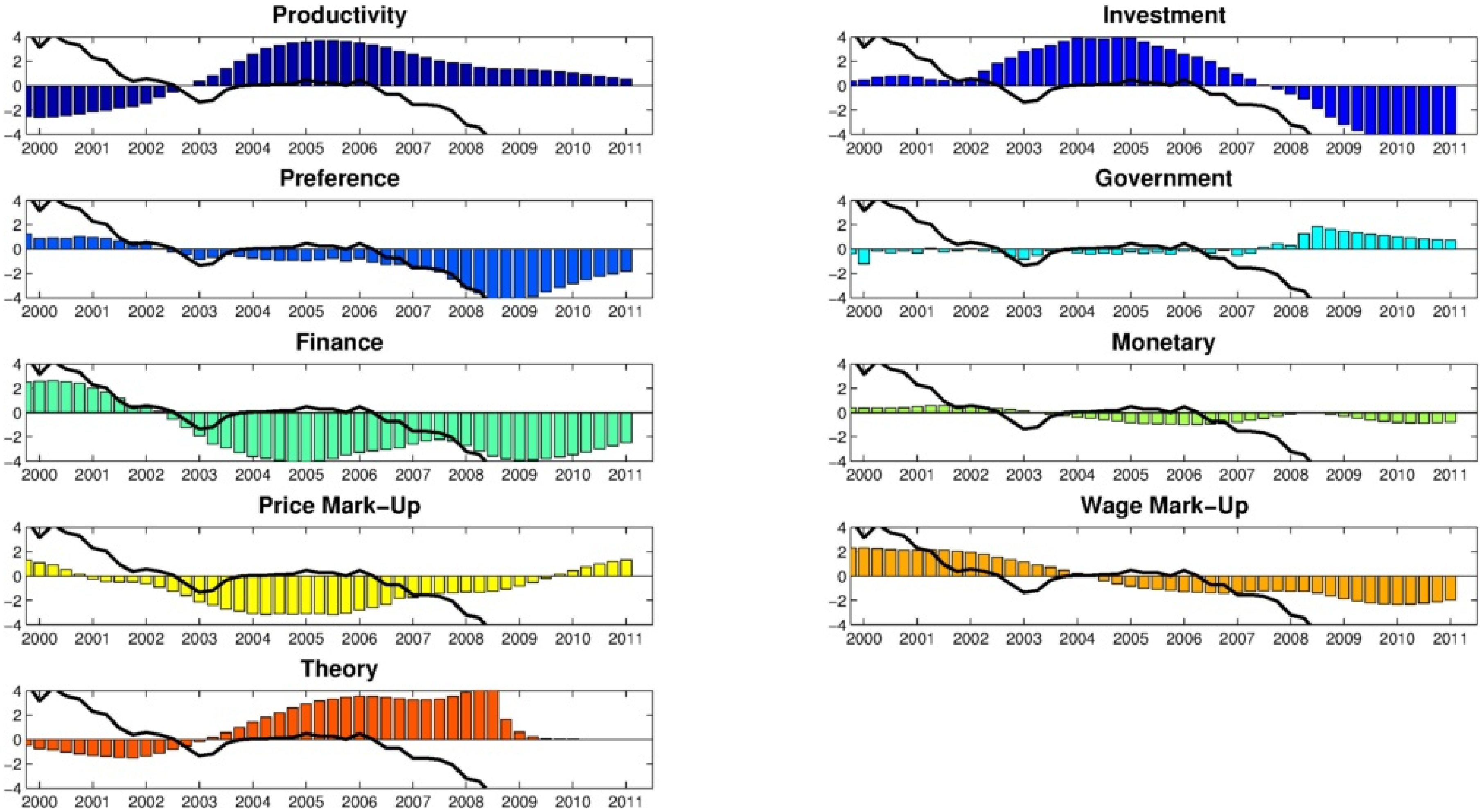


Figure 19: Historical Decomposition of S&P 500 in SW-DFM

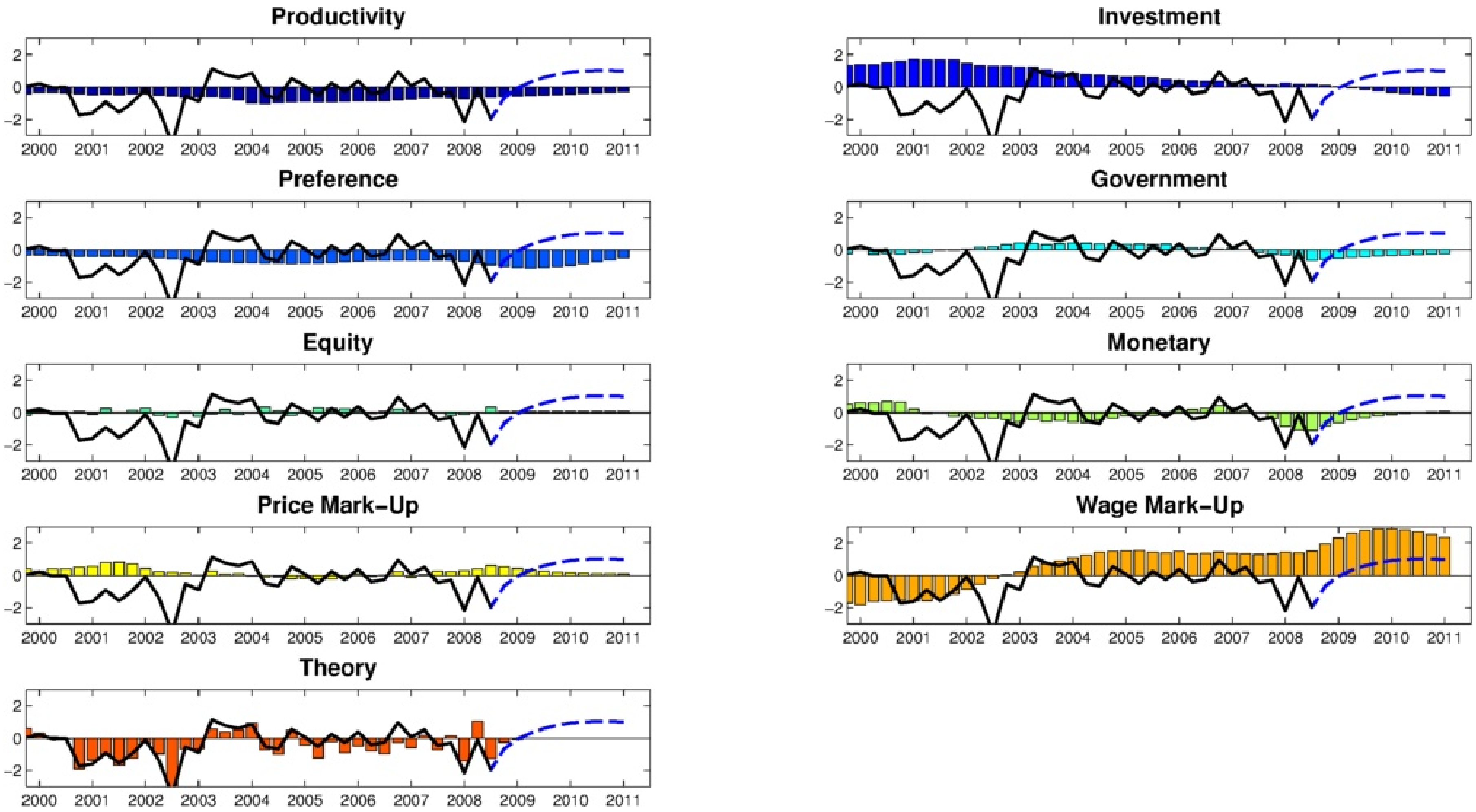


Figure 20: Average Standardized Deviation of Output Components & Financial Series

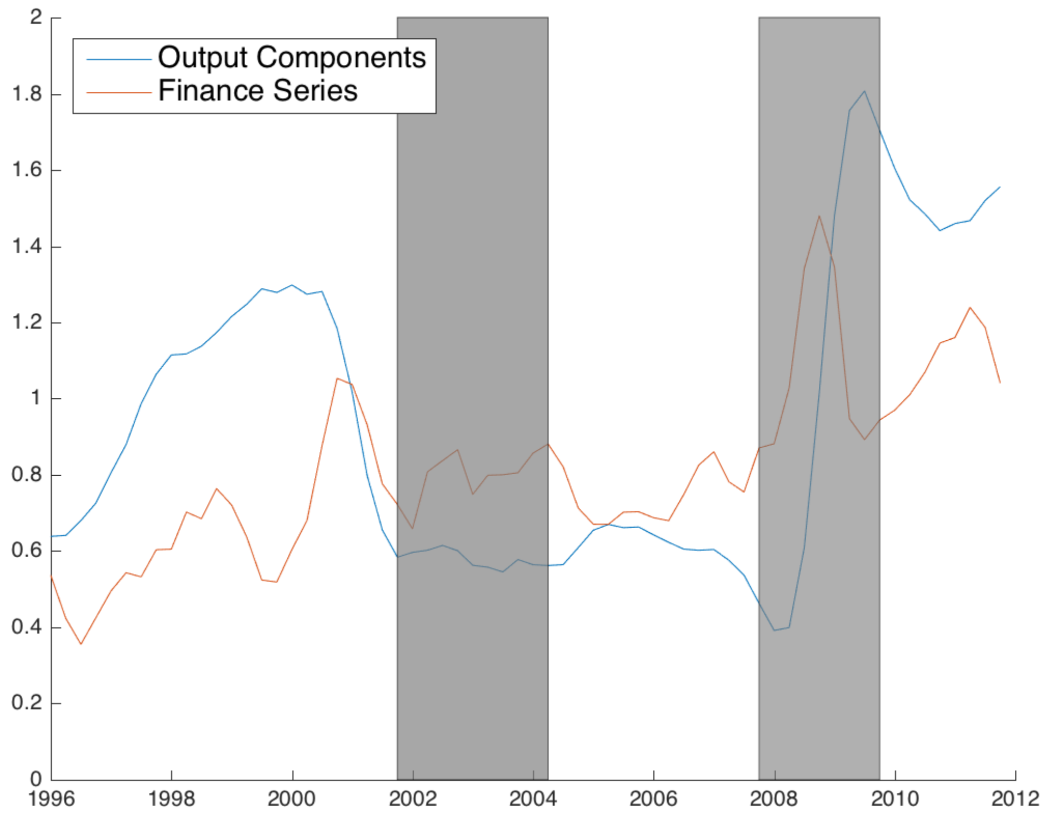
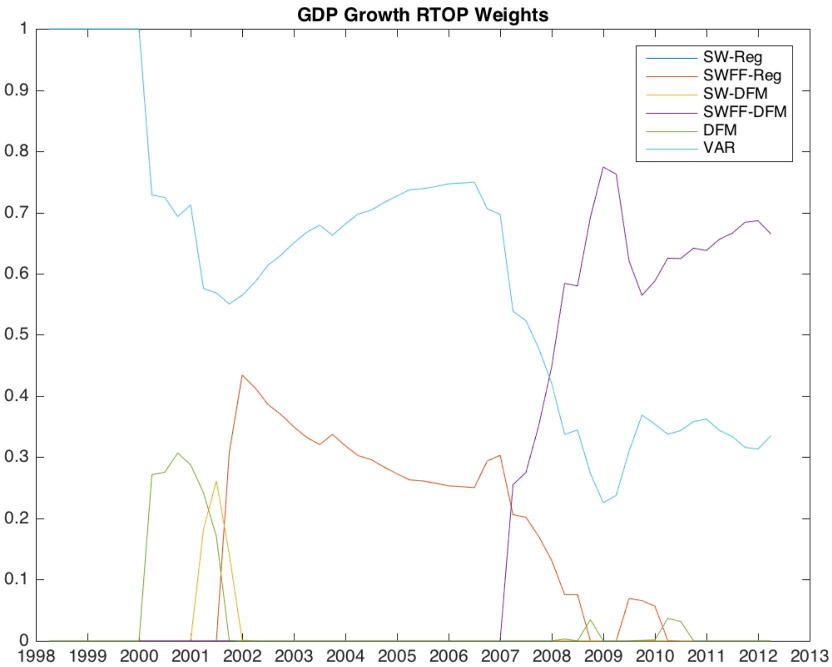
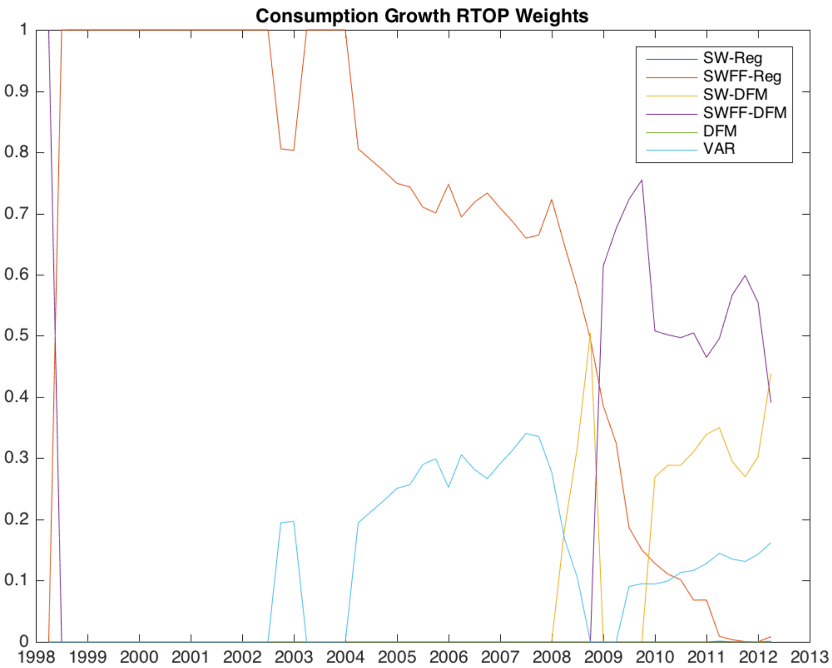
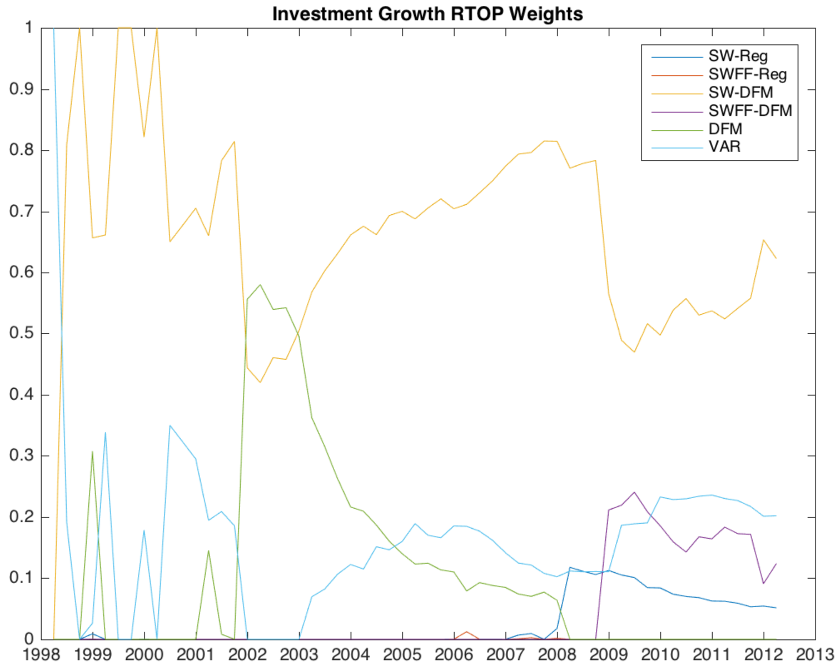


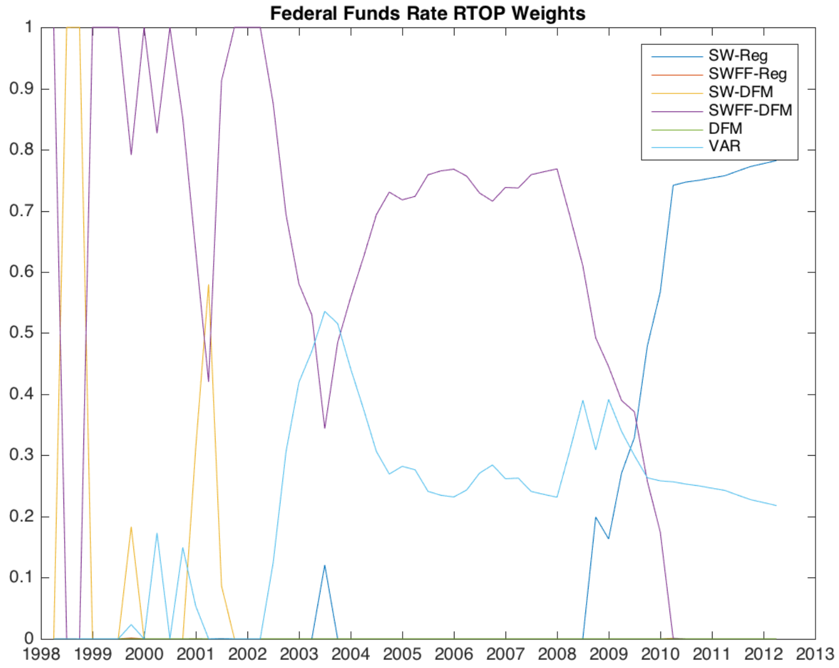
Figure 20 plots the absolute value of the normalized standard deviations of all output component and finance series grouped in Appendix B. The shaded bars correspond to the time frames that Del Negro & Schorfheide (2012) found the SWFF model out forecasted the SW model in both output growth and inflation

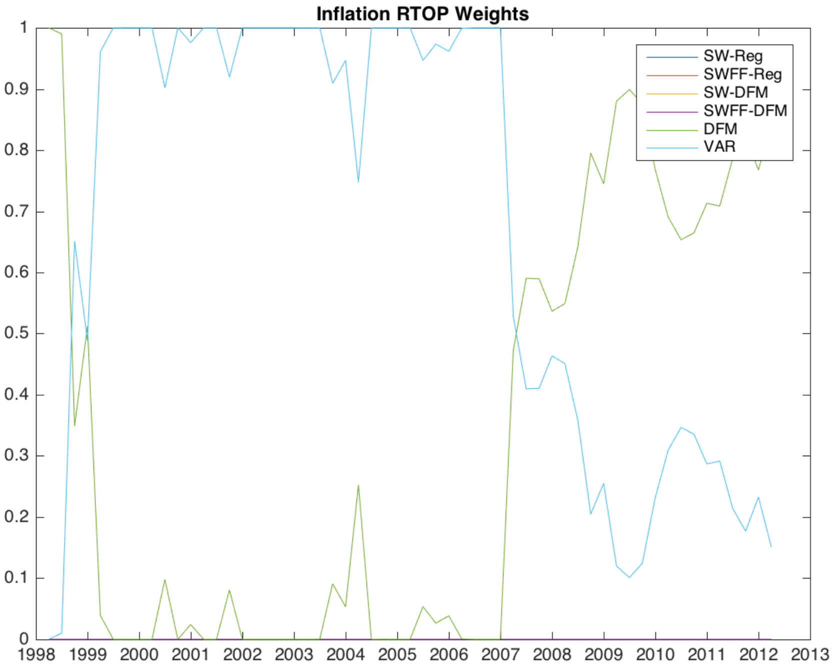
Figure 21: Assigned RTOP Weights






Investment Growth RTOP Weights
SW-Reg
SWFF-Reg
SW-DFM
SWFF-DFM
DFM
VAR
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013


Federal Funds Rate RTOP Weights
SW-Reg
SWFF-Reg
SW-DFM
SWFF-DFM
DFM
VAR
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013


Inflation RTOP Weights
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
SW-Reg
SWFF-Reg
SW-DFM
SWFF-DFM
DFM
VAR

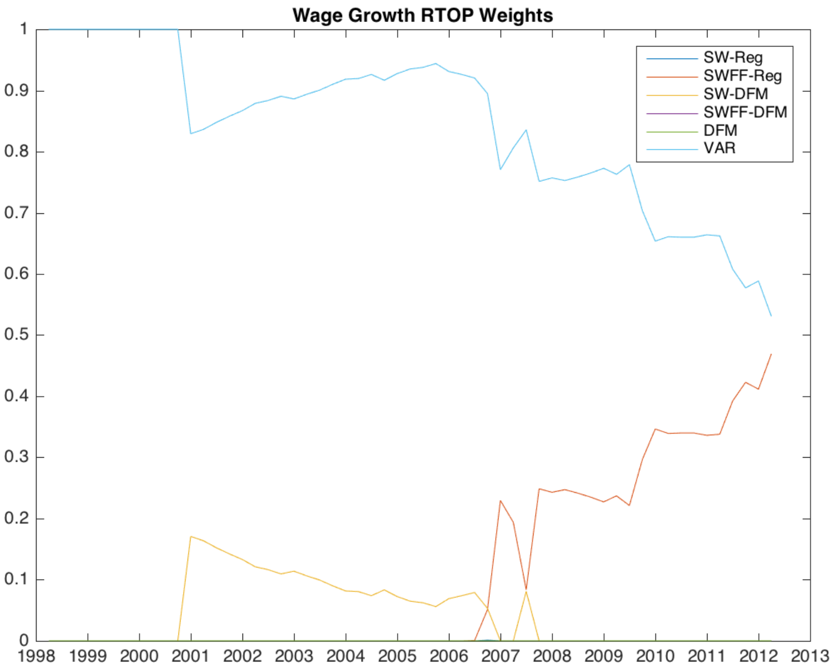

Wage Growth RTOP Weights
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
SW-Reg
SWFF-Reg
SW-DFM
SWFF-DFM
DFM
VAR

Figure 22: Evaluation of Forecast Densities: Output Growth

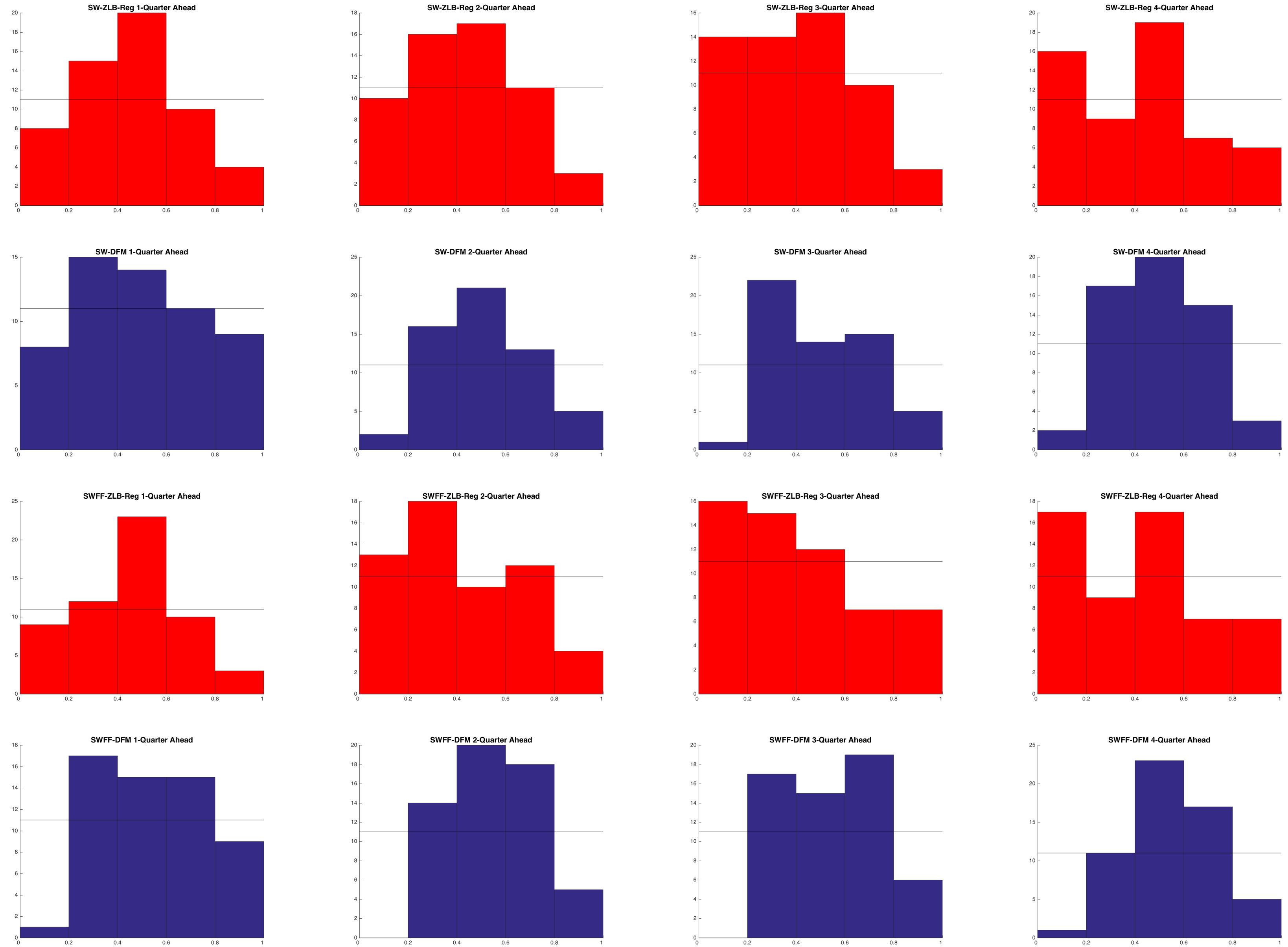


Figure 23: Evaluation of Forecast Densities: Inflation

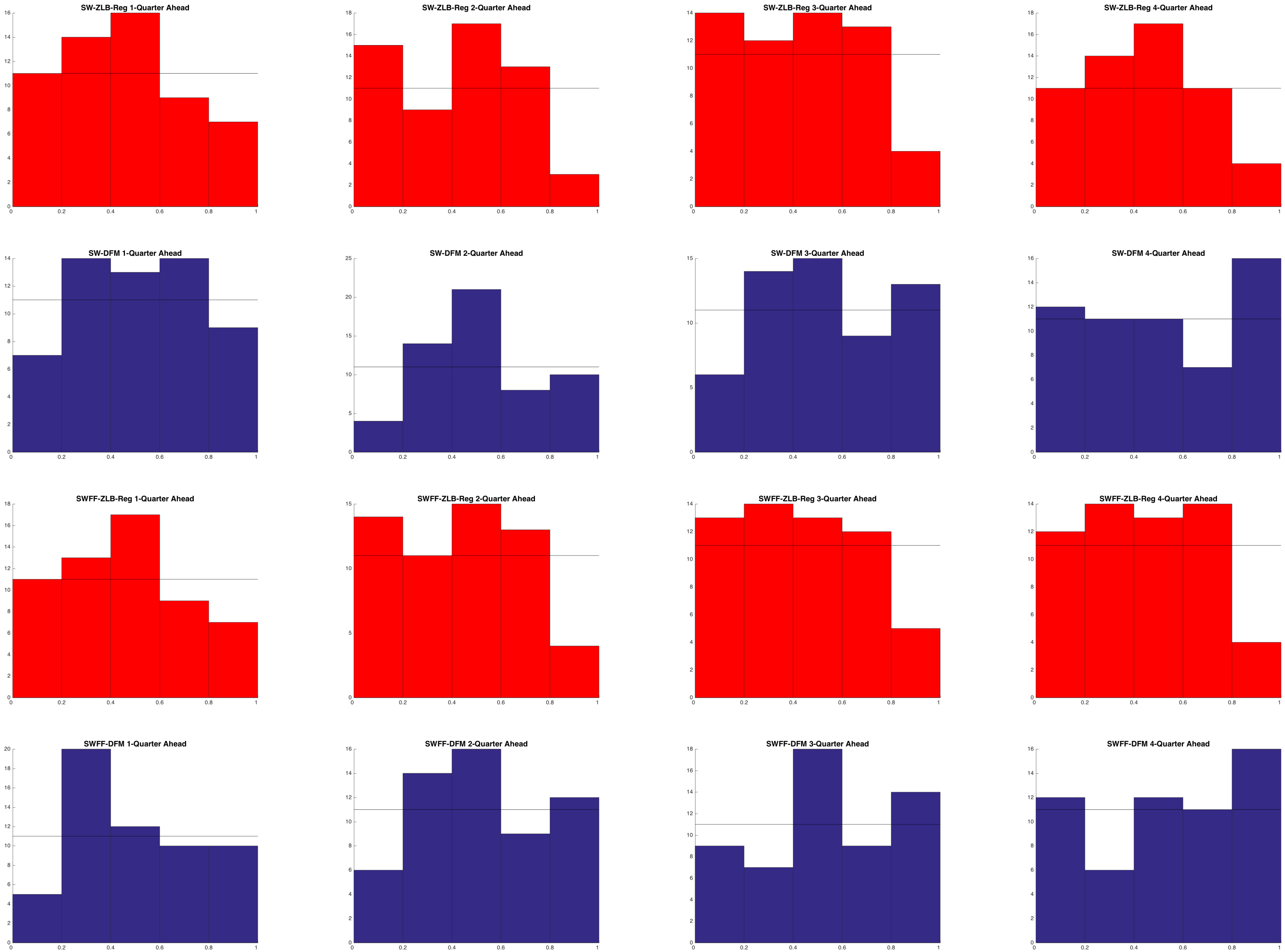


Figure 24: Evaluation of Forecast Densities: Equal Weights vs RTOP

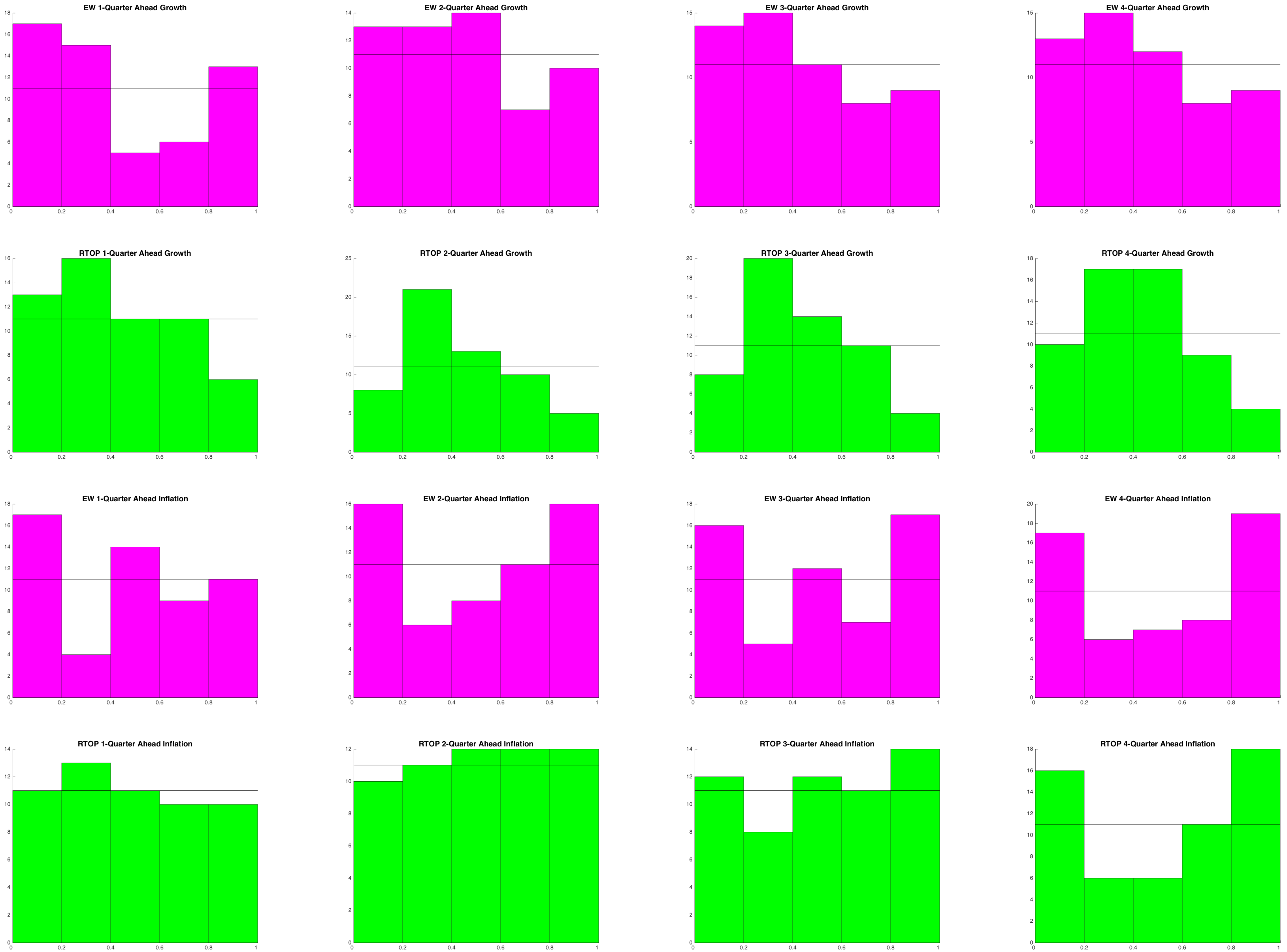


Table 15: Calibrated Parameters

	Description	Value
Parameters		
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
π	S.S level of inflation (1984-2011 Annual %)	2.2
λ_w	Degree of wage markup	0.3
Specific to Financial Accelerator		
γ	Survival rate of entrepreneur	0.99
F^*	Loan default rate	0.0075
S	S.S. Spread (Annual %)	1.4
Specific to Adaptive Learning Estimation		
t	Rolling Window of Residuals in Bayesian Weights Calculation	15
$\pi_{training}$	S.S level of inflation (1978-1984 Annual %)	6.5

Table 16: 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	4	1.5
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
u_p	Price Markup Moving Average	Beta	0.5	0.2
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*
Financial Accelerator Parameters				
$\chi*$	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*
Adaptive Learning Estimation Parameters				
γ	Constant Learning Gain	Gamma	0.035	0.03

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 17: Estimated Marginal Likelihoods and Posterior Model Probability

	PLM(1)	**PLM(2)**	**PLM(3)**	**BW**	**Equal Weights**	**REE**
Marginal Likelihood	-781.268	-805.320	-799.832	-781.862	-780.252	-846.711
NW Standard Error	0.331	0.121	0.114	0.126	0.110	0.164
Model Probability	0.232	0.000	0.000	0.128	0.640	0.000

Note: The marginal likelihood is calculated using the modified harmonic mean estimator in all six different expectation formation modeling assumptions that were estimated. **PLM(*i*)** corresponds to the models that just used one particular PLM throughout the sample period. **BW** corresponds to applying Bayesian forecast weights to each PLM to produce an aggregate PLM. **Equal Weights** gives equal weight to each PLM to produce an aggregate PLM. **REE** corresponds to the model estimated under rational expectations.

Table 18: Posterior Estimates of REE and BW

	Rational Expectations			**Adaptive Learning (BW)**		
	Mean	5%	95%	Mean	5%	95%
Structural Parameters						
ψ	0.507	0.365	0.642	0.474	0.326	0.617
ι_p	0.164	0.066	0.294	0.649	0.429	0.843
ι_w	0.155	0.068	0.259	0.273	0.129	0.437
ξ_p	0.903	0.873	0.930	0.880	0.855	0.902
ξ_w	0.932	0.911	0.948	0.739	0.693	0.784
ν_l	1.778	1.072	2.668	1.508	0.846	2.336
σ_c	1.666	0.984	2.498	1.031	0.550	1.659
h	0.853	0.744	0.931	0.740	0.601	0.857
ϕ	0.148	0.036	0.326	0.348	0.116	0.667
S	3.156	1.954	4.699	2.537	1.425	3.819
χ	0.042	0.042	0.042	0.044	0.037	0.051
Policy Parameters						
r_{π_1}	1.884	1.535	2.272	2.016	1.637	2.425
r_{y_1}	0.154	0.102	0.213	0.196	0.104	0.298
r_{π_2}	-0.312	-0.473	-0.150	-0.294	-0.457	-0.132
r_{y_2}	-0.061	-0.143	0.022	-0.087	-0.163	-0.012
ρ	0.901	0.873	0.926	0.931	0.904	0.956
Exogenous Processes AR(1) Parameters						
ρ_a	0.939	0.919	0.956	0.982	0.965	0.994
ρ_b	0.738	0.604	0.850	0.576	0.461	0.694
ρ_G	0.965	0.945	0.982	0.967	0.942	0.987
ρ_I	0.729	0.641	0.806	0.528	0.405	0.653
ρ_F	0.973	0.948	0.992	0.930	0.882	0.972
ρ_p	0.850	0.785	0.903	0.382	0.246	0.535
ρ_w	0.578	0.455	0.702	0.637	0.533	0.735
u_p	0.539	0.385	0.674	0.562	0.425	0.686
Exogenous Processes Standard Deviation Parameters						
σ_a	0.805	0.726	0.897	0.801	0.711	0.900
σ_b	0.090	0.059	0.126	0.535	0.478	0.599
σ_G	0.431	0.386	0.482	0.402	0.357	0.452
σ_r	0.135	0.120	0.152	0.129	0.115	0.144
σ_I	0.896	0.757	1.053	3.086	2.758	3.448
σ_F	0.090	0.080	0.101	0.092	0.082	0.103
σ_p	0.081	0.064	0.101	0.187	0.166	0.211
σ_w	0.041	0.030	0.052	0.203	0.181	0.228
Constant Gain Learning Parameter						
γ	-	-	-	0.017	0.015	0.020

Table 19: Forecast Correlations between DFM and SPF

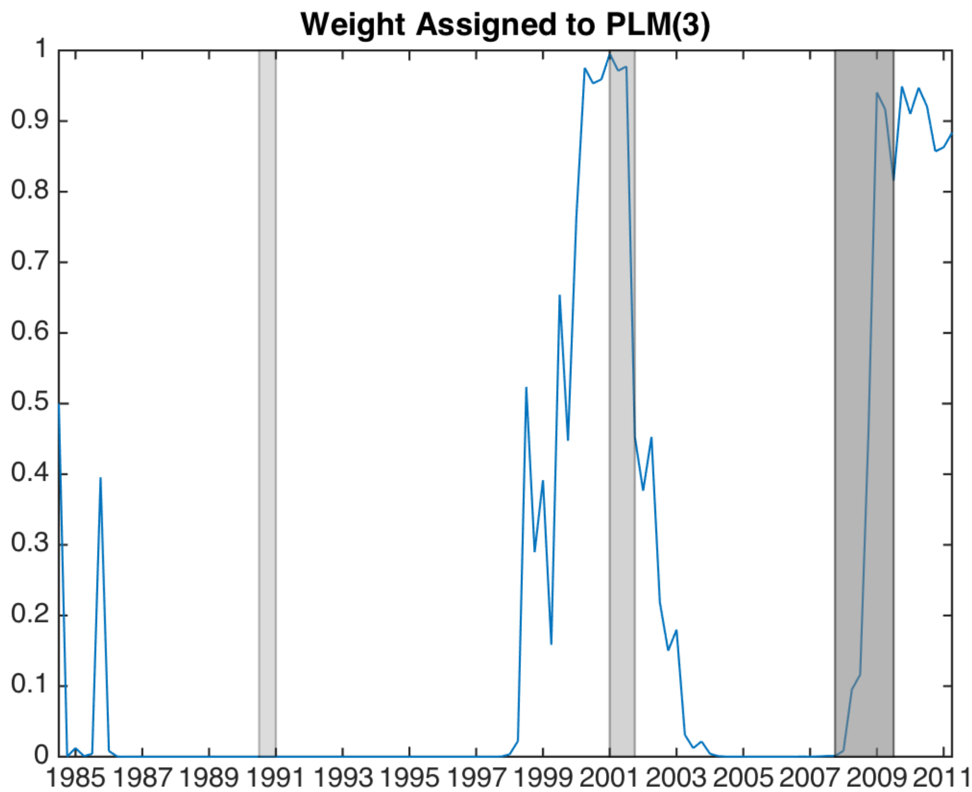
	1 Quarter Ahead Forecast	2 Quarters Ahead Forecast
Inflation	0.90	0.86
Output Growth	0.28	0.68
Consumption Growth	0.03	0.28
Investment Growth	0.04	0.31
Unemployment Rate	0.87	0.90

Table 20: Simulation Results across Different Expectation Formation Assumptions

	PLM(1)	**BW**	**PLM(3)**	**BW Low Noise**	**BW High Noise**	**BW Biased Up**	**BW Biased Down**
Standard Deviations							
π	1.27	1.12	0.93	1.24	1.26	1.17	1.18
R	3.13	2.95	2.62	3.16	3.14	3.07	3.10
L	8.02	7.87	7.37	8.06	8.11	8.01	8.01
ΔY	1.054	1.046	1.047	1.053	1.063	1.047	1.047
ΔC	0.662	0.660	0.658	0.663	0.669	0.661	0.661
ΔI	3.692	3.678	3.674	3.694	3.703	3.686	3.681
ΔW	0.303	0.297	0.293	0.303	0.306	0.300	0.301
Autocorrelations							
π	0.71	0.64	0.49	0.69	0.70	0.66	0.67
R	0.97	0.98	0.97	0.97	0.96	0.98	0.98
L	0.98	0.98	0.97	0.98	0.98	0.98	0.98
ΔY	0.36	0.35	0.35	0.35	0.36	0.35	0.35
ΔC	0.58	0.57	0.56	0.58	0.58	0.57	0.57
ΔI	0.54	0.53	0.52	0.53	0.54	0.53	0.53
ΔW	0.55	0.54	0.53	0.55	0.56	0.55	0.55

Notes: The table gives the simulated standard deviations and autocorrelations for *Inflation*, *Interest Rate*, *Hours Worked*, *Output*, *Consumption*, *Investment* and *Wage Growth* under various exception formation assumptions. **PLM(1)** corresponds to agents only using an AR(1) model to forecast future variables, **BW** assumes agents use equation (IV.2.20) to weigh each PLM when calculating their aggregate PLM and **PLM(3)** assumes agents only use the third PLM that incorporates both a lagged component and the public forecast announcement to forecast future variables. The second and third columns assume agents use the **BW** model but they receive the public forecast with either noise or bias.

Figure 25: Bayesian Weight placed on PLM(3)



Note: Plotted is the weight assigned to PLM(3) which uses both the private and public signal to forecast future variables. These weights are calculated at the median posterior parameter levels of the **BW** model.

Figure 26: 2 Quarters Ahead Forecasts of Inflation Rate

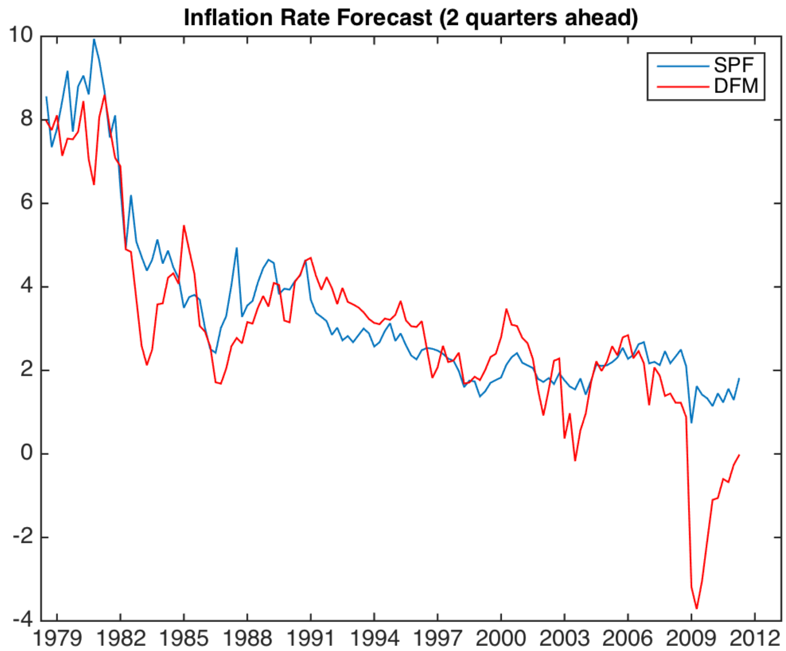


Figure 27: 2 Quarters Ahead Forecasts of Output Growth

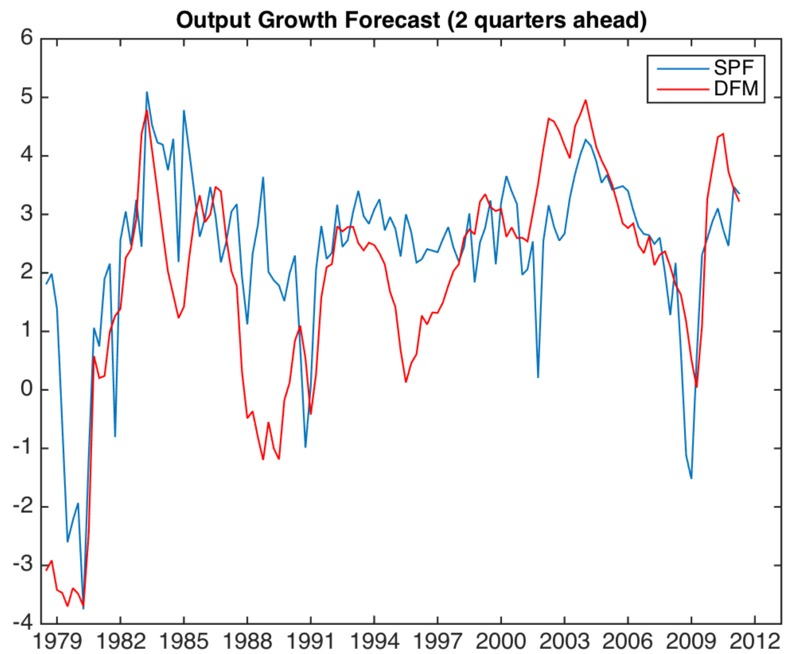
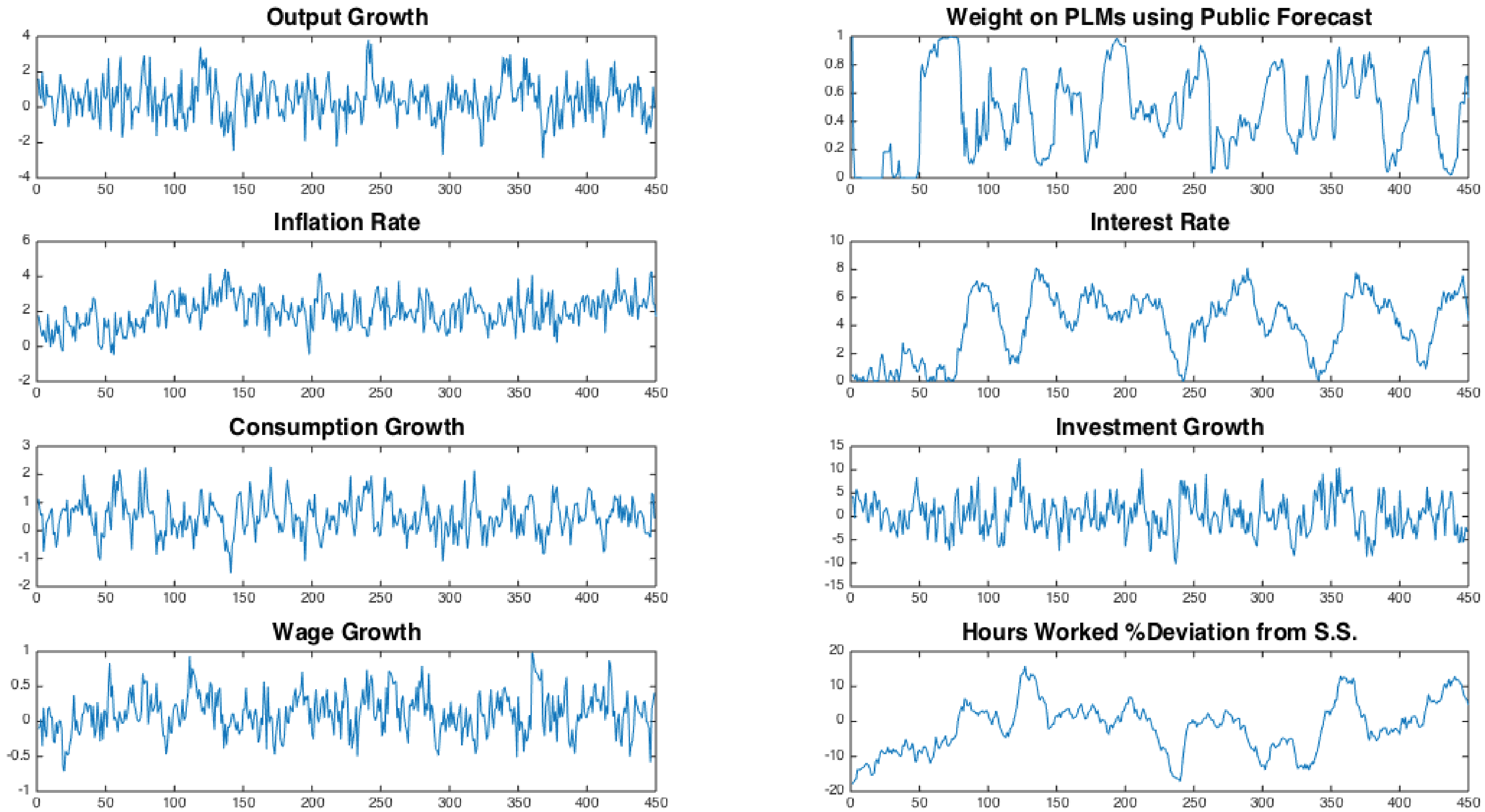


Figure 28: Simulated Path of Economy: BW model with no noise



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