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Abstract

The years following the Great Recession were challenging for forecasters. Unlike other deep downturns, this recession was not followed by a swift recovery, but generated a sizable and persistent output gap that was not accompanied by deflation as a traditional Phillips curve relationship would have predicted. Moreover, the zero lower bound and unconventional monetary policy generated a policy environment without precedents. We document the *real* real-time forecasting performance of the New York Fed dynamic stochastic general equilibrium (DSGE) model during this period and explain the results using the *pseudo* real-time forecasting performance results from a battery of DSGE models. We find the New York Fed DSGE model's forecasting accuracy to be comparable to that of private forecasters—and notably better, for output growth, than the median forecasts from the FOMC's Summary of Economic Projections. The model's financial frictions were key in obtaining these results, as they implied a slow recovery following the financial crisis.

Key words: DSGE models, real-time forecasts, Great Recession, financial frictions

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1 Introduction

The years following the Great Recession have been quite challenging from a forecasting point of view. The deep recession was not followed by a swift recovery, unlike in previous post-war deep recessions, but instead generated a persistent output gap. This large gap was however not associated with negative inflation, as a traditional Phillips curve relationship would have predicted, resulting in what Coibion and Gorodnichenko (2012) called the "missing deflation" (see also Hall, 2011; Ball and Mazumder, 2011; and Del Negro et al., 2015a). At the same time the federal funds rate was stuck at near zero levels for several years. This prompted the central bank to use tools that had never been used before, such as quantitative easing (henceforth, QE) and forward guidance. On top of all this, the U.S. economy found itself in the middle of both a demographic transition caused by the retirement of baby boomers, and a secular downward shift in the growth rate of total factor productivity, at least according to some authors (see, among others, Fernald, 2015; Fernald et al., 2017; Gordon, 2015) .

This combination of unusual, far-from-steady-state conditions presented a challenging environment for any econometric model, but in particular for dynamic stochastic general equilibrium (DSGE) models in the tradition of Smets and Wouters (2003, 2007), due to their rigid structure and tight cross-equation restrictions. Over the past decade, these models have become part of many central banks' forecasting and policy analysis toolbox, and the post-Great Recession setting surely provided an important real-time test of their predictive accuracy. So how did these models fare?

Against this backdrop, this paper pursues two objectives. The first objective consists in addressing the question above as far as the Federal Bank of New York DSGE model (henceforth, NY Fed DSGE) is concerned. Specifically, Section 2 of the paper documents how the NY Fed DSGE model fared in terms of real-time forecasting accuracy relative to forecasters such as those surveyed in the Blue Chip survey or the Survey of Professional Forecasters (henceforth, SPF), as well as the Federal Reserve System's Summary of Economic Projections (henceforth, SEP), and how researchers using the model coped with the difficulties discussed above. It will also discuss how the model changed to incorporate financial frictions anduse financial data as observables.

The second objective of the paper consists in complementing this *real* real-time forecasting exercise with a *pseudo* real-time analogue (Section 3). The main goal of this exercise is to understand what model features, and observables, explain the performance of the NY

Fed DSGE model. In addition, this exercise extends the historical forecast accuracy comparison of Edge and Gürkaynak (2010) and Del Negro and Schorfheide (2013) both in terms of the period and the models considered. In fact, their comparison did not focus on the post-Great Recession years, which were not considered at all in Edge and Gürkaynak (2010) and barely included in Del Negro and Schorfheide (2013) (their sample ends in early 2011). Moreover, Edge and Gürkaynak (2010) only consider the Smets and Wouters (2007) model while Del Negro and Schorfheide (2013) mainly focus on the performance of close variants of this model. Here, the centerpiece of our analysis will be models with financial frictions (e.g., Christiano et al., 2014; Del Negro et al., 2015b; Del Negro et al., 2016) that incorporate corporate spreads as observables.

We find that in the short and medium run —from one through eight quarters ahead— the NY Fed's root mean squared errors (henceforth, RMSEs) are comparable to the error of the median forecasts of both the Blue Chip and the SPF surveys. Relative to the median of the FOMC's SEP, the NY Fed DSGE model performs much better in terms of the accuracy of output growth forecasts, especially at longer horizons (three years ahead). The NY Fed DSGE model's inflation forecast performs worse than the median SEP up to a two year horizon, but better at a three year horizon and beyond. The results of the pseudo real-time forecasting exercise show that financial frictions play a major role, especially in terms of the projections for economic activity, as they imply a slow recovery from financial crisis —a result reminiscent of the findings of Reinhart and Rogoff (2009).

2 Real Real-Time Forecasts of NY Fed DSGE Model

This section begins with a brief description of the main features of the NY Fed DSGE model and of how they evolved over time. For the sake of brevity this description acts as a broad-level overview, whereas all of the technical details are relegated to the Appendix and to other sources. The section then continues by documenting the model's forecasting accuracy from 2011, which was the first year in which the model was used to produce regular projections.

2.1 A Short History of the New York Fed DSGE Model

The New York Fed DSGE model came to existence around 2004 as a three-equation New Keynesian model (see Sbordone et al., 2010). At the time, the model was used for a variety of policy analysis exercises but not for forecasting. In 2008, that model was replaced by a medium-scale (that is, similar to the model by Smets and Wouters, 2007, in terms of features) New Keynesian DSGE model built along the lines of Del Negro and Schorfheide (2008) and estimated with Bayesian methods using five time series: real GDP growth, core PCE inflation, hours, the labor share, and the federal funds rate.[1]

In mid-2010, the model began to be used internally for forecasting the U.S. economy, and from the end of 2010 onward, the model's forecasts have been produced systematically almost every FOMC cycle and incorporated into internal policy documents. At the time the zero lower bound on nominal interest rates (henceforth, ZLB) was an important constraint on monetary policy (and remained so for another six years). We incorporated this constraint into the DSGE forecasts by augmenting the measurement equation with federal funds rate expectations obtained from financial markets, following the approach described in Del Negro and Schorfheide (2013) and Del Negro et al. (2012). This approach amounted to forcing the model's expectations for the policy instrument to coincide with market expectations. Since the latter of course took the ZLB into account, so did the DSGE projections. In order to enhance the model with the ability to accommodate federal funds rate expectations the policy rule in the model was augmented with anticipated policy shocks as used in Laseen and Svensson, 2011. These policy "news" shocks capture constraints on future policy, whether they are contractionary (i.e., when the anticipated policy rate is higher than predicted by the reaction function) or stimulative (i.e., when the anticipated policy rate is lower than predicted by the reaction function, as under a "forward guidance" policy).

In 2010, the model was further transformed by the addition of financial frictions, following the work of Christiano et al. (2003, 2014). Specifically, the model incorporated a financial accelerator à la Bernanke et al. (1999), implying that firms' ability to invest is constrained by their leverage and more broadly by financial market conditions. In order to capture financial conditions quantitatively, we added the spreads between the yields of Baa corporate bonds and Treasuries to the model's set of observables. In June 2011, the NY Fed DSGE forecasts obtained from the model with financial frictions became part of a memo produced four times a year for the FOMC (Dotsey et al., 2011; see also page 2 of the June 2011 FOMC Minutes).

The model built in 2010, which is described in some detail in Del Negro et al. (2013), continued to be the main workhorse for DSGE projections and policy analysis at the NY Fed until the end of 2014. It was then replaced by another New Keynesian model with

[1]Del Negro and Schorfheide (2008) and Del Negro et al. (2013) provide a detailed description of the model, priors, data, and estimation procedure.

financial frictions – referred to henceforth as the SWFF model and used in Del Negro and Schorfheide (2013) and Del Negro et al. (2015a). Relative to the financial friction model introduced in 2010, SWFF was closer to the original Smets and Wouters (2007) model in terms of the specification of the household's utility function and other modeling details. Importantly, its forecasting accuracy, especially in periods of financial stress such as the financial crisis, had been demonstrated in Del Negro and Schorfheide (2013) and Del Negro et al. (2016). In addition, it had the advantage of adding investment and consumption to the set of observables.[2]

The SWFF model itself was never actually used in production at the NY Fed. Rather, we adopted a variant of this model, which we will call SWFF$^+$. This was partly because the SWFF model used in academic papers measured inflation using the GDP deflator. However, the core PCE deflator was a more relevant measure for policy purposes. We therefore added this variable to the set of observables under the assumption that inflation in the model is the common component between these two empirical measures of inflation.[3] Moreover, at the time a debate on a possible secular decline in productivity growth begun in the early 2000s was raging (e.g., Gordon, 2015; Fernald, 2015). Given the important policy implications of this debate we also added John Fernald's measure of total factor productivity growth (henceforth, TFP) to the data on which the model was estimated. In order to give the DSGE a chance to capture secular shifts in productivity growth we modeled TFP as the sum of two components: a trend-stationary one (as in Smets and Wouters, 2007) and a non-stationary component whose growth rates follow an autoregressive process. As the autocorrelation coefficient approaches one, the latter component can in principle capture very persistent shifts in TFP growth. Furthermore, we also added the 10-Year Treasury Yield to the set of observables in order to capture changes in financial conditions stemming from quantitative easing operations as well as forward guidance. Finally, the last change so far to the NY Fed DSGE model took place in early 2016. Model SWFF^{++} differed from model SWFF$^+$ by including an additional measure for output, GDI, following the work of

[2]SWFF is estimated on the same observables as Smets and Wouters (2007) (namely the growth rates in GDP, consumption, investment, and wages, all expressed in real terms, the level of hours, GDP deflator inflation, and the federal funds rate), plus spreads and long-run inflation expectations obtained from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The latter are included because Del Negro and Schorfheide (2013) found that they improve the model's accuracy in forecasting inflation even when the prior on the steady-state inflation parameter is relaxed substantially relative to Smets and Wouters (2007)'s paper.

[3]This choice was inspired by the work of Boivin and Giannoni (2006) and Justiniano et al. (2013).

Aruoba et al. (2016).[4]

Starting in September 2014, the NY Fed DSGE model forecasts have been made public on the Liberty Street Blog twice a year, and by the beginning of 2017, forecasts were being published four times a year (specifically made available in May and December 2015, May and November 2016, and in February, May, August and November 2017). The current model specification is also available online, as are the Matlab code for the early financial friction model and SW$^+$, and the Julia code for SW^{++}.[5]

2.2 NY Fed DSGE Forecasts

In this section, we examine the performance of NY Fed DSGE forecasts of real GDP growth and core PCE inflation, focusing on forecasts made for each FOMC cycle from 2011Q1 to 2016Q1. First, we consider the RMSEs of the DSGE model's real output growth and core PCE inflation forecasts relative to the output forecasts of the Blue Chip Economic Indicators (henceforth, BCEI) survey and the output and inflation forecasts of the SPF and the FOMC's SEP.[6] We do not show the federal funds rate projections because during this period the NY Fed DSGE forecasts were conditional on external forecasts of this variable in order to take the ZLB and forward guidance into account, as discussed above. Second, we examine the evolution of the NY Fed DSGE model's forecasts for output and inflation and compare them to contemporaneous SEP forecasts and realized data in order to explain some of the differences in forecast accuracy. The NY Fed DSGE forecasts considered in this comparison range from January 2011 to March 2016.

To compute RMSEs, we create for each survey forecast a sample of comparable DSGE forecasts. For a given survey forecast, we search for the nearest *preceding* DSGE model forecast with the same first forecast quarter. If we cannot find such a forecast, then we drop that observation from the sample.[7] This matching scheme ensures that the DSGE forecasts

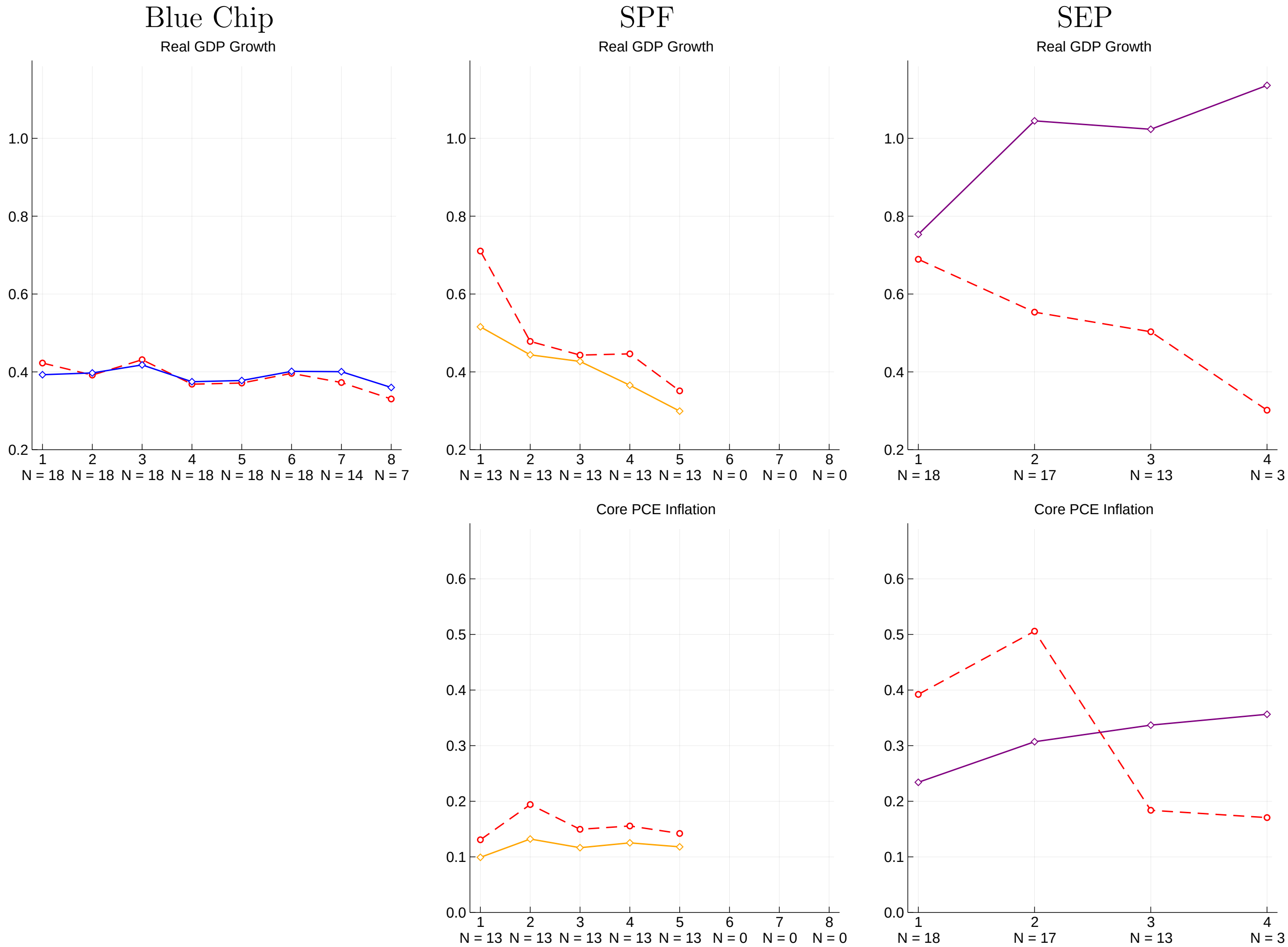
[4]The Appendix provides all the equilibrium conditions, the prior specification, and data definitions for models SWFF, SWFF$^+$ and SWFF^{++}. As mentioned earlier, Del Negro et al. (2013) contains this information for the early financial friction model.

[5]The code for the three models is available at `https://github.com/FRBNY-DSGE` in the `DSGE-2014-Sep`, `DSGE-2015-Apr`, and `DSGE.jl` respositories, respectively.

[6]We cannot compare historic DSGE forecasts of inflation to BCEI forecasts as the latter reports GDP deflator inflation instead of core PCE inflation.

[7]Although we historically ran DSGE forecasts at least one to two times each quarter, the times within the quarter at which they were run were not always consistent. For this reason, sometimes there is not a suitable DSGE forecast preceding the survey forecast.

Figure 1: Historic RMSEs for NY Fed DSGE Model Forecasts



Note: These panels compare the RMSEs for NY Fed DSGE model forecasts (red circles) of real GDP growth and core PCE inflation from January 2011 to March 2016 to those of the Blue Chip Economic Indicators survey (blue diamonds, left), the Survey of Professional Forecasters (SPF) (yellow diamonds, center), and the Summary of Economic Projections (SEP) (purple diamonds, right). The Blue Chip and SPF forecasts are in terms of Q/Q percent rates and the SEP forecasts are expressed in Q4/Q4 average rates. When computing RMSEs, each external forecast is matched to the nearest preceding DSGE forecast in order to ensure comparability of results. Below each horizon we show out the number of observations.

are not given an informational advantage.[8]

The BCEI forecasts are reported in quarter-to-quarter (henceforth, Q/Q) percent change and are released monthly. We consider the April, July, October and January forecasts, as these are the last ones that are released prior to the release of the Q1, Q2, Q3, and Q4 GDP measurements. Under our matching scheme, these forecasts are typically paired with the forecasts produced for the March, June, September, and December FOMC meetings, respectively. The Blue Chip survey asks respondents to forecast from the current quarter until

[8]Once a matching DSGE forecast is found, we transform and trim it to match the units and forecast horizon, respectively, of the survey forecast.

the end of the next calendar year, which sets the forecast horizon to range from 9 quarters in January (beginning in Q4 of the previous year) to 6 quarters in October. We follow the literature and compare the NY Fed DSGE forecast with the average BCEI projection, which is often referred to as the Consensus Blue Chip forecast.

The SPF is released at the beginning of the second month of each quarter, and is therefore matched with DSGE forecasts from the January, April, July, and October FOMC meetings, whenever possible. The SPF forecasts for core PCE inflation and real GDP growth are also in Q/Q percent change. Its forecast horizon is consistently five quarters. Fewer observations are available to compute this set of RMSEs because there are less often DSGE forecasts that both precede the SPF release and share the same first forecast quarter, as GDP is released at the end of the first month of each quarter. We compare the NY Fed DSGE forecast with the median SPF projection.[9]

Lastly, the SEP is released every other FOMC meeting beginning with the March meeting (the January meeting until June 2012). SEP participants project Q4/Q4 real GDP growth rates and core PCE inflation rates for the current year and up to three subsequent years. We compare the DSGE forecast with the median SEP projection.[10] Since DSGE forecasts are also produced in anticipation of each FOMC meeting, the corresponding DSGE forecasts are a natural match for the SEP projections. Note that while both Blue Chip and SPF surveys produce "fixed horizon" projections (that is, they are always released at a fixed interval before the quarter being forecasted), the SEP does not: in each year, there are four SEP releases which share the same first forecast year, but were made using different information sets. This is in contrast to the Blue Chip and SPF forecasts.

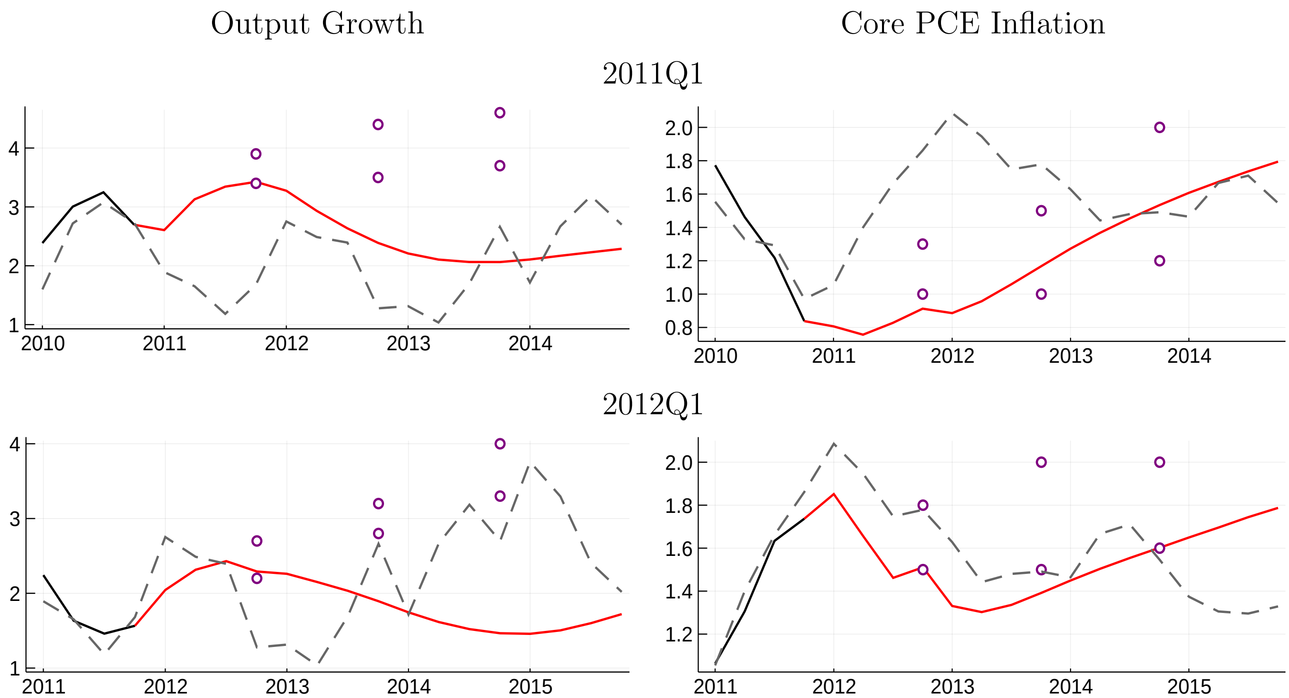
The three sets of RMSE comparisons shown in Figure 1 illustrate that over the 2011-2016 period the NY Fed DSGE projections are broadly competitive with survey forecasts in terms of accuracy. The left panel of Figure 1 shows that the NY Fed DSGE and BCEI RMSEs for output growth are virtually they same throughout the forecast horizon.[11] The DSGE model's output growth and core PCE inflation forecasts are moderately worse than

[9]The median, rather than the mean, is used as the headline number on the Philadelphia Fed's website.

[10]When the median is not available, we use the average of the upper and lower limits of the SEP central tendency, a range which excludes the three highest and three lowest forecasts of each variable in each year.

[11]It may be surprising that the first quarter ahead DSGE forecasts (that is, the nowcasts) are as accurate as the BCEI's, given the latter's informational advantage. This results is driven by the fact that the NY Fed DSGE model conditions its projections on judgemental nowcasts from the staff in order to improve the short-run accuracy of its forecasts (see Del Negro and Schorfheide, 2013). Section 3.4 elaborates on this issue.

Figure 2: Evolution of NY Fed DSGE Model Forecasts



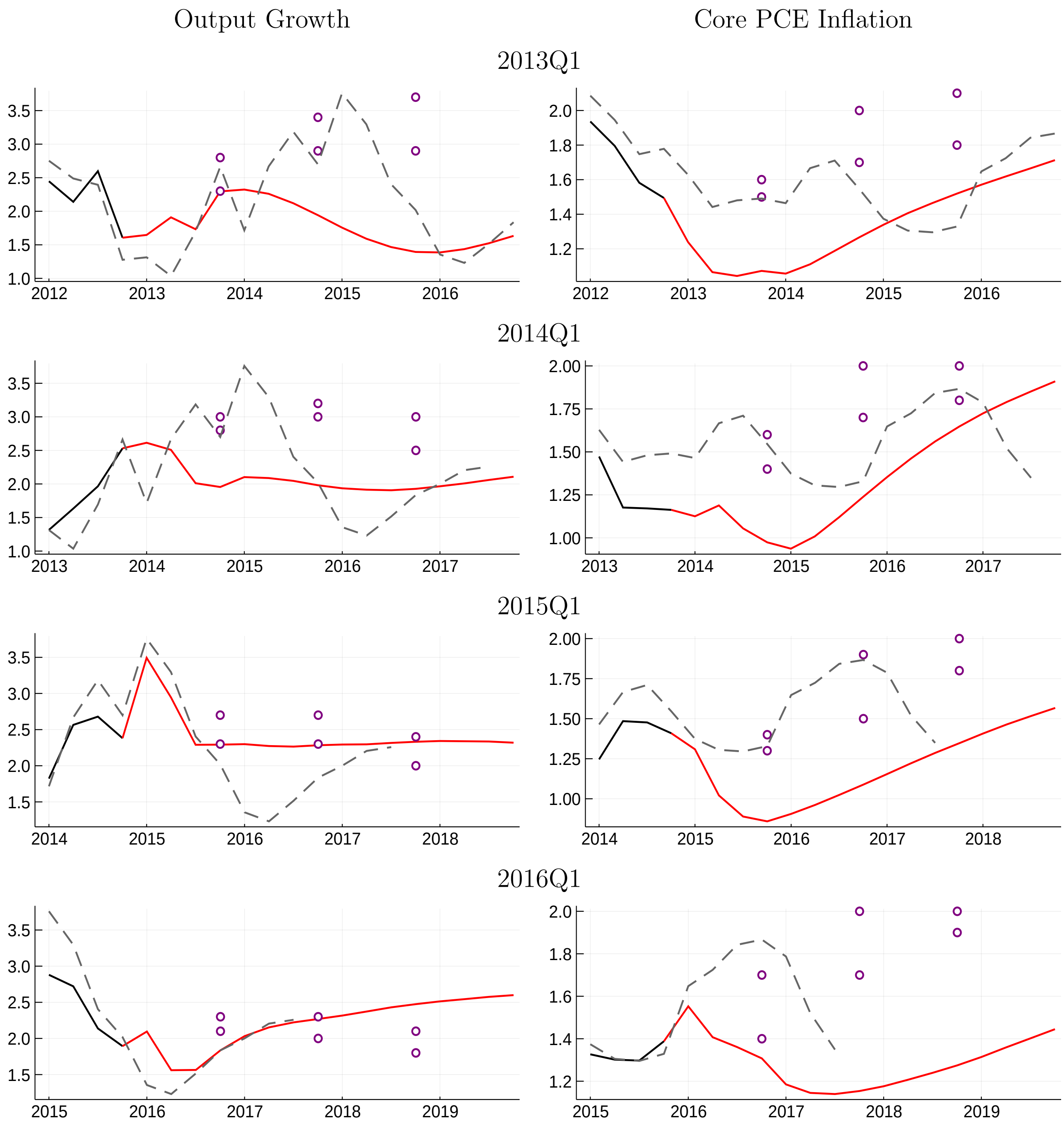
Note: These panels show NY Fed DSGE model forecasts of four quarter average real GDP growth (left column, red lines) and core PCE inflation (right column, red lines) from March 2011 and April 2012. In addition, these plots show the realized data as of the forecast date (solid black lines), the revised series as of November 1, 2017 (dashed black lines), and the upper and lower bounds of the central tendency of the Summary of Economic Projections (SEP) forecasts (purple circles) from the corresponding FOMC meetings.

the SPF forecasts, but generally comparable.[12] The NY Fed DSGE model performs notably better than the SEP's output forecasts over all horizons from one to four years ahead (but we have only three four-year ahead observations). In terms of inflation, the median SEP is more accurate for one to two years ahead, but less accurate for three years ahead.

Next, Figure 2 shows NY Fed DSGE forecasts of four-quarter average real GDP growth and core PCE inflation made in the first quarters of each year from 2011 to 2016, and provide some context for the RMSEs discussed previously. For comparison, we also include the revised data series as of November 2017 and contemporaneous SEP projections. (We show the SEP's "central tendency", which includes all SEP participants except the top and bottom three.) Early in 2011, we see that the SEP projected that the recovery from the Great Recession would be relatively quick, with growth rates above four percent. The NY

[12]The discrepancy between the DSGE's output RMSEs on the left and middle two plots and the relatively worse performance of the DSGE versus the SPF are likely due to the fact that for the reasons discussed above, there are many fewer DSGE forecasts matching the SPF forecast vintages. Moreover, we think that for some of these forecasts, the information set is actually smaller than that of the SPF, in that the latest quarter GDP release was not available when the forecast was produced.

Figure 2: Evolution of NY Fed DSGE Model Forecasts – Continued



Note: These panels show NY Fed DSGE model forecasts of four quarter average real GDP growth (left column, red lines) and core PCE inflation (right column, red lines) from March 2013, March 2014, March 2015, and March 2016. In addition, these plots show the realized data as of the forecast date (solid black lines), the revised series as of November 1, 2017 (dashed black lines), and the upper and lower bounds of the central tendency of the Summary of Economic Projections (SEP) forecasts (purple circles) from the corresponding FOMC meetings.

Fed DSGE model instead projects a very slow recovery from the financial crisis, a finding that echoes the results of Reinhart and Rogoff (2009), although it is obtained in a completely different setting. As we now know, the more pessimistic forecasts of the NY Fed DSGE model were much closer to the realized growth rates through 2013. As discussed at length in Section 3.2, the model's financial frictions play a key role in these projections. The DSGE model's inflation projections are also very subdued. For this reason, they miss the spike in inflation associated with the so-called Arab Spring in late 2011-2012. However, they are quite in line with the low inflation experienced after 2013.

In the latter half of the sample, that is, from 2014 onward,the DSGE models' forecasts are less accurate over the short run but still reasonably accurate over the medium and long term. It is worth noting that by 2015, the SEP and DSGE output growth forecasts have largely aligned. For inflation, the DSGE models' forecasts are often more downbeat than the SEP, predicting only a gradual return of inflation to the FOMC's long-run goal of two percent. Especially in later years, the DSGE tends to systematically under-predict inflation, while the SEP tends to over-predict it, as it always projects inflation to return to two percent inflation within a couple of years.

3 Pseudo Real-Time Forecasts

This section uses the results of a *pseudo* real-time forecasting exercise to understand what model features and observables explain the performance of the NY Fed DSGE model. While in a *real* real-time environment, we only have the forecasts from the specific model used at that time, a pseudo real-time setting offers the possibility of running counterfactual experiments, such as: What forecasts would we have obtained if we had stripped financial frictions from the model (Section 3.2)? What if we did not condition the forecast on external expectations for the policy rate (Section 3.3)? What if we did not condition on the nowcast (Section 3.4)? Moreover, while the forecasts discussed in Section 2 only pertain to the post-2011 year, in a pseudo-real time setting we can investigate the models' performance from 1992 onward (this is the beginning of the sample used in Edge and Gürkaynak, 2010, and Del Negro and Schorfheide, 2013) in Section 3.5. Last, we saw in Section 2.1 that the current version of the NY Fed model, SWFF^{++}, has a number of additions, both in terms of features and data, relative to the baseline SWFF model used in Del Negro and Schorfheide (2013), Del Negro et al. (2015a), and Del Negro et al. (2016). We then ask whether these additions helped or hindered the model's forecasting performance (Section 3.6). The next section provides some details regarding the construction of the real-time dataset and of the DSGE model forecasts.

3.1 Real-Time Dataset and DSGE Forecasts Setup

The models used in this section are the prototypical Smets and Wouters (2007) model (henceforth, SW), which does not have financial frictions; the SWFF model; and the two "descendants" of SWFF mentioned in Section 2.1, SWFF^{+} and SWFF^{++}. In this section, we first discuss the data series used for these models (shown below in Table 1) and the process of constructing a real-time dataset. Next, we discuss the construction of the Blue Chip forecasts dataset – our benchmark for evaluating the accuracy of the DSGE forecasts. In the construction of both the real-time and the Blue Chip forecasts datatset we follow the approach of Del Negro and Schorfheide (2013, section 4.1) and Edge and Gürkaynak (2010). Last, we discuss the DSGE forecast setup.

Table 1: Data series used in each model

Variable	SW	SWFF	SWFF^{+}	SWFF^{++}
GDP growth	X	X	X	X
Consumption growth	X	X	X	X
Investment growth	X	X	X	X
Real wage growth	X	X	X	X
Hours worked	X	X	X	X
GDP deflator inflation	X	X	X	X
Federal funds rate	X	X	X	X
10y inflation expectations		X	X	X
Spread		X	X	X
Core PCE inflation			X	X
10y bond yield			X	X
TFP growth			X	X
GDI growth				X

3.1.1 Data Series

Data on nominal GDP (GDP), nominal GDI (GDI), the GDP deflator (GDPDEF), core PCE inflation (JCXFE), nominal personal consumption expenditures (PCEC), and nominal fixed private investment (FPI) are produced at a quarterly frequency by the Bureau of Economic

Analysis, and are included in the National Income and Product Accounts (NIPA). Average weekly hours of production and nonsupervisory employees for total private industries (AWHNONAG), civilian employment (CE16OV), and the civilian non-institutional population (CNP16OV) are produced by the Bureau of Labor Statistics (BLS) at a monthly frequency. The first of these series is obtained from the Establishment Survey, and the remaining from the Household Survey. Both surveys are released in the BLS Employment Situation Summary. Since our models are estimated on quarterly data, we take averages of the monthly data. Compensation per hour for the non-farm business sector (COMPNFB) is obtained from the Labor Productivity and Costs release, and produced by the BLS at a quarterly frequency.

The federal funds rate (in the remainder of the paper we will sometimes use the acronym FFR) is obtained from the Federal Reserve Board's H.15 release at a business day frequency. Long-run inflation expectations are obtained from the Blue Chip Economic Indicators survey and the Survey of Professional Forecasters available from the FRB Philadelphia's Real-Time Data Research Center. Long-run inflation expectations (average CPI inflation over the next 10 years) are available from 1991Q4 onward. Prior to 1991Q4, we use the 10-year expectations data from the Blue Chip survey to construct a long time series that begins in 1979Q4.[13] We measure spread as the difference between the annualized Moody's Seasoned Baa Corporate Bond Yield and the 10-Year Treasury Note Yield at Constant Maturity. Both series are available from the Federal Reserve Board's H.15 release.

Lastly, TFP growth is measured using John Fernald's TFP growth series, unadjusted for changes in utilization. We use his estimate of $(1-\alpha)$ to convert it into labor-augmenting terms. The details of the data transformations are given in Section A.6 of the appendix.

3.1.2 Blue Chip Forecasts

We primarily compare our pseudo real-time forecasts to contemporaneous ones from the Blue Chip Economic Indicators (BCEI) and the Blue Chip Financial Forecasts (BCFF), two monthly surveys of business economists' projections for macroeconomic and financial variables, respectively. In this paper, we are interested in forecasts of real GDP growth and (GDP deflator) inflation from the BCEI and forecasts of the federal funds rate from

[13] Since the Blue Chip survey reports long-run inflation expectations only twice a year, we treat these expectations in the remaining quarters as missing observations and adjust the measurement equation of the Kalman filter accordingly.

the BCFF. In the RMSE comparisons below, we compare our DSGE model forecasts to the mean BCEI GDP growth and inflation forecasts and the median BCFF federal funds rate forecast. The BCEI survey is published on the 10th of each month, using data that were available at the beginning of the month; the BCFF survey is published on the 1st of each month. Though both surveys are released on a monthly basis, we restrict our attention to the January, April, July, and October forecasts. These are the months in which the last forecast for each quarter is made.

For example, the BEA publishes the first estimate of fourth-quarter GDP at the end of January, and the first estimate of first-quarter GDP at the end of April. Hence the Blue Chip surveys released in February, March, and April contain forecasts in which the first forecasted quarter is Q1. The April Blue Chip survey is the last one to forecast Q1, and choosing it gives the Blue Chip forecasters the greatest informational advantage as they have access to all of the information released during Q1, and can potentially incorporate higher-frequency financial and other data into their forecasts.

The sample we consider contains the Blue Chip forecasts from January 1991 to April 2016 (this is the same sample of Section 2). Within this sample, we construct real-time datasets using data vintages available on the 10th of January, April, July, and October of each year. We use the St. Louis Fed's ALFRED database as our primary source of vintaged data. Hourly wage vintages are only available on ALFRED beginning in 1997; we use pre-1997 vintages from Edge and Gürkaynak (2010). The GDP, GDP deflator, PCE, investment, hours, and employment series have vintages available for the entire sample. The earliest available vintages for the core PCE index and GDI are July 29th, 1999 and December 20th, 2012 respectively. Before these dates, we use the earliest available vintage of each series. John Fernald's capital share and TFP growth series are not available on ALFRED. Though there do seem to be revisions, particularly to the TFP growth estimates, we treat these two series as unrevised, using the February 28th, 2017 vintage.[14] The financial variables and the population series are not revised. For each real-time vintage, we use the Hodrick-Prescott filter on the population data observations available as of the forecast date.

When we compare the RMSEs of DSGE model and Blue Chip forecasts below, we only use as many DSGE forecast horizons as are available in the corresponding Blue Chip release. As mentioned in Section 2.2, BCEI respondents submit quarterly forecasts through the end of the next calendar year, so that they forecast 9 quarters in January (beginning with Q4 of

[14]Note that model SWFF does not use core PCE, GDI, or TFP as observables, so the lack of real-time data for these variables is an issue for $SWFF^{+}$ and $SWFF^{++}$ only.

the previous year) but only 6 quarters in October. For the majority of our sample (beginning in April 1997), BCFF respondents submit forecasts for 6 quarters in the months of January, April, July, and October and for 5 quarters in all other months.[15] The RMSEs are computed using data downloaded on November 1st, 2017.

3.1.3 DSGE Forecast Setup

In our baseline setup, we condition on external interest rate forecasts following Section 5.4 of Del Negro and Schorfheide (2013) because this was the approach taken in generating the NY Fed DSGE model forecasts. We augment the measurement equation to add

$$R^e_{t+k|t} = R_* + \mathbb{E}_t R_{t+k}, \qquad k = 1, \ldots, K$$

where we use the median k-period ahead forecast from the BCFF for the observed series $R^e_{t+k|t}$, $\mathbb{E}_t R_{t+k}$ is the model-implied k-period ahead interest rate expectation, and R_* is the steady-state interest rate. (See Section A in the Appendix for additional details.) In order to provide the model with the ability to accommodate federal funds rate expectations, the policy rule in the model was augmented with anticipated policy shocks, as discussed in section 2.1. We take the number of anticipated shocks K to be 6, which is the maximum number of BCFF forecast quarters (excluding the observed quarterly average that we impute in the first forecast period).

Specifically, in a given quarter t, the interest rate expectations observables $R^e_{t+1|t}, \ldots, R^e_{t+K|t}$ come from the BCFF forecast released in the first month of quarter $t+1$.[16] For example, for t = 2008Q4, we use the January 2009 BCFF forecasts of interest rates. We first use interest rate expectations data beginning in 2008Q4 and continue their use through liftoff, reflecting the post-financial crisis era of central bank forward guidance. Unlike in Del Negro and Schorfheide (2013), after 2008Q4, we use the expanded dataset containing interest rate forecasts in both estimation and forecasting — again, because this was the approach taken

[15] Before April 1997, BCFF submit forecasts for 5 quarters in January, April, July, and October and for 4 quarters in all other months. Unlike the macroeconomic variables forecasted in the BCEI, which are released on a lag, the quarterly averages for the financial variables in the BCFF are immediately observed at the end of each quarter. To maintain consistency with the output growth and inflation forecasts, we impose that the first forecasted period for the interest rate is the previous quarter, which is perfectly forecasted to be the observed quarterly average. This gives us a total FFR forecast horizon of 7 quarters.

[16] Since the BCFF survey is released during the first few days of the month, the information set of BCFF forecasters is effectively t – that is, they have no information about quarter $t+1$.

in forecasting with the NY Fed DSGE. However, rather than estimating a separate standard deviation $\sigma_{r^m,k}$ for each of the K anticipated shocks, we impose the restriction $\sigma^2_{r^m,k} = \dfrac{\sigma^2_{r^m}}{K}$, which implies that the sum of the variances of the anticipated shocks equals the variance of the contemporaneous shock $\sigma^2_{r^m}$. We do so because at the beginning of the ZLB period, we have too few observations to estimate these variances independently.[17]

Table 2: Summary of $T+1$ conditioning information

Variable	Source
GDP growth$_{T+1}$	BCEI forecast of $T+1$ GDP growth
GDP deflator inflation$_{T+1}$	BCEI forecast of $T+1$ GDP deflator inflation
Spread	Observed Data
R_{T+1}	Observed Data
$R_{T+2\vert T+1}$	$R^e_{T+2\vert T+1}$
$\vdots$	$\vdots$
$R_{T+K+1\vert T+1}$	$R^e_{T+K+1\vert T+1}$

We furthermore follow section 5.3 of Del Negro and Schorfheide (2013) in conditioning on nowcasts — forecasts of the current quarter — of GDP growth, GDP deflator inflation, and financial variables. We accomplish this by appending an additional period of partially observed data for period $T+1$ (the current quarter, given our timing convention).[18] Specifically, for each real-time forecast vintage, we condition on the corresponding BCEI release's mean forecasts of GDP growth and GDP deflator inflation in period $T+1$. Our choice of forecast origin months means that the entire first forecast quarter has already elapsed by the time the forecast is made, so quarterly averages of financial variables have been observed in their entirety. Finally, we use the BCFF interest rate forecast $R^e_{T+2:T+K+1|T+1}$ as observed expectations of future interested in quarter $T+1$. Table 2 summarizes the $T+1$ conditioning information. Note that we do not use any of this $T+1$ information in estimating the model parameters: these are estimated only using time T information. In fact, in the pseudo real-time forecasting exercise, we do not reestimate the DSGE model in every quarter, but

[17] This restriction was also imposed when producing the NY Fed DSGE projections.

[18] Unlike in Del Negro and Schorfheide (2013), we treat the nowcast for $T+1$ as a perfect signal of y_{T+1}, a specialization of both of the *Noise* and *News* assumptions in that paper in which we set $\eta_{T+1} = 0$. This is also what we do in the production of the NY Fed DSGE forecasts, although we usually rely on the staff's nowcast rather than the BCEI's.

only once a year using the January vintage.

3.2 The Importance of Financial Frictions

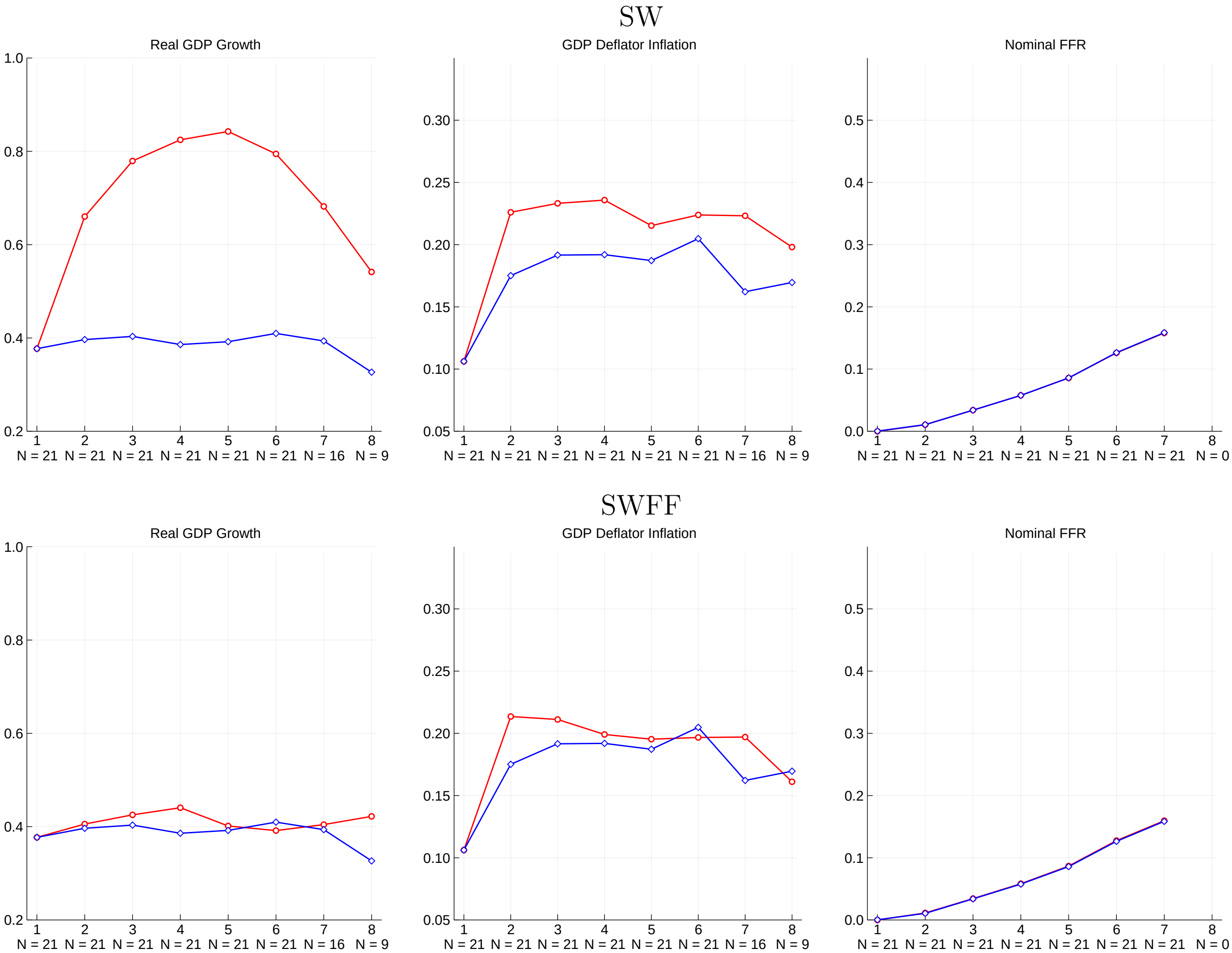
This section investigates the importance of financial frictions for the DSGE models' forecasting performance during the recovery. It does so by comparing the forecasting performance of the prototypical SW model with that of SWFF, a version of that model augmented with financial frictions.

The top and bottom panels of Figure 3 compare the RMSEs for SW (top row, red circles) and SWFF (bottom row, red circles) with the Blue Chip (blue diamonds) for output growth, inflation, and interest rates projections one through eight quarters ahead, computed from April 2011 to April 2016. For both models, the forecasts are conditional on the BCFF forecasts for the federal funds rate and the BCEI nowcasts for output growth and inflation. (We do so because conditioning on external forecasts for the policy instrument and nowcasts was the standard procedure for the NY Fed DSGE projections during this period, as discussed above.)

Figure 3 shows that the accuracy of the SWFF projections for output growth and inflation is comparable to that of the BCEI median forecasts. In fact, the output growth RMSEs for SWFF are also very similar to those of the NY Fed DSGE model shown in Figure 1 (upper left panel). The accuracy of the forecasts from the SW model is considerably worse however, especially for output. SWFF differs from SW because of both the addition of financial frictions (and spreads as observables) and the use of long run inflation expectations (and a time-varying inflation target). Figure A-1 in the Appendix shows that the key difference between the two models in terms of forecasting performance is the financial frictions: the SW model with long run inflation expectations —called SWπ in Del Negro and Schorfheide (2013)— performs as poorly as SW for output during this period (although it does perform slightly better for inflation, consistent with the findings in Del Negro and Schorfheide, 2013).

In order to understand why the SWFF model's forecasts are so much more accurate than SW's, Figure 4 shows the two models' forecasts computed using the January 2012 vintage. The top and bottom rows show the forecast for the SW and SWFF model, respectively. Specifically, the figure shows the DSGE model forecast (red solid line); the January 2012 Blue Chip forecast (blue solid line); real-time data (black solid); and revised final data from November 1st, 2017 (gray dashed) of output, inflation, and the interest rate. Similar to the SEP forecasts showed in Figure 2, the SW model believes in a fast recovery after the Great

Figure 3: RMSEs for SW and SWFF models



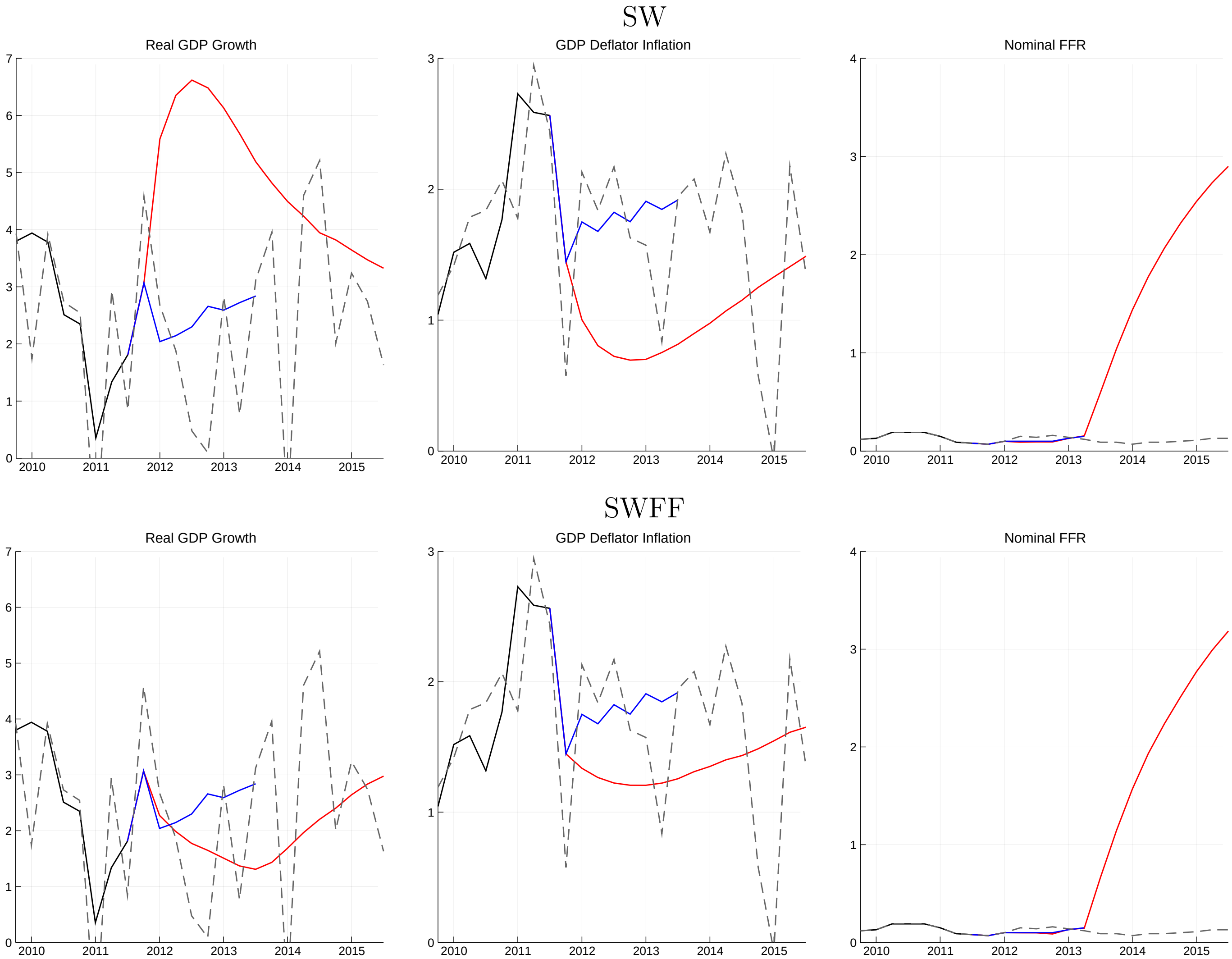
Note: The top and bottom panels compare the RMSEs for the SW (top row, red circles) and SWFF (bottom row, red circles) DSGE models with the Blue Chip (blue diamonds) for one through eight quarters ahead for output growth, inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. The forecasts included in these calculations are from April 2011 to April 2016. The DSGE forecasts are conditional on the BCFF forecasts for the federal funds rate, and the BCEI nowcasts for output growth and inflation. Section 3.2 provides the details of the forecast comparison exercise.

Recession. Like the NY Fed DSGE model, the SWFF model instead projects a slow recovery – its forecasts are indeed even more subdued than the BCEI projections. The January 2012 inflation projections from SW are also more off the mark than those from SWFF.[19]

The differences in the forecasts between SW and SWFF are not surprising if we consider

[19]This is partly explained by the fact that the degree of nominal rigidities is lower in SW than in SWFF, as documented in Table A-1. Hence, inflation depends more on current marginal costs and less on future marginal costs (see the discussion in Del Negro et al., 2015a). Since in terms of levels, the output gap is still open in 2012 also for the SW model, current marginal costs are still low and inflation projections are lower.

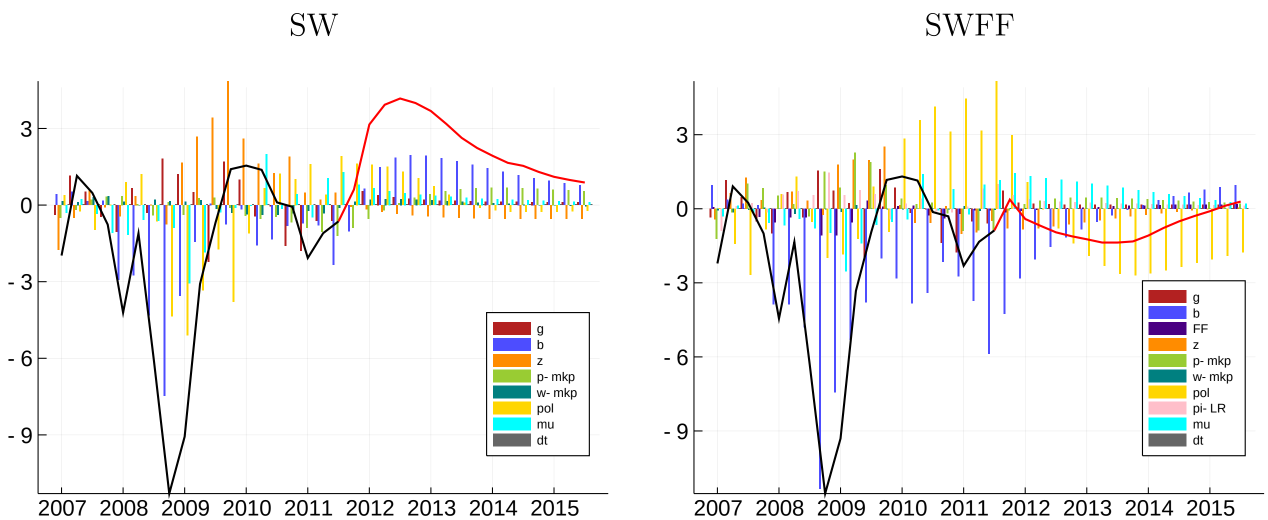
Figure 4: SW and SWFF forecasts using January 2012 data



Note: The panels show the DSGE forecasts obtained using data available as of January 2012 (red solid), the January 2012 Blue Chip forecast (blue solid line); real-time data (black solid); and revised final data from November 1st, 2017 (gray dashed) of output, inflation, and the interest rate. The DSGE forecasts are conditional on the BCFF forecasts for the federal funds rate, and the BCEI nowcasts for output growth and inflation. The top and bottom rows show the forecast for the SW and SWFF model, respectively. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points.

the different explanations these two models have for the Great Recession. Figure 5 decomposes the history of real GDP growth, as of 2012, into the various disturbances affecting the economy in the two models. The SWFF model (right panel) attributes the Great Recession almost exclusively to financial shocks, mostly the so-called "risk premium" shocks. (These are the shocks labeled b in Figure 5, represented by blue bars.) The impulse responses in Figure 6 (bottom panel) show that these risk premium shocks have a very persistent effect on the economy: they have a negative effect on *growth rates* of almost 12 quarters, implying that the *level* of GDP begins to recover only after three years.

Figure 5: Shock Decompositions of GDP Growth

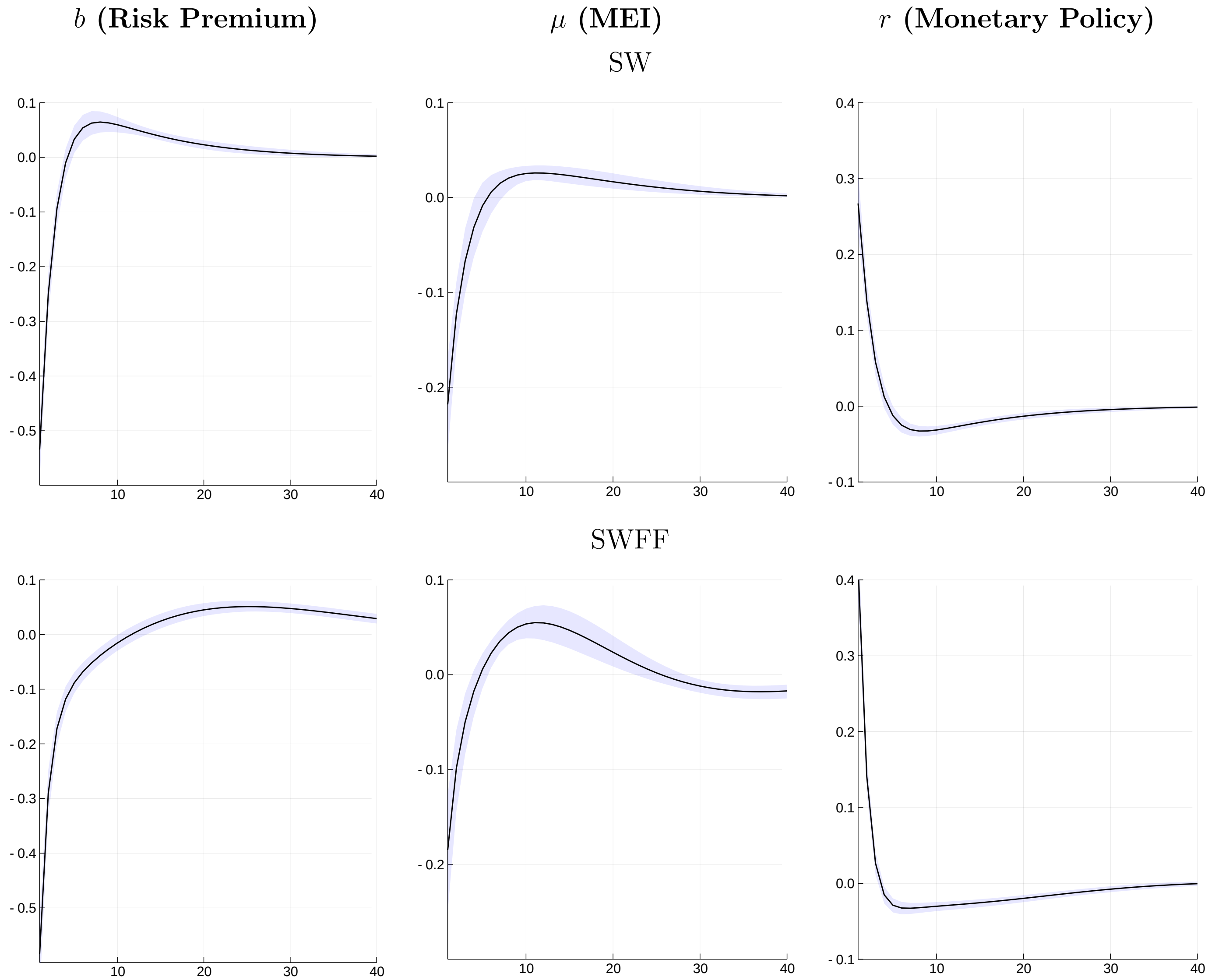


Note: The panels show the SW (left) and SWFF (right) models' shock decompositions of real GDP growth from the January 2012 forecast origin. The solid line (black for realized data, red for mean forecast) shows output growth in deviation from steady state in Q/Q percent annualized terms. The bars represent the contribution of each shock to the deviation from steady state, computed as the counterfactual values obtained when all other shocks are zero. Some of the shocks have been aggregated in this decomposition. In order, the SWFF shocks are categorized into aggregate demand, discount factor, financial frictions, productivity, price markup, wage markup, monetary policy, inflation target, and marginal efficiency of investment. The gray bars represent the deterministic trend, the counterfactual values obtained from iterating the initial state vector forward without any shocks. The shock categories for the SW model are a strict subset of the SWFF shock categories.

The SW model also attributes the Great Recession in part to risk premium shocks. (See the left panel of Figure 5.) However, the role of these shocks is not as important as in SWFF, partly because the SW model does not use spreads as observables. Moreover, because the SW model lacks financial frictions, the impulse responses to these shocks are far less persistent (top panel of Figure 6), with growth rebounding only a few quarters after the shock. In that model, the Great Recession is driven in large part by policy shocks (which capture the ZLB constraint; yellow bars in left panel of Figure 5) and by marginal efficiency of investment shocks (these are the so-called MEI shocks emphasized in Justiniano et al., 2010; they are labeled μ in Figure 5 and are represented by light blue bars). Figure 6 shows that both of these shocks have much less persistent effects on GDP growth than risk premium shocks in SWFF.

In conclusion, the SW model interprets the Great Recession as due to disturbances whose effects on the economy are relatively transitory, in contrast to the SWFF model in which financial shocks have much more persistent effect on output growth. This implies that the SW model expects a faster return of the economy to steady state, and therefore high growth rates of the economy. In addition, when these high growth rates do not materialize in the aftermath of the recession, the model attributes these forecast misses to *additional*

Figure 6: Impulse Responses of Real GDP Growth



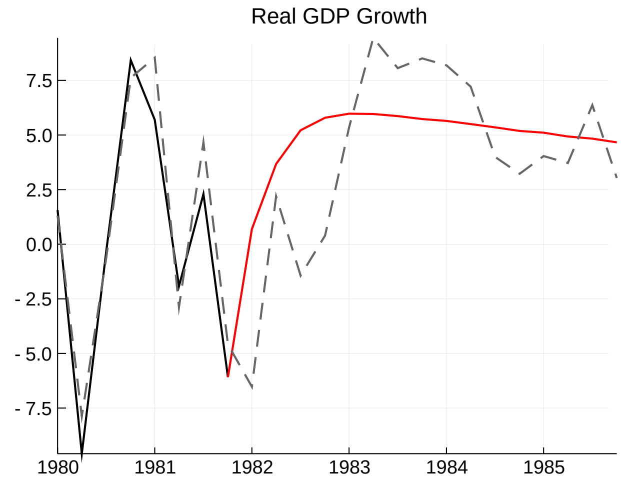
Note: The panels compare the SW (top panels) and SWFF (bottom panels) DSGE models' impulse response functions of real GDP growth to one-standard-deviation innovations in the discount factor (left), marginal efficiency of investment (center), and contemporaneous monetary policy (right) shocks. Parameters estimated using the baseline January 2012 dataset are used.

temporary negative shocks, that are followed by a quick recovery. As the effect of these shocks compounds, SW ends up predicting very high growth rates for the economy, as shown in Figure 4.

Does SWFF predicts a slow recovery after *every* recession? Figure 7 reveals that this is not the case. The figure shows the real GDP growth projections using the April 1982 data vintage — that is, at the trough of the 1982 recession.[20] The SWFF model predicts a very fast recovery after the 1982 recession, and its predictions are strikingly in line with *ex post*

[20]We use the end-of-sample parameter estimates, but otherwise the forecast is out-of-sample.

Figure 7: SWFF Forecast of the 1982 Recession



Note: The figure shows the SWFF forecast for real GDP growth beginning in 1982Q1 (red solid); real-time data (black solid); and revised final data from November 1st, 2017 (gray dashed) of real GDP growth. The forecast was generated using April 1982 data, using the parameters from the January 2016 estimation.

outcomes. This is the case because the model attributes the recession to disturbances whose effect on the economy is more transient than that of financial shocks, such as monetary policy shocks.

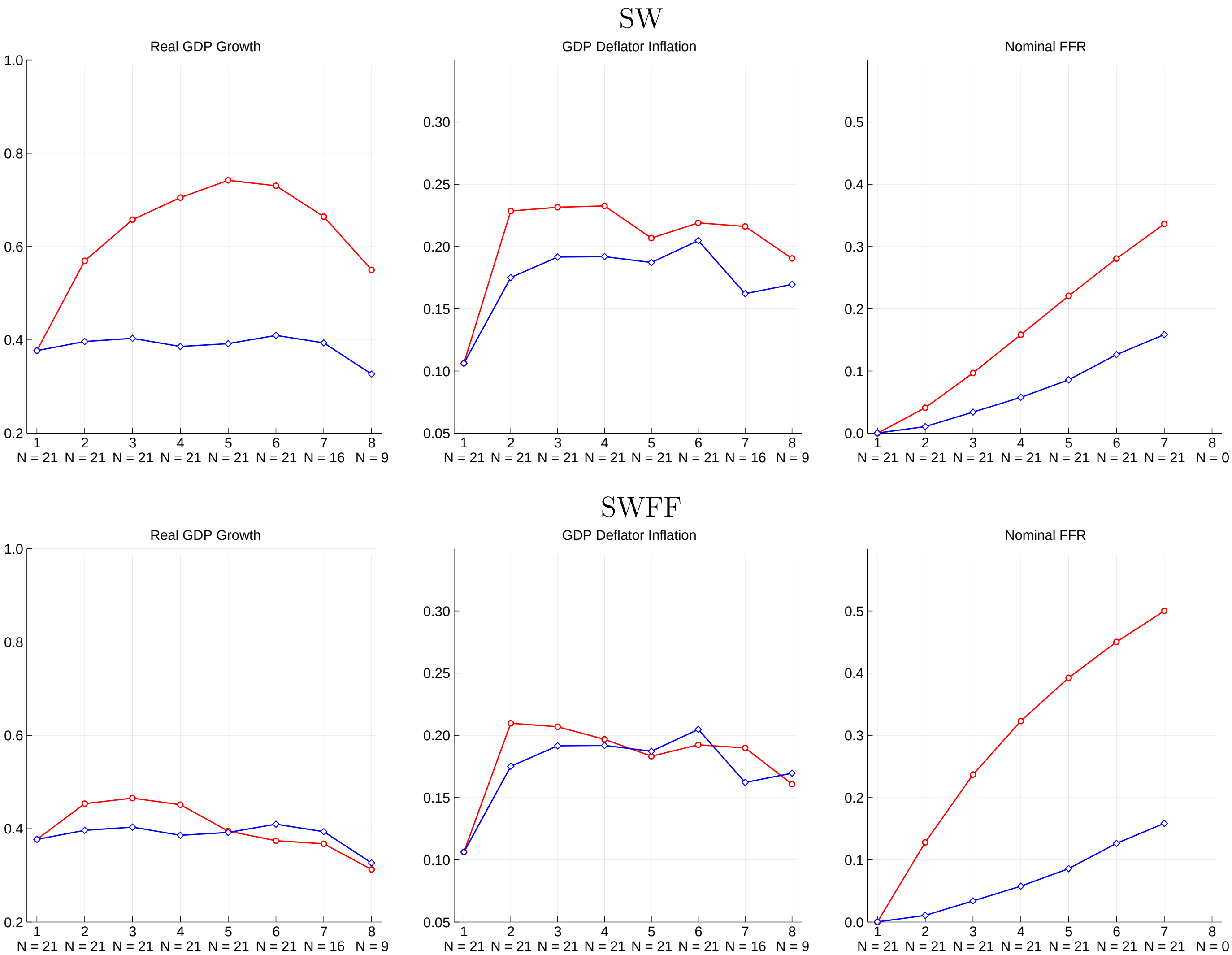
3.3 Conditioning on FFR Expectations

As discussed before, in our baseline analysis, we condition on interest rate forecasts from the BCFF in both the estimation and forecast steps in order to incorporate additional information available in the era of central bank forward guidance. This section investigates the impact of that choice. Figure 8 shows the RMSEs of the SW and SWFF models when we do not use BCFF interest rate forecasts.[21] The sample is the same as Figure 3 —April 2011 to April 2016— and we continue to condition on the BCEI nowcasts of output growth and inflation, as well as on the observed quarterly average interest rate in the first period.

The main takeaway of Figure 8 is that, in the absence of interest rate expectations data, the RMSEs for output growth and inflation in the SWFF model are very similar to those computed in Figure 3, even though the RMSEs for the federal funds rate deteriorate substantially. Regarding the SW model, the RMSEs for output growth improve somewhat

[21] For the results in Figure 8 we continue to use the parameter estimates obtained from the estimation *with* the FFR expectations data. However, Figure A-2 in the Appendix for RMSEs shows that we obtain very similar results when we do not use FFR expectations data at all, including in the estimation.

Figure 8: RMSEs for SW and SWFF vs. Blue Chip, without conditioning on FFR expectations

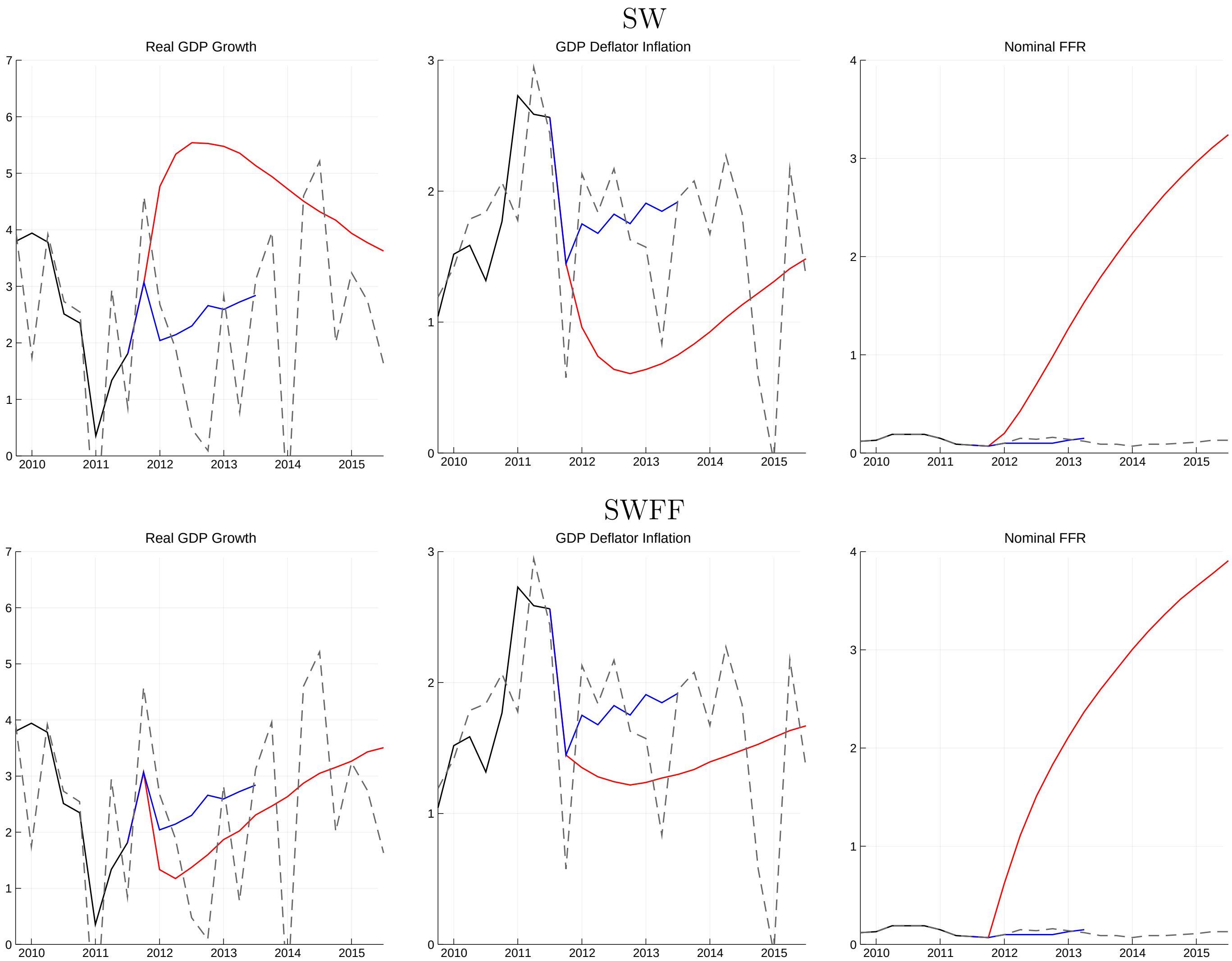


Note: The top and bottom panels compare the RMSEs for the SW (top row, red circles) and SWFF (bottom row, red circles) DSGE models with the Blue Chip (blue diamonds) for one through eight quarters ahead for output growth, inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. The forecasts included in these calculations are from April 2011 to April 2016. The DSGE forecasts are conditional on the BCEI nowcasts for output growth and inflation. Section 3.3 provides the details of the forecast comparison exercise.

in the absence of interest rate expectations data, but remain sensibly above those of the SWFF model.

In order to understand the effect of conditioning on FFR expectations on the two models, we again focus on a specific set of forecasts — those computed using the January 2012 vintage. Figure 9 is analogous to Figure 4, except that the DSGE projections are computed without using FFR expectations. Clearly, both DSGE models predict an earlier liftoff of the

Figure 9: SW and SWFF forecasts using January 2012 data, without conditioning on FFR expectations



Note: The panels show the DSGE forecasts obtained using data available as of January 2012 (red solid); the January 2012 Blue Chip forecast (blue solid line); real-time data (black solid); and revised final data from November 1st, 2017 (gray dashed) of output, inflation, and the interest rate. The DSGE forecasts are conditional on the BCEI nowcasts for output growth and inflation. The top and bottom rows show the forecasts for the SW and SWFF models, respectively. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points.

federal funds rate relative to both the BCFF projections and ex-post outcomes. This is not surprising: Blue Chip forecasters are aware of the Federal Reserve's forward guidance while the DSGE econometrician, without conditioning on either market or survey expectations, is not (which is why in the NY Fed DSGE model we condition on federal funds rate expectations). We also note that SWFF projects a faster liftoff of the policy rate than SW. This is not surprising in light of the fact that SW projects inflation to be (counterfactually) lower than SWFF, and that the estimated policy reaction function, which is the basis of the FFR projections for the DSGE models, depends positively on inflation. This observation explains why the RMSEs for the federal funds rate shown in Figure 9 are worse for SWFF than for SW.

The differences in the DSGE forecasts for output growth and inflation between Figures 4 and 9 illustrate the effect of conditioning on FFR expectations. From the perspective of the DSGE econometrician, forward guidance can be interpreted in two different ways, as either “Odyssean” or “Delphic” (see Campbell et al., 2012). The Odyssean interpretation amounts to anticipated future monetary policy accommodation — the policy “news” shocks discussed in Section 2.1. The Delphic interpretation instead leads the econometrician to revise her assessment of the state of the economy, which is of course latent in DSGE models: the lower FFR projections are then interpreted as an indication that the state of the economy is worse than previously estimated.

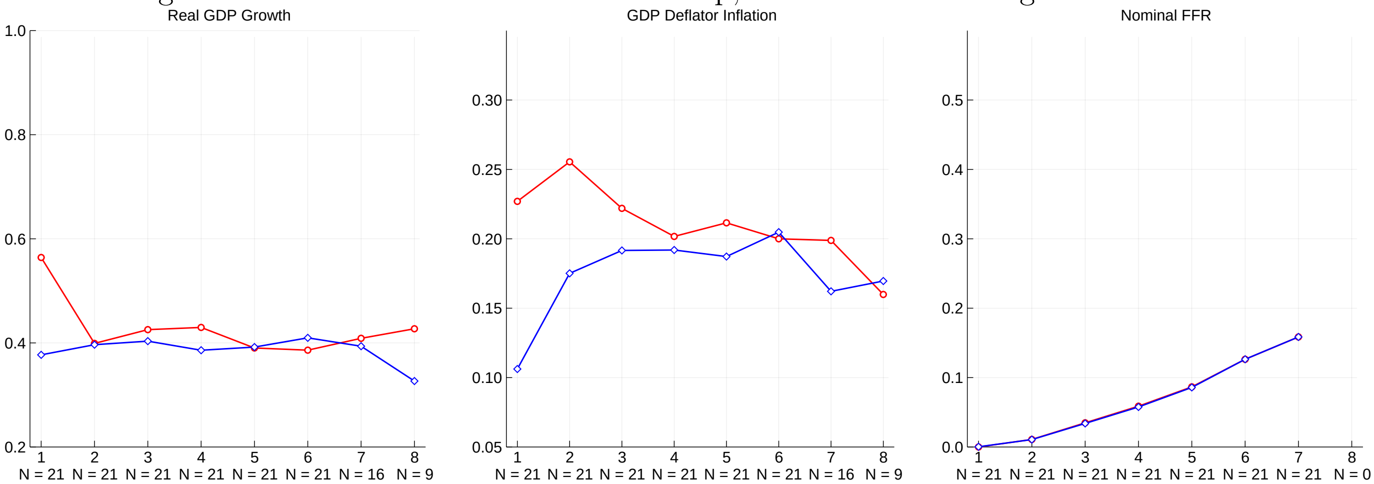
Both effects are at play in the DSGE projections. However, the comparison of Figures 4 and 9 indicates that the Odyssean effect is very strong particularly for the SW model: In Figure 9 the SW projections for output growth are still overly optimistic relative to ex-post outcomes, but much less so than in Figure 4. The comparison of Figures 4 and 9 therefore reveals that the SW model suffers from what Del Negro et al. (2012) called the “forward guidance puzzle”: incorporating the accommodation resulting from forward guidance results in overly optimistic projections for the economy. This also explains why the SW RMSEs for real GDP growth shown in Figure 8 are smaller than those in Figure 3. For the SWFF model, the differences in both forecasts and RMSEs with and without conditioning on FFR expectations are much more muted than for the SW model. This is both because the way SWFF interprets forward guidance is different from SW, and because SWFF is less affected by the “forward guidance puzzle”.[22]

3.4 Conditioning on Nowcasts

Del Negro and Schorfheide (2013) discuss the challenges facing the DSGE econometrician. One well-understood challenge is of course model misspecification (e.g., see Del Negro and

[22]This is partly because the SWFF model has higher nominal rigidities than the SW model. (See Del Negro et al., 2015a, and the parameter estimates shown in Table A-1 of the Appendix.) We should note that it is not straightforward to assess the relative importance of Odyssean and Delphic effects, or to attribute the different responses across models to forward guidance shocks to specific model features. We leave these questions to future research.

Figure 10: RMSEs for SWFF vs. Blue Chip, without conditioning on nowcast



Note: The panels compare the RMSEs for SWFF (red circles) with the Blue Chip (blue diamonds) for one through eight quarters ahead for output growth, inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. Forecast origins from April 2011 to April 2016 only are included in these calculations. Section 3.4 provides the details of the forecast comparison exercise.

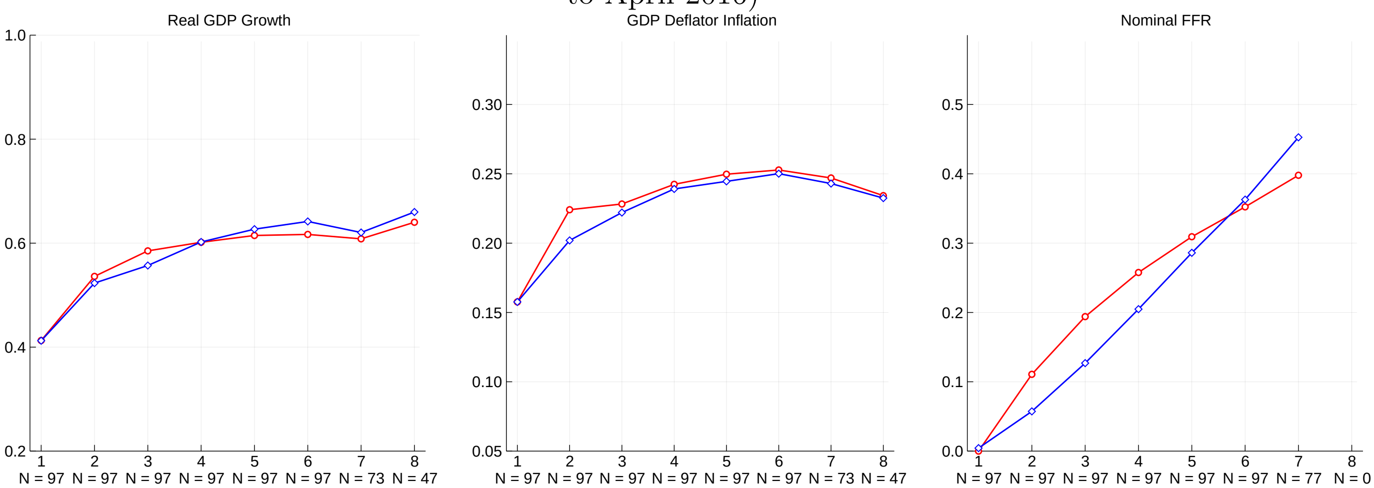
Schorfheide, 2004; Del Negro et al., 2007). Another challenge arises from the limitations of the econometrician's information set—that is the set of observables used in estimating the model and generating forecasts. Augmenting the set of observables with spreads, for instance, as the SWFF model does, provides valuable information to the econometrician regarding financial conditions. Similarly, conditioning on FFR expectations informs the econometrician about the degree of future policy accommodation. A third challenge is given by the timeliness of the econometrician's information set: The majority of the data series — both "hard" (monthly releases of inflation and consumption) and "soft" (e.g., from surveys, such as the Institute for Supply Management survey, or ISM) — used in the estimation of our model become available at a quarterly frequency and therefore do not include all the information available at higher frequency. Blue Chip forecasters use this information to produce nowcasts for output and inflation. For this reason, the DSGE model current-quarter forecasts stand to benefit from conditioning on the nowcasts obtained from the Blue Chip survey. Similarly, the NY Fed forecasts discussed in Section 2 incorporate the nowcast from in-house forecasters.

How much does incorporating the nowcast improve the DSGE forecasts? Figure 10 depicts RMSEs for SWFF and the Blue Chip forecasts for output growth, inflation, and the nominal federal funds rate without conditioning on nowcasts. The sample is the same as Figure 3 —April 2011 to April 2016— and we continue to condition on the BCFF FFR expectations. Not surprisingly, the Blue Chip nowcasts are much more accurate than the

DSGE's for both output growth and inflation. However, for output growth the RMSEs are quite similar to those in Figure 3 from horizon 2 onward, while for inflation the improvement associated with including nowcasts persists for about 4 quarters. Therefore, we confirm the results in Del Negro and Schorfheide (2013) that the positive effect of conditioning on the nowcast on inflation is much more persistent than the corresponding effect on GDP, which is not surprising in light of the different persistence in the two series.[23]

3.5 Whole Sample vs. Post-Great Recession

Figure 11: RMSEs for SWFF vs. Blue Chip, computed from whole sample (January 1992 to April 2016)



Note: The panels compare the RMSEs for SWFF (red circles) with the Blue Chip (blue diamonds) for one through eight quarters ahead for output growth, inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. The forecasts included in these calculations are from January 1991 to April 2016. The DSGE forecasts are conditional on the BCFF forecasts for the federal funds rate, and the BCEI nowcasts for output growth and inflation. Section 3.5 provides the details of the forecast comparison exercise.

The results so far, and in much of the paper, focus on forecasting during the recovery from the Great Recession, because this is the period of interest and the one for which we have forecasts from the NY Fed DSGE model. This section turns to the question of how the DSGE models fared across our entire available sample of 1992-2017, for the sake of comparison with the previous literature on the accuracy of DSGE model forecasts for the U.S. As in the previous sections, we condition on time $T+1$ BCEI forecasts of output

[23] As noted in Section 3.1, the nowcast is treated simply as $T+1$ data, as opposed to a noisy measurement of the forecasted variables at time $T+1$ as in Del Negro and Schorfheide (2013). We do so because this is the approach taken in producing the NY Fed DSGE forecasts.

and inflation. Interest rate expectations are incorporated starting in 2008Q4, to match the beginning of the ZLB period.

Figure 11 shows that the SWFF model's performance is remarkably similar to that of the Blue Chip forecasts across all horizons and variables. As far as output and inflation are concerned, this finding is in line with that of Del Negro and Schorfheide (2013). Interest rate projections are moderately worse in the short to medium run, but overall are comparable in performance. This last point is notable given the lack of interest rate expectations from 1992-2008Q3, and indicates that the model is capable of producing reasonable interest rate forecasts away from the zero lower bound.

Edge and Gürkaynak (2010)'s results showed that the accuracy of DSGE models' forecasts is comparable to that of private forecasters. One could dismiss those findings on the ground that they applied to the Great Moderation period, an easy period to forecast.[24] These results shown here are notable because they document that the accuracy of DSGE models' forecasts is comparable to that of private forecasters even though almost half of the sample includes periods that are particularly difficult for DSGE models, such as the Great Recession and its aftermath.

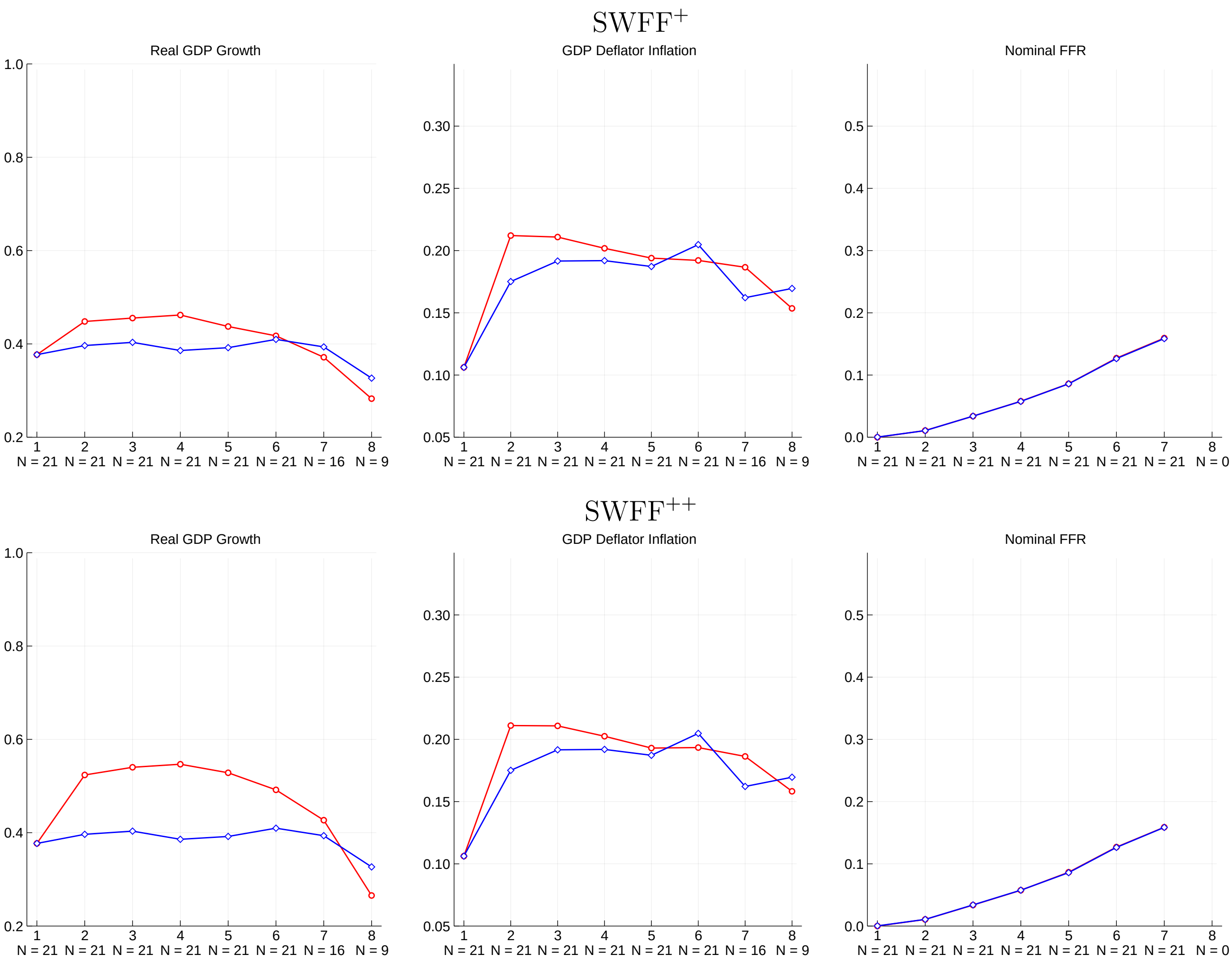
3.6 SWFF vs. Its Descendants

As described in Section 2.1, the main models used in producing the various internal policy materials and forecasts were built on top of SWFF, mainly by adding more observables (and more features to accommodate these observables).[25] In this section, we ask to what extent these choices changed the DSGE's forecasting accuracy. Comparing the RMSEs from SWFF in Figure 3 to the RMSEs shown below in Figure 12, we see that the near-term and medium-term output growth forecast performance slightly declined from SWFF to SWFF$^+$ and from SWFF$^+$ to SWFF^{++}, whereas long-term forecasting performance improved a bit from horizons 7 and beyond, even outperforming the Blue Chip forecast at that horizon. Near-term and medium-term forecasts of inflation remained largely on par between SWFF and its descendants, but in a similar fashion to the output growth forecasts, long-term performance from horizon 6 and beyond improved.

[24] Del Negro and Schorfheide (2013)'s showed that this is still true if the sample is extended to 2011.

[25] The technical details of the additional features included in these models, SWFF$^+$ and SWFF^{++}, are in sections A.4 and A.5 of the appendix respectively.

Figure 12: RMSEs for SWFF^{+} and SWFF^{++} vs. Blue Chip



Note: The top and bottom panels compare the RMSEs for the SWFF^{+} (top row, red circles) and SWFF^{++} (bottom row, red circles) DSGE models with the Blue Chip (blue diamonds) for one through eight quarters ahead for output growth, inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. The forecasts included in these calculations are from April 2011 to April 2016. The DSGE forecasts are conditional on the BCFF forecasts for the federal funds rate, and the BCEI nowcasts for output growth and inflation. Section 3.6 provides the details of the forecast comparison exercise.

4 Conclusions

The paper documents the accuracy of the projections of the NY Fed DSGE model during the recovery from the financial crisis. We find that in the short and medium run —from one through eight quarters ahead— our DSGE models' RMSEs are comparable to those obtained from the mean and median forecasts of the Blue Chip and SPF surveys, respectively. Relative to the median of the FOMC's Summary of Economic Projections, however, the NY Fed

DSGE model performed much better in terms of the accuracy of its output growth forecasts, especially at longer horizons. For inflation, the DSGE performed worse than the median SEP up to a two year horizon, but better at a three year horizon. The paper then uses a pseudo real-time forecasting exercise to assess which model features explain the results. It finds that financial frictions play a major role, especially in terms of the projections for economic activity, as they imply a slow recovery from financial crises.

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Online Appendix for "DSGE Forecasts of the Lost Recovery"

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A DSGE Model Descriptions

This section of the appendix contains the model specifications for SW, SWπ, SWFF, SW$^+$, and SW^{++}, along with a description of how we construct our data, and a table with the priors on the parameters of the various models.

A.1 SW

We include a brief description of the log-linearized equilibrium conditions of the Smets and Wouters (2007) model to establish the foundation for explaining the later models. We deviate from the original Smets-Wouters specification by detrending the non-stationary model variables by a stochastic rather than a deterministic trend. This is done in order to express the equilibrium conditions in a flexible manner that accommodates both trend-stationary and unit-root technology processes. The model presented below is the model referred to in the paper as the SW model.

Let $\tilde{z}_t$ be the linearly detrended log productivity process, defined here as:

$$\tilde{z}_t = \rho_z \tilde{z}_{t-1} + \sigma_z \epsilon_{z,t},\ \epsilon_{z,t} \sim N(0,1) \tag{A-1}$$

All non-stationary variables are detrended by $Z_t = e^{\gamma t + \frac{1}{1-\alpha}\tilde{z}_t}$, where γ is the steady-state growth rate of the economy. The growth rate of Z_t in deviations from γ, which is denoted by z_t, follows the process:

$$z_t = \ln(Z_t/Z_{t-1}) - \gamma = \frac{1}{1-\alpha}(\rho_z - 1)\tilde{z}_{t-1} + \frac{1}{1-\alpha}\sigma_z \epsilon_{z,t} \tag{A-2}$$

All of the variables defined below will be given in log deviations from their non-stochastic steady state, where the steady state values will be denoted by *-subscripts.

A.1.1 Equilibrium Conditions

The *optimal allocation of consumption* satisfies the following Euler equation:

$$
\begin{aligned}
c_t = &-\frac{(1-he^{-\gamma})}{\sigma_c(1+he^{-\gamma})}\left(R_t - I\!E_t[\pi_{t+1}] + b_t\right) + \frac{he^{-\gamma}}{(1+he^{-\gamma})}\left(c_{t-1} - z_t\right) \\
&+ \frac{1}{(1+he^{-\gamma})} I\!E_t\left[c_{t+1} + z_{t+1}\right] + \frac{(\sigma_c - 1)}{\sigma_c(1+he^{-\gamma})}\frac{w_* L_*}{c_*}\left(L_t - I\!E_t[L_{t+1}]\right). \quad \text{(A-3)}
\end{aligned}
$$

where c_t is consumption, L_t denotes hours worked, R_t is the nominal interest rate, and π_t is inflation. The exogenous process b_t drives a wedge between the intertemporal ratio of the marginal utility of consumption and the riskless real return, $R_t - I\!E_t[\pi_{t+1}]$, and follows an AR(1) process with parameters ρ_b and σ_b. The parameters σ_c and h capture the relative degree of risk aversion and the degree of habit persistence in the utility function, respectively.

The *optimal investment decision* comes from the optimality condition for capital producers and satisfies the following relationship between the level of investment i_t and the value of capital, q_t^k, both measured in terms of consumption:

$$
q_t^k = S'' e^{2\gamma}(1+\beta e^{(1-\sigma_c)\gamma})\left(i_t - \frac{1}{1+\beta e^{(1-\sigma_c)\gamma}}(i_{t-1} - z_t) - \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}} I\!E_t[i_{t+1} + z_{t+1}] - \mu_t\right) \quad \text{(A-4)}
$$

This relationship is affected by investment adjustment costs (S'' is the second derivative of the adjustment cost function) and by the marginal efficiency of investment μ_t, an exogenous process which follows an AR(1) with parameters ρ_μ and σ_μ, and that affects the rate of transformation between consumption and installed capital (see Greenwood et al. (1998)).

The *installed capital*, which we also refer to as the capital stock, evolves as:

$$
\bar{k}_t = \left(1 - \frac{i_*}{\bar{k}_*}\right)\left(\bar{k}_{t-1} - z_t\right) + \frac{i_*}{\bar{k}_*} i_t + \frac{i_*}{\bar{k}_*} S'' e^{2\gamma}(1+\beta e^{(1-\sigma_c)\gamma})\mu_t \quad \text{(A-5)}
$$

where $\frac{i_*}{\bar{k}_*}$ is the steady-state ratio of investment to capital. The parameter β captures the intertemporal discount rate in the utility function of the households.

The *arbitrage condition between the return to capital and the riskless rate* is:

$$
\frac{r_*^k}{r_*^k + (1-\delta)} I\!E_t[r_{t+1}^k] + \frac{1-\delta}{r_*^k + (1-\delta)} I\!E_t[q_{t+1}^k] - q_t^k = R_t + b_t - I\!E_t[\pi_{t+1}] \quad \text{(A-6)}
$$

where r_t^k is the rental rate of capital, r_*^k its steady-state value, and δ the depreciation rate.

The relationship between $\bar{k}_t$ and the *effective capital* rented out to firms k_t is given by:

$$k_t \ = \ u_t - z_t + \bar{k}_{t-1}. \tag{A-7}$$

where capital is subject to variable capacity utilization, u_t.

The optimality condition determining the *rate of capital utilization* is given by:

$$\frac{1-\psi}{\psi} r_t^k = u_t. \tag{A-8}$$

where ψ captures the utilization costs in terms of foregone consumption.

From the optimality conditions of goods producers it follows that all firms have the same *capital-labor ratio*:

$$k_t \ = \ w_t - r_t^k + L_t. \tag{A-9}$$

Real marginal costs for firms are given by:

$$mc_t \ = \ (1-\alpha) \ w_t + \alpha \ r_t^k. \tag{A-10}$$

where α is the income share of capital (after paying markups and fixed costs) in the production function.

All of the equations mentioned above have the same form regardless of whether or not technology has a unit root or is trend-stationary. A few small differences arise for the following two equilibrium conditions.

The *production function* under trend stationarity is:

$$y_t \ = \ \Phi_p \left(\alpha k_t + (1-\alpha) L_t\right) + \mathcal{I}\{\rho_z < 1\}(\Phi_p - 1)\frac{1}{1-\alpha}\tilde{z}_t. \tag{A-11}$$

The last term $(\Phi_p - 1)\frac{1}{1-\alpha}\tilde{z}_t$ drops out if technology has a stochastic trend because then one must assume that the fixed costs are proportional to the trend.

The *resource constraint* is:

$$y_t = g_t + \frac{c_*}{y_*}c_t + \frac{i_*}{y_*}i_t + \frac{r_*^k k_*}{y_*}u_t - \mathcal{I}\{\rho_z < 1\}\frac{1}{1-\alpha}\tilde{z}_t, \tag{A-12}$$

The term $-\frac{1}{1-\alpha}\tilde{z}_t$ disappears if technology follows a unit root process.

Government spending, g_t, is assumed to follow the exogenous process:

$$g_t = \rho_g g_{t-1} + \sigma_g \epsilon_{g,t} + \eta_{gz}\sigma_z \epsilon_{z,t} \tag{A-13}$$

The *price and wage Phillips curves* respectively are:

$$\begin{aligned}\pi_t =& \frac{(1-\zeta_p \beta e^{(1-\sigma_c)\gamma})(1-\zeta_p)}{(1+\iota_p \beta e^{(1-\sigma_c)\gamma})\zeta_p((\Phi_p - 1)\epsilon_p + 1)} mc_t \\ &+ \frac{\iota_p}{1+\iota_p \beta e^{(1-\sigma_c)\gamma}}\pi_{t-1} + \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\iota_p \beta e^{(1-\sigma_c)\gamma}} \mathbb{E}_t[\pi_{t+1}] + \lambda_{f,t}\end{aligned} \tag{A-14}$$

$$\begin{aligned}w_t =& \frac{(1-\zeta_w \beta e^{(1-\sigma_c)\gamma})(1-\zeta_w)}{(1+\beta e^{(1-\sigma_c)\gamma})\zeta_w((\lambda_w - 1)\epsilon_w + 1)} \left(w_t^h - w_t\right) \\ &- \frac{1+\iota_w \beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}}\pi_t + \frac{1}{1+\beta e^{(1-\sigma_c)\gamma}}\left(w_{t-1} - z_t - \iota_w \pi_{t-1}\right) \\ &+ \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}} \mathbb{E}_t\left[w_{t+1} + z_{t+1} + \pi_{t+1}\right] + \lambda_{w,t}\end{aligned} \tag{A-15}$$

where ζ_p, ι_p, and ϵ_p are the Calvo parameter, the degree of indexation, and the curvature parameters in the Kimball aggregator for prices, with the equivalent parameters with subscript w corresponding to wages.

The variable w_t^h corresponds to the *household's marginal rate of substitution between consumption and labor* and is given by:

$$\frac{1}{1-he^{-z_*^*}}\left(c_t - he^{-z_*^*}c_{t-1} + he^{-z_*^*}z_t\right) + \nu_l L_t = w_t^h. \tag{A-16}$$

where η_l is the curvature of the disutility of labor (equal to the inverse of the Frisch elasticity in the basence of wage rigidities).

The mark-ups $\lambda_{f,t}$ and $\lambda_{w,t}$ follow exogenous ARMA(1, 1) processes:

$$\lambda_{f,t} = \rho_{\lambda_f}\lambda_{f,t-1} + \sigma_{\lambda_f}\epsilon_{\lambda f,t} + \eta_{\lambda_f}\sigma_{\lambda_f}\epsilon_{\lambda_f,t-1} \tag{A-17}$$

$$\lambda_{w,t} = \rho_{\lambda_w}\lambda_{w,t-1} + \sigma_{\lambda_w}\epsilon_{\lambda w,t} + \eta_{\lambda_w}\sigma_{\lambda_w}\epsilon_{\lambda_w,t-1} \tag{A-18}$$

Lastly, the monetary authority follows a *policy feedback rule*:

$$R_t \;=\; \rho_R R_{t-1} + (1-\rho_R)\left(\psi_1 \pi_t + \psi_2(y_t - y_t^f)\right) + \psi_3\left((y_t - y_t^f) - (y_{t-1} - y_{t-1}^f)\right) + r_t^m \tag{A-19}$$

where the flexible price/wage output y_t^f is obtained from solving the version of the model absent nominal ridigities (without equations (3)-(12) and (15)), and the residual r_t^m follows an AR(1) process with parameters ρ_{r^m} and σ_{r^m}.

The exogenous component of the policy rule r_t^m evolves according to the following process:

$$r_t^m = \rho_{r^m} r_{t-1}^m + \epsilon_t^R + \sum_{k=1}^{K} \epsilon_{k,t-k}^R \tag{A-20}$$

where ϵ_t^R is the usual contemporaneous policy shock and $\epsilon_{k,t-k}^R$ is a policy shock that is known to agents at time $t-k$, but affects the policy rule k periods later — that is, at time t. As outlined in Laseen and Svensson (2011), these *anticipated policy shocks* allow us to capture the effects of the zero lower bound on nominal interest rates, as well as the effects of forward guidance in monetary policy.

A.1.2 Measurement Equations

The SW model is estimated using seven quarterly macroeconomic time series, whose measurement equations are given below:

$$\begin{aligned}
\textit{Output growth} &= \gamma + 100(y_t - y_{t-1} + z_t) \\
\textit{Consumption growth} &= \gamma + 100(c_t - c_{t-1} + z_t) \\
\textit{Investment growth} &= \gamma + 100(i_t - i_{t-1} + z_t) \\
\textit{Real Wage growth} &= \gamma + 100(w_t - w_{t-1} + z_t) \\
\textit{Hours} &= \bar{l} + 100 l_t \\
\textit{Inflation} &= \pi_* + 100\pi_t \\
\textit{FFR} &= R_* + 100 R_t \\
\textit{FFR}^e_{t,t+j} &= R_* + \mathbb{E}_t[R_{t+j}], j = 1, ..., 6
\end{aligned} \tag{A-21}$$

where all variables are measured in percent, π_* and R_* measure the steady-state levels of net inflation and short term nominal interest rates, respectively, and $\bar{l}$ represents the mean of the hours (this variable is measured as an index).

The priors for the DSGE model parameters are the same as in Smets and Wouters (2007) and are summarized in Panel I of the priors table listed in the SW^{++} section.

A.2 SWπ

The SWπ model builds on SW by allowing the inflation target to be time-varying. The time-varying inflation target, π_t^*, allows us to capture the dynamics of inflation and interest rates in the estimation sample.

The time-varying *inflation target* evolves according to

$$\pi_t^* = \rho_{\pi^*}\pi_{t-1}^* + \sigma_{\pi^*}\epsilon_{\pi^*,t} \tag{A-22}$$

where $0 < \rho_{\pi^*} < 1$ and $\epsilon_{\pi^*,t}$ is an i.i.d. shock. π_t^* is a stationary process, although the prior on ρ_{π^*} forces this process to be highly persistent.

A.2.1 Measurement Equations

As in Aruoba and Schorfheide (2008) and Del Negro and Eusepi (2011), we use data on long-run inflation expectations in the estimation of SWπ. This allows us to pin down the target inflation rate to the extent that long-run inflation expectations contain information about the central bank's objective.

Thus there is an additional measurement equation for 10 year inflation expectations that augments (A-21), given by

$$\mathit{10y\ Infl.\ Expectations} = \pi_* + \mathbb{E}_t\left[\frac{1}{40}\sum_{j=0}^{39}\pi_{t+j}\right] \tag{A-23}$$

A.3 SWFF

Financial frictions are incorporated into the SW model following the work of Bernanke et al. (1999) and Christiano et al. (2009).

A.3.1 Equilibrium Conditions

SWFF replaces (A-6) with the following equation for the *excess return on capital* — that is, the spread between the expected return on capital and the riskless rate — and the definition of the *return on capital*, $\tilde{R}_t^k$, respectively:

$$\mathbb{E}_t\left[\tilde{R}^k_{t+1} - R_t\right] = -b_t + \zeta_{sp,b}(q^k_t - \bar{k}_t - n_t) + \tilde{\sigma}_{\omega,t} \tag{A-24}$$

and

$$\tilde{R}^k_t - \pi_t = \frac{r^k_*}{r^k_* + (1-\delta)} r^k_t + \frac{(1-\delta)}{r^k_* + (1-\delta)} q^k_t - q^k_{t-1} \tag{A-25}$$

where $\tilde{R}^k_t$ is the gross nominal return on capital for entrepreneurs, n_t is entrepreneurial equity, and $\tilde{\sigma}_{\omega,t}$ captures mean-preserving changes in the cross-sectional dispersion of ability across entrepreneurs (see Christiano et al. (2009)) and follows an AR(1) process with parameters ρ_{σ_ω} and σ_{σ_ω}.

The following equation outlines the *evolution of entrepreneurial net worth*:

$$\hat{n}_t = \zeta_{n,\tilde{R}^k_t}\left(\tilde{R}^k_t - \pi_t\right) - \zeta_{n,\tilde{R}^k_t}(R_{t-1} - \pi_t) + \zeta_{n,qK}(q^k_{t-1} + \bar{k}_{t-1}) + \zeta_{n,n} n_{t-1} - \frac{\zeta_{n,\sigma_\omega}}{\zeta_{sp,\sigma_\omega}} \tilde{\sigma}_{\omega,t-1} \tag{A-26}$$

A.3.2 Measurement Equations

SWFF's additional measurement equation for the spread (given below) augments the standard set of SW measurement equations (A-21) along with (A-23).

$$Spread = SP_* + 100\mathbb{E}_t\left[\tilde{R}^k_{t+1} - R_t\right] \tag{A-27}$$

where SP_* measures the steady-state spread. Priors are specified for the parameters SP_*, $\zeta_{sp,b}$, ρ_{σ_ω}, σ_{σ_ω}, and the parameters $\bar{F}_*$ and γ_* (the steady-state default probability and the survival rate of entrepreneurs, respectively), are fixed.

A.4 SWFF$^+$

The SW$^+$ model augments the technology process, Z^*_t, with a long-run component, Z^p_t, such that $Z^*_t = e^{\frac{1}{1-\alpha}\tilde{z}_t} Z^p_t e^{\gamma t}$. Recall the previous specification of the growth rate of the technology process (A-2). Now with an additional term, $z^p_t = ln(Z^p_t / Z^p_{t-1})$, the growth rate of the technology process follows:

$$z_t = \ln(Z^*_t / Z^*_{t-1}) - \gamma = \frac{1}{1-\alpha}(\rho_z - 1)\tilde{z}_{t-1} + \frac{1}{1-\alpha}\sigma_z \epsilon_{z,t} + z^p_t \tag{A-28}$$

where

$$z^p_t = \rho_{z^p} z^p_{t-1} + \sigma_{z^p}\epsilon_{z^p,t},\ \epsilon_{z^p,t} \sim N(0,1) \tag{A-29}$$

A.4.1 Measurement Equations

SW$^+$ adds an additional set of measurement equations for core PCE, the 10 year nominal bond yield, and TFP.

$$\begin{aligned} \textit{Core PCE Inflation} &= \pi_* + \pi_t + e_t^{pce} \\ \textit{10y Nominal Bond Yield} &= R_* + \mathbb{E}_t\left[\frac{1}{40}\sum_{k=1}^{40} R_{t+k}\right] + e_t^{10y} \\ \textit{TFP growth, demeaned} &= z_t + \frac{\alpha}{1-\alpha}(u_t - u_{t-1}) + e_t^{tfp} \end{aligned} \tag{A-30}$$

All the e_t^* processes follow exogenous AR(1) specifications, and can be thought of either as measurement errors or some other unmodelered source of discrepancy between the model and the data (e.g., risk premia for the long term nominal rate).

A.5 SWFF^{++}

A.5.1 Measurement Equations

SW^{++} adds the additional measurement equation for GDI and modifies the equation for GDP given in Section A-21:

$$\begin{aligned} \textit{GDP growth} &= 100\gamma + (y_t - y_{t-1} + z_t) + e_t^{gdp} - \mathcal{C}_{me} e_{t-1}^{gdp} \\ \textit{GDI growth} &= 100\gamma + (y_t - y_{t-1} + z_t) + e_t^{gdi} - \mathcal{C}_{me} e_{t-1}^{gdi} \end{aligned} \tag{A-31}$$

The e_t^* terms follow exogenous AR(1) specifications as similarly described in Section A.4. Furthermore, we introduce correlation in the measurement errors for GDP and GDI, which evolve as follows:

$$e_t^{gdp} = \rho_{gdp} e_{t-1}^{gdp} + \sigma_{gdp}\epsilon_t^{gdp},\ \epsilon_t^{gdp} \sim i.i.d.N(0,1)$$

$$e_t^{gdi} = \rho_{gdi} e_{t-1}^{gdi} + +\varrho_{gdp}\sigma_{gdp}\epsilon_t^{gdp} + \sigma_{gdi}\epsilon_t^{gdi},\ \epsilon_t^{gdi} \sim i.i.d.N(0,1)$$

We assume that $\mathcal{C}_{me} = 1$. The measurement errors for GDP and GDI are thus stationary in levels, and enter the observation equation in first differences (e.g. $\epsilon_t^{gdp} - \epsilon_{t-1}^{gdp}$ and $\epsilon_t^{gdi} - \epsilon_{t-1}^{gdi}$). GDP and GDI are also cointegrated as they are driven by a common stochastic trend.

A.6 Data Transformation

The data are transformed following Smets and Wouters (2007), with the exception of the civilian population data, which are filtered using the Hodrick-Prescott filter to remove jumps around census dates. For each financial variable, we take quarterly averages of the annualized daily data and divide by four. Let Δ denote the temporal difference operator. Then:

$$
\begin{array}{lcl}
\text{GDP growth} & = & 100 * \Delta LN((GDP/GDPDEF)/CNP16OV) \\
\text{GDI growth} & = & 100 * \Delta LN((GDI/GDPDEF)/CNP16OV) \\
\text{Consumption growth} & = & 100 * \Delta LN((PCEC/GDPDEF)/CNP16OV) \\
\text{Investment growth} & = & 100 * \Delta LN((FPI/GDPDEF)/CNP16OV) \\
\text{Real wage growth} & = & 100 * \Delta LN(COMPNFB/GDPDEF) \\
\text{Hours worked} & = & 100 * LN((AWHNONAG * CE16OV/100)/CNP16OV) \\
\text{GDP deflator inflation} & = & 100 * \Delta LN(GDPDEF) \\
\text{Core PCE inflation} & = & 100 * \Delta LN(JCXFE) \\
\text{FFR} & = & (1/4) * \text{FEDERAL FUNDS RATE} \\
\text{FFR}^e_{t+k|t} & = & (1/4) * \text{BLUE CHIP } k\text{-QUARTERS AHEAD FFR FORECAST} \\
\text{10y inflation exp} & = & (\text{10-year average CPI inflation forecast} - 0.50)/4 \\
\text{Spread} & = & (1/4) * (\text{Baa Corporate} - \text{10 year Treasury}) \\
\text{10y bond yield} & = & (1/4) * (\text{10 year Treasury}) \\
\text{TFP growth, demeaned} & = & (1/4) * (\text{Fernald's TFP growth, unadjusted, demeaned})/(1-\alpha)
\end{array}
$$

In the long-term inflation expectation transformation, 0.50 is the average difference between CPI and GDP annualized inflation from the beginning of the sample to 1992.

A.7 Inference, Prior and Posterior Parameter Estimates

We estimate the model using Bayesian techniques. This requires the specification of a prior distribution for the model parameters. For most parameters common with Smets and Wouters (2007), we use the same marginal prior distributions. As an exception, we favor a looser prior than Smets and Wouters (2007) for the quarterly steady-state inflation rate π_*; it is centered at 0.75% and has a standard deviation of 0.4%. Regarding the financial frictions, we specify priors for the parameters SP_*, $\zeta_{sp,b}$, ρ_{σ_ω}, and σ_{σ_ω}, while we fix the parameters corresponding to the steady-state default probability and the survival rate of entrepreneurs, respectively. In turn, these parameters imply values for the parameters of (A-26). Information on the priors and posterior mean is provided in Table A-1.

Table A-1: Parameter Estimates

Parameter	SWFF Prior Type	SWFF Prior Mean	SWFF Prior SD	SWFF Posterior Mean	SWFF Posterior 90.0% LB	SWFF Posterior 90.0% UB	SW Posterior Mean	SW Posterior 90.0% LB	SW Posterior 90.0% UB
Steady State									
100γ	N	0.400	0.100	0.406	0.382	0.431	0.367	0.320	0.414
α	N	0.300	0.050	0.142	0.112	0.172	0.143	0.115	0.171
$100(\beta^{-1}-1)$	G	0.250	0.100	0.127	0.062	0.193	0.168	0.071	0.265
σ_c	N	1.500	0.370	0.776	0.614	0.937	1.063	0.854	1.270
h	B	0.700	0.100	0.521	0.428	0.615	0.611	0.531	0.690
ν_l	N	2.000	0.750	2.574	1.741	3.410	2.161	1.278	3.005
δ	-	0.025	0.000	0.025	0.025	0.025	0.025	0.025	0.025
Φ	N	1.250	0.120	1.582	1.444	1.713	1.559	1.435	1.690
S''	N	4.000	1.500	3.325	1.813	4.717	6.590	4.927	8.197
ψ	B	0.500	0.150	0.684	0.562	0.821	0.759	0.626	0.896
$\bar{L}$	N	-45.000	5.000	-46.042	-48.189	-43.815	-45.106	-47.011	-43.251
λ_w	-	1.500	0.000	1.500	1.500	1.500	1.500	1.500	1.500
π_*	G	0.750	0.400	1.151	0.808	1.490	0.681	0.526	0.839
g_*	-	0.180	0.000	0.180	0.180	0.180	0.180	0.180	0.180
Nominal Rigidities									
ζ_p	B	0.500	0.100	0.926	0.903	0.950	0.844	0.799	0.888
ζ_w	B	0.500	0.100	0.923	0.905	0.942	0.856	0.811	0.904
ι_p	B	0.500	0.150	0.294	0.139	0.443	0.223	0.092	0.345
ι_w	B	0.500	0.150	0.445	0.256	0.633	0.484	0.279	0.687
ε_p	-	10.000	0.000	10.000	10.000	10.000	10.000	10.000	10.000
ε_w	-	10.000	0.000	10.000	10.000	10.000	10.000	10.000	10.000
Policy									
ψ_1	N	1.500	0.250	1.148	1.039	1.250	1.847	1.584	2.100
ψ_2	N	0.120	0.050	0.004	-0.005	0.013	0.110	0.064	0.156
ψ_3	N	0.120	0.050	0.193	0.160	0.225	0.207	0.171	0.241
ρ	B	0.750	0.100	0.724	0.693	0.754	0.868	0.840	0.897
ρ_{rm}	B	0.500	0.200	0.182	0.106	0.257	0.257	0.170	0.342
Financial Frictions									
$F(\omega)$	-	0.030	0.000	0.030	0.030	0.030	-	-	-

Note: N, B, G, and IG stand, respectively, for the normal, beta, gamma, and root inverse gamma distributions. Under the inverse gamma prior mean and SD, the mode τ and degrees of freedom ν are reported.

Table A-1: Parameter Estimates

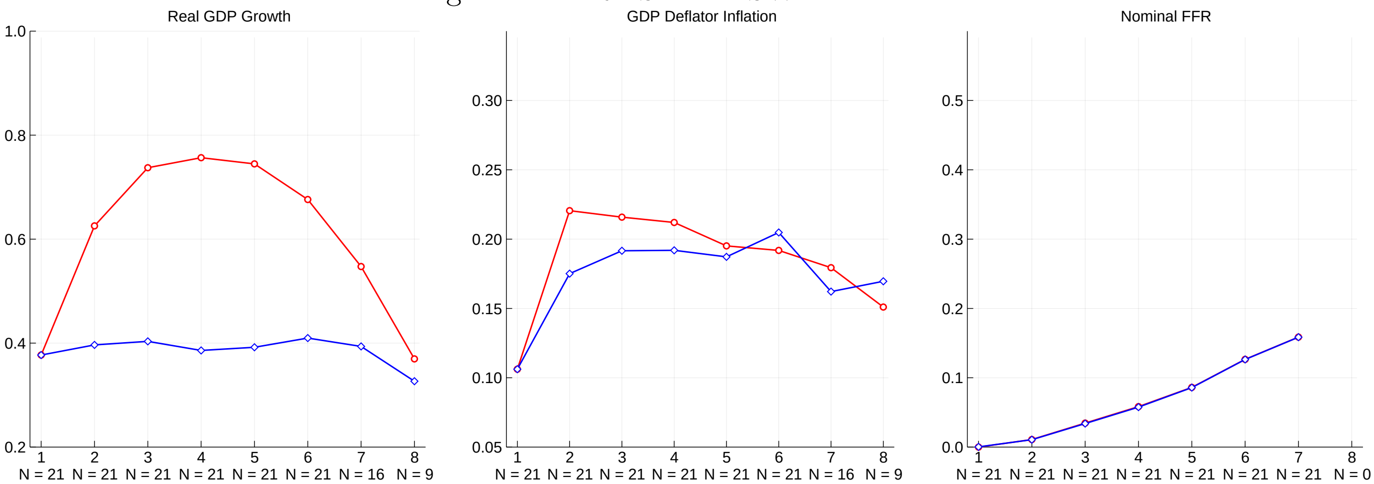
	SWFF Prior			SWFF Posterior			SW Posterior		
Parameter	Type	Mean	SD	Mean	90.0% LB	90.0% UB	Mean	90.0% LB	90.0% UB
spr_*	G	2.000	0.100	1.914	1.775	2.054	-	-	-
ζ_{spb}	B	0.050	0.005	0.052	0.045	0.059	-	-	-
γ_*	-	0.990	0.000	0.990	0.990	0.990	-	-	-
				Exogenous Processes					
ρ_g	B	0.500	0.200	0.983	0.974	0.992	0.978	0.965	0.992
ρ_μ	B	0.500	0.200	0.874	0.827	0.924	0.713	0.623	0.801
ρ_z	B	0.500	0.200	0.940	0.918	0.964	0.978	0.960	0.995
ρ_{λ_f}	B	0.500	0.200	0.725	0.594	0.862	0.858	0.794	0.924
ρ_{λ_w}	B	0.500	0.200	0.403	0.135	0.668	0.980	0.966	0.994
η_{λ_f}	B	0.500	0.200	0.637	0.461	0.816	0.731	0.596	0.866
η_{λ_w}	B	0.500	0.200	0.421	0.176	0.656	0.972	0.957	0.988
η_{gz}	B	0.500	0.200	0.796	0.622	0.974	0.796	0.635	0.974
σ_g	IG	0.100	2.000	2.919	2.677	3.147	2.891	2.660	3.118
σ_μ	IG	0.100	2.000	0.401	0.320	0.474	0.365	0.301	0.431
σ_z	IG	0.100	2.000	0.509	0.465	0.554	0.517	0.473	0.563
σ_{λ_f}	IG	0.100	2.000	0.145	0.126	0.164	0.128	0.106	0.150
σ_{λ_w}	IG	0.100	2.000	0.381	0.336	0.425	0.356	0.326	0.386
ρ_b	B	0.500	0.200	0.950	0.944	0.957	0.888	0.857	0.920
σ_b	IG	0.100	2.000	0.035	0.029	0.040	0.094	0.078	0.108
ρ_{σ_ω}	B	0.750	0.150	0.982	0.971	0.990	-	-	-
ρ_{π^*}	-	0.990	0.000	0.990	0.990	0.990	-	-	-
σ_{σ_ω}	IG	0.050	4.000	0.067	0.060	0.074	-	-	-
σ_{π^*}	IG	0.030	6.000	0.018	0.014	0.022	-	-	-
σ_{rm}	IG	0.100	2.000	0.185	0.172	0.199	-	-	-

Note: N, B, G, and IG stand, respectively, for the normal, beta, gamma, and root inverse gamma distributions. Under the inverse gamma prior mean and SD, the mode τ and degrees of freedom ν are reported.

B Additional Results

B.1 Financial Frictions vs. Time-Varying $\pi*$

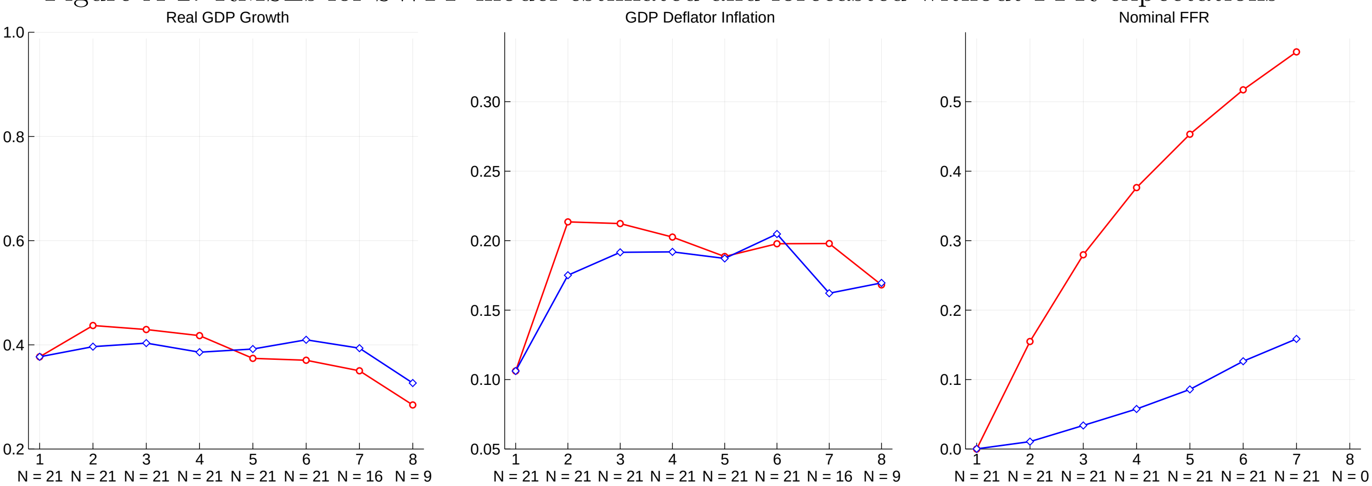
Figure A-1: RMSEs for SWπ model



Note: The panels compare the RMSEs for the SWπ DSGE model (red circles) with the Blue Chip (blue diamonds) for one through eight quarters ahead for real output growth, GDP deflator inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. Forecast origins from January 2011 to January 2016 only are included in these calculations.

B.2 Estimating and Forecasting without FFR Expectations

Figure A-2: RMSEs for SWFF model estimated and forecasted without FFR expectations



Note: The panels compare the RMSEs for the SWFF DSGE model (red circles) with the Blue Chip (blue diamonds) for one through eight quarters ahead for real output growth, GDP deflator inflation, and interest rates. Output growth and inflation are expressed in Q/Q percent annualized terms, whereas interest rates are in quarterly annualized percentage points. The $N = n$ labels under each x-axis tick indicate the number of observations available for both the BCEI and DSGE forecasts at that horizon. Forecast origins from January 2011 to January 2016 only are included in these calculations. In this exercise, we re-estimated and forecasted the SWFF model without FFR expectations data. Compare to the RMSEs in Figure 8, which were computed from the baseline parameter draws (estimated using FFR expectations data).