Forecasting with instabilities: an application to DSGE models with financial frictions

by Roberta Cardani, Alessia Paccagnini and Stefania Villa
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FORECASTING WITH INSTABILITIES:
AN APPLICATION TO DSGE MODELS WITH FINANCIAL FRICTIONS

by Roberta Cardani*, Alessia Paccagnini** and Stefania Villa***

Abstract

We assess the importance of parameter instabilities from a forecasting standpoint in a set of medium-scale DSGE models with and without financial frictions using US real-time data. We find that failing to update DSGE model parameter estimates with new data arrival deteriorates point forecasts due to the estimated parameters variation. We also find that the presence of financial frictions helps to better forecast GDP and inflation.

JEL Classification: C11, C13, C32, E37.
Keywords: Bayesian estimation, forecasting, financial frictions, parameter instabilities.

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1 Introduction

Recent macroeconometric literature suggests that estimated dynamic stochastic general equilibrium (DSGE) models are suitable for forecasting purposes (see Del Negro and Schorfheide, 2013; Kolasa and Rubaszek, 2015b; Caraiani, 2016, among others). However, the forecasting evaluation of these macroeconomic models is subject to the estimation of the parameters of the model and, as discussed in Giacomini and Rossi (2016), there is ample evidence of instabilities in parameters that might affect their forecasting performance. Gürkaynak et al. (2013) find that the forecasting performance of the medium-scale DSGE model of Smets and Wouters (2007) (hereafter, SW) has been unstable over time. In particular, this model started to fail to produce accurate forecasts when researchers included data following the recent crisis. One of the main reasons of this failure is that the modeling choices of the SW model reflect the properties of the sample data before the Great Recession (see Giacomini and Rossi, 2015).

The DSGE empirical literature offers alternative approaches to deal with the issue of parameters instability (see Fernández-Villaverde et al., 2010; Inoue and Rossi, 2011; Bianchi, 2013; Caldara et al., 2012; Castelnuovo, 2012; Bekiros and Paccagnini, 2013; Hurtado, 2014; Bekiros et al., 2016; Galvao et al., 2016, among others).

A practical way to deal with the parameter instability in a DSGE model forecasting analysis is discussed in Kolasa and Rubaszek (2015b). They observe that central banks are used to re-estimate DSGE models only occasionally but this practice might affect the forecasting performance. Hence, they investigate how frequently models should be re-estimated so that the accuracy of forecasts they generate may be unaffected. They find that updating the model parameters only once a year generally does not lead to a significant deterioration in the accuracy of point forecasts, while increasing the frequency of re-estimation is better in terms of density forecasts.
We investigate the role of parameters instabilities in forecasting analysis by addressing two main questions: (1) does failing to update model parameter estimates with new data arrival affect the quality of point forecasts? and (2) does a DSGE model featuring financial frictions provide a better forecasting performance compared to a standard medium-scale model?

We borrow the first research question from Kolasa and Rubaszek (2015b), where they provide evidence about the role of parameters re-estimation only in case of the SW model. In our exercise, we compare the workhorse SW model with two models incorporating the financial sector: a SW economy augmented by a banking sector as in Gertler and Karadi (2011) (hereafter, SWBF); and a SW economy augmented with financial frictions as Bernanke et al. (1999) (hereafter, SWSWBGG). DSGE models with financial frictions have become popular, as financial factors have played a central role in the recent financial crisis by affecting the amount of credit available in the economy. The seminal DSGE model proposed by Bernanke et al. (1999) considers financial frictions at the level of firms. Their model implies that borrowers can obtain funds directly from lenders without any active role for the banking sector. In the wake of the financial turmoil understanding the disruption in financial intermediation has become a priority. This explains why we consider the model by Gertler and Karadi (2011), in which an endogenous leverage constraint on banks effectively links the provision of credit to the real economy.

We estimate, using Bayesian techniques, the three models – SW, SWBF and SWBGG – on US real-time data using rolling windows of 120 observations. The out-of-sample forecasting period is from 2003Q2 to 2018Q1.  

Second, we compare the forecasting performance of the three models conducting both point forecast, using Root Mean Square Forecast Error (RMSFE) and Fluctuations test as in Giacommini and Rossi (2010, 2016), as well as density forecast using the average of the log predictive density scores (LPDS). The out-of-sample forecasting period is split into two sub-samples when computing RMSFE and LPDS: (pre-crisis) 2003Q2-2008Q4 and (post-crisis) 2009Q1-2018Q1. In this way we investigate whether the forecasting performance changes across the two sub-samples.

Our main findings are as follows. First, re-estimating every quarter the model parameters leads to a better forecasting performance due to the estimated parameters instabilities, differently from the result in Kolasa and Rubaszek (2015b). It should be noted that Kolasa and Rubaszek (2015b) investigate only the SW model and consider another sample period: their

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3The forecasting literature has partly assessed the empirical relevance of DSGE models with financial frictions for the US economy (see Villa, 2016; Kolasa and Rubaszek, 2015a). Differently from them, we study the role of parameter instabilities in a forecasting comparison of a set of DSGE models using revised data.
estimation period is 1966Q1-1989Q4, while their forecasting sample is 1990Q1-2011Q4. The different results are driven by these features. In order to rationalize these results, we show the rolling estimation of the main parameters of the three DSGE models and we find a considerable degree of parameters variation. Second, forecasting analysis based on the RMSFE and LPDS suggests that models with financial frictions outperform the SW model in terms of forecasting accuracy particularly in the post-crisis period. A forecasting analysis conducted using the Fluctuations test shows that the prediction performance of the models with financial frictions is statistically different from that of the SW model for GDP growth rate and inflation, except for a few quarters around 2008 where the performance of the SW model is not statistically different from that of the SWBF model for inflation.

The remainder of the paper is organized as follows. Section 2 briefly sketches the three models and describes the Bayesian estimation procedure. Section 3 presents the two forecasting comparisons. Finally, Section 4 concludes.

2 Models and estimation procedure

The economy is composed by households, labor unions, labor packers, a productive sector and a monetary authority. Households consume, accumulate government bonds and supply labor. A labor union differentiates labor and sets wages in a monopolistically competitive market. Competitive labor packers buy labor services from the union, package and sell them to intermediate goods firms. Output is produced in several steps, including a monopolistically competitive sector with producers facing price rigidities. The monetary authority sets the short-term interest rate according to a Taylor rule. In the SWBF model, the presence of an agency problem limits the ability of financial intermediaries to obtain deposits from households. This, in turn, affects the leverage ratio of financial intermediaries. On the contrary, in the SWBGG model firms stipulate a financial contract to obtain funds from the lenders in presence of a costly state verification problem. The equations of the three models are reported in Table 1.

The SW model features seven exogenous disturbances: total factor productivity, price mark-up, wage mark-up, investment-specific technology, risk premium, exogenous spending, and monetary policy shocks. The SWBF and SWBGG models also feature a net worth shock.

The three DSGE models are recursively estimated for the US quarterly real-time data (Edge and Gurkaynak, 2011; Wolters, 2015). To estimate the SW model we use the standard seven
observables: GDP, investment, consumption, wages, hours of work, GDP deflator inflation, and the federal funds rate. In the SWBF model we also include net worth of financial intermediaries as a financial observable since the model features a net worth shock.\textsuperscript{4} The additional financial observable in the SWBGG model is, instead, the credit spread similarly to Del Negro and Schorfheide (2013).

In particular, we build our variables as described in Kolasa and Rubaszek (2015a).\textsuperscript{5} All the models are estimated with a number of shocks equal to the number of observable variables to avoid the stochastic singularity.\textsuperscript{6}

Our general calibration and estimation strategy follow the standard procedure proposed by Smets and Wouters (2007) adapted to models augmented with financial frictions. In particular, we calibrate the parameters i) using \textit{a priori} source of information and ii) to match some stylized facts over the period of consideration. The time period in the model corresponds to one quarter in the data. As shown in Table 2, the discount factor, $\beta$, is set equal to 0.99, implying a quarterly steady state real interest rate of 1\%.\textsuperscript{7} The depreciation rate of capital, $\delta$, is set equal to 0.025. The Kimball aggregators in the goods and labor market are equal to 10, and the steady state gross wage mark-up is set to 1.5. The share of government to GDP is equal to 0.18. Similarly to Villa (2016), in the SWBF model $\varpi$, $\phi$ and $\chi$ are calibrated to target an average working life of bankers of almost a decade, a steady state spread of 150 basis points and a steady state leverage ratio of financial intermediaries equal to 4. In the SWBGG model, the expected working life of firms is almost a decade and the leverage ratio is set equal to 2, as in Bernanke et al. (1999).

The remaining parameters governing the dynamics of the model are estimated using Bayesian techniques. The locations of the prior mean correspond to those in Smets and Wouters (2007). Similarly to De Graeve (2008), we set a Uniform distribution between 0 and 0.3 for the parameter measuring the elasticity of external finance premium with respect to the leverage position of firms in the SWBGG model.

\textsuperscript{4}The Appendix contains a detailed discussion of real-time data sources, definitions and transformations.
\textsuperscript{5}See Casares and Vázquez (2016) and Galvão (2017) for a discuss about a possible combination of real-time and revised data for estimation of DSGE models.
\textsuperscript{6}Equation 2 in the Appendix reports the set of measurement equations linking the observable variables in the dataset with the endogenous variables of the DSGE models.
\textsuperscript{7}In the more recent period a different value for the discount factor could have been more appropriate. However, for the sake of simplicity, we set a unique value for $\beta$ over the whole sample.
3 Evaluating forecast accuracy

This section illustrates the forecasting exercises. In Section 3.1, we compare the forecasting accuracy of the three DSGE models re-estimated by updating the models parameters each quarter versus a fixed scheme in which parameters are estimated only once, at the beginning of the forecast evaluation sample. We investigate the role of instabilities in order to rationalize the results of this first comparison. In Section 3.2, we compare the forecasting accuracy of the three models by evaluating the point and density forecasts. As described in Wolters (2015) and in Kolasa and Rubaszek (2015a), for each parameter a large number of values are drawn from the parameter’s posterior distribution. We take each 20th draw from the final 150,000 parameter draws calculated by the Metropolis-Hastings algorithm, which produces 7,500 draws from the posterior distribution. For each of them, we draw seven shock trajectories to generate the predictions for the seven macro-variables of interest. The obtained 52,500 trajectories are draws from the predictive density and hence can be used to evaluate the density forecasts. The point forecasts are calculated as means of these draws (see Wolters, 2015, for technical details).

The forecasting scheme is rolling in any exercise and the evaluation sample spans the period 2003Q2 to 2018Q1. The first set of forecasts is generated for the period 2003Q2-2006Q1, with models estimated on the sample spanning 1973Q2-2003Q1 (120 quarters), the second set of forecasts is for the period 2003Q3-2006Q2, with models estimated on the sample spanning 1973Q3-2003Q2, and so on. As our dataset ends in 2018Q1, we can calculate forecast errors on the basis of between 60 (1-quarter-ahead) and 49 (12-quarter-ahead) forecasts. Our evaluation sample is split into two parts: 2003Q2 - 2008Q4 and 2009Q1 - 2018Q1. In such a way it is possible to distinguish between a pre-crisis period and a post-crisis period. A multi-steps forecasting analysis is implemented with forecasts for the horizon $h \in \{1, 2, 4, 8, 12\}$.8

3.1 Comparison #1: Update or not to update the models parameters?

We compare the accuracy of forecasts generated by the three models (SW, SWBF, and SWBGG), the parameters of which are re-estimated every quarter versus a fixed forecasting scheme with constant parameters. This exercise makes it possible to examine whether parameters instabilities might affect the accuracy of forecasts, evaluated by means of the RMSFE. In particular, Table 3 reports the ratio of the RMSFE of the models with fixed parameters and that of the models

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8Our results are qualitatively robust if we stop the first sample at 2007 and we include 2008 in the second sample.
updated each quarter for the period 2003Q2-2008Q4. Hence values lower than one indicate that the updated model has a higher RMSFE than the fixed model. For each forecast horizon we report the ratio of RMSFEs for each model for the seven standard observable variables of the SW model. In general, the forecasting accuracy for output growth, inflation, and FFR are always better if parameters are re-estimated instead of taking them fixed. Same findings are in favor of re-estimation for the other variables.

Table 4 reports the ratio of the RMSFE of the models with fixed parameters and that of the models updated each quarter for the period 2009Q1-2018Q1. In the post-crisis sample it is always better to re-estimate the parameters of the three models for all variables. This gain is statistically significant particularly for the SWBGG model and, to a minor extent, for the SW and SWBF models.

Our findings suggest that the re-estimation scheme is always preferred to the fixed parameters scheme. Our results are robust to the model specification. In fact, the superiority of the updating procedure is common to the three models. Second, overall it is better to re-estimate the models parameters, in particular, as expected, in “turbulent” periods such as the second sub-sample. Kolasa and Rubaszek (2015b) evidence that updating the model parameters only once a year does not produce better accuracy of point forecast during the “turbulent” period. However, their sample stops at 2011, meanwhile we include years up to 2018 long after the turbulent period of the Great Recession.

Differently from Kolasa and Rubaszek (2015b), we compare quarterly re-estimated parameters vs fixed parameters forecasting and we do not consider intermediate re-estimation patterns. Our general results have the conclusion that re-estimation is important.

Tables 3 and 4 provide evidence in favor of re-estimated parameters model. For instance, the RMSFE ratio for output growth is always bigger than 1.10, with this value being statistically significant in the SWBF model at horizon 1, in the SW model at horizon 2 for the first sub-sample; and in the SWBGG model at horizons 2 and 12 in the second sub-sample. A similar pattern is found for FFR and inflation, as well for investment. The gain in forecast precision is smaller for wage. These results are broadly similar across the two sub-samples but for consumption and hours for which considerable gains are more evident in the first and second sub-sample, respectively.
3.1.1 Parameters instabilities

In order to rationalize these results, we check for possible instabilities in the time dimension of the structural parameters, which might affect the forecasting analysis.

All parameters and shocks of the DSGE models are hence estimated in a rolling scheme with the first window covering the period 1973Q2-2003Q1 and the last window the period 1988Q1-2018Q2, with real-time data. The evaluation sample 2003Q2-2018Q1 yields 60 different posterior densities of all parameters, each of which is computed with the Metropolis-Hasting algorithm with two chains of 250,000 draws each.\(^9\)

Our chosen methodology has the caveat that the DSGE models do not feature a zero lower bound (ZLB) constraint on the nominal interest rate, which is instead observed in the data starting from December 2008. Hirose and Inoue (2016) investigate how and to what extent parameter estimates can be biased in DSGE models lacking this constraint. They find that the bias becomes large when the probability of hitting the ZLB increases. Given our estimation sample, the bias in parameter estimates could be potentially relevant. Alternatively, we could have used the shadow rate as in De Polis and Pietrunti (2019).

Figure 1 shows the evolution of selected shock processes and parameters of the SW model.\(^10\) The standard deviation of the risk shocks shows a considerable degree of variation. In the Smets and Wouters (2007) model the risk premium shock captures the wedge between different interest rates. Here we consider two measures as proxies for spreads: (i) Moody’s BAA corporate bond yield minus ten-year Treasury constant maturity rate, as in Del Negro and Schorfheide (2013); and (ii) the difference between the 3-month bank prime loan rate and the quarterly Treasury bill rate. In the data the volatility of the spreads increased after the 2000Q1 recession. The standard deviations of the other shocks also change over time, similarly to Bekiros et al. (2016) and Giacomini and Rossi (2016). The volatility of the monetary policy shock decreases steadily over time.

The figure also shows that instabilities are particularly evident for the most relevant parameters. The coefficient of relative risk aversion is quite volatile. Hence, the willingness of households to substitute consumption over different periods is changing particularly after the financial crisis. The Taylor rule has become more inertial over time.

\(^9\)We implement the sensitivity analysis and identification test proposed by Ratto (2011) and Ratto and Iskrev (2011) in Dynare. For all the samples, the SW, SWBF, and SWBGG models do not present identification issues.

\(^10\)For the sake of brevity, we do not report charts on the rolling estimates of all shocks and parameters, which are available upon request.
In the SWBF model the volatility is particularly evident for estimated shocks, as shown by Figure 2.\textsuperscript{11} The volatility of the net worth shock seems to be related to the number of bank failures, which peaked in the period 2009-2012 (by looking at Federal Deposit Insurance Corporation data). The number of bank failures in 2002 was higher than those in preceding and subsequent years, while in 2005 there has been a serious concern on the surge in bank credit (Melina and Villa, 2018). The volatility of the monetary policy shock increased in the second part of the sample. The comparison with the SW model reveals that the standard deviation of the risk premium shock is lower. The two peaks in the volatility of the monetary policy shock correspond to the announcement of third round of Quantitative Easing by the FOMC in 2012Q4 and to the end of this program. As far as the parameters are concerned, they all display variation over time.

Figure 3 shows rolling estimates of selected shock processes and of structural parameters in the SWBGG model. The volatility of the risk premium shock and of the investment-specific technology shock has decreased in the most recent sample, whereas the net worth shock is extremely volatile almost over the whole sample.\textsuperscript{12} The parameters of the SWBGG model are

\begin{itemize}
  \item Canova et al. (2015) study how parameter variation can affect the decision rules in a DSGE model. Similar to us and to Cardani et al. (2015), they evidence an importance role of time-variation for the identification of DSGE parameters, even if it is not only related to the Gertler and Karadi (2011) set up.
  \item It should be noted that the volatility of the financial variable used in the estimation – the credit spread – has increased from 2008.
\end{itemize}
Overall, the presence of parameter instabilities in all the three models explains why we find evidence in favour of re-estimating the model parameters from a forecasting viewpoint.

### 3.2 Comparison #2: Which model forecasts better?

#### 3.2.1 Point Forecast Evaluation

We perform a point forecast comparison among the three models re-estimating the parameters. In particular, we compare the second moments of the forecast errors. Table 5 shows the ratio of the RMSFE of the SWBF and SWBGG models relative to the SW model for the forecasting periods 2003Q1-2008Q4, whereas Table 6 shows the same ratios for the period 2009Q1-2018Q1. Values greater than one denote that the SW model has a lower RMSFE than the alternative model featuring financial frictions. To check the statistical significance of these ratios, we report the Clark and West (2006) test which is suitable for non-nested and nested models. As far as the SWBF model is concerned, in the period 2001-2008 there is not a clear result against the SW model for the three key macro variables (output growth, inflation and FFR). For output

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13 For more details about the implications of real time data, see Bekiros et al. (2016), Galvão (2017) and Masolo and Paccagnini (2019).
For the period 2009-2016, Table 6 shows that the SWBF model outperforms the SW model for almost all variables, in particular in the short horizon. The results are statistically significant for output growth rate, inflation, and consumption for the medium horizon (2 and 4 quarters) and for FFR and investment for the short horizon. Similarly, the SWBGG model outperforms the SW model for all variables; in particular results are statistically significant for output growth, FFR, and consumption. In general, during the Great Recession and in the aftermath, the models including financial variables outperform the standard new-Keynesian model. This finding is in line with the recent literature which provides evidence of the role of financial variables to improve
the forecasting of the business cycle (see Gertler and Gilchrist, 2018; Paccagnini, 2019, among others).

To assess the validity of the point forecast, we employ the Fluctuation test as in Giacomini and Rossi (2010), Giacomini and Rossi (2016) and Fawcett et al. (2015) to assess the predictive ability when there are instabilities over time.14 As noted by Giacomini and Rossi (2010), in the presence of structural instability, the forecasting performance of two alternative models may itself be time-varying.

Figures 4 and 5 report the Fluctuation tests based on Clark - West test for GDP growth and CPI inflation. The four graphs show the relative performance between the SW model and the SWBF or SWBGG models. There are three possible cases. First, if the statistic drawn in blue is located above the upper bound (the red line) the SWBF or SWBGG model has a superior forecasting performance; second, the statistic is located below the lower bound, then the SW model is preferred.15 Finally, if a blue line between the two bounds means that the predictably performance is not statistically different between the models. Figure 4 shows that for GDP growth rate the forecasting performance of the SWBF and SWBGG models is always statistically different from the SW model. Figure 5 shows that for CPI inflation the SWBF and SWBGG models produce better predictive performances than that of the SW model except for some quarters during the Great Recession when the forecasting performance of the two models is not statistically different. In general, the Fluctuation test suggests that: (i) the results produced using point forecast analysis are robust; and (ii) both models featuring financial frictions outperform the SW model in forecasting output growth and inflation virtually over the whole period. Three considerations are in order. First, an obvious remark should be made about the information set of the different models. The SW model features seven shocks and seven observable variables, while both models featuring financial frictions include an additional shock and an additional observable variable. Obviously the information set used for the forecasting exercise is richer in the latter models compared to the former one and this clearly goes into the direction of improving forecasting accuracy (Stock and Watson, 1999; Bernanke and Boivin, 2003). In addition, it should be noted that the forecasting horizon 2003-2018 covers a period in which leverage by the corporate sector has increased significantly, with financial factors likely

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14 We implement the Fluctuation test using a rolling window setup as described by Giacomini and Rossi (2010), Algorithm 1. The rolling window scheme allows the test to have a non-time variant critical value. For more details about the test implemented in case of Clark and West (2006), the null hypothesis, as well as the critical values obtained using a Monte Carlo experiment, see Giacomini and Rossi (2010).

15 In the figures we report only the upper bound since the statistics never cross the lower bound.
to affect business cycle fluctuations also in “normal times”. Therefore, taking financial variables into account might help the forecasting performance even in the pre-crisis period. Households leverage, instead, has dramatically increased only in the latest financial crisis (Smets and Villa, 2016). The SWBF and SWBGG models do not feature household indebtedness and this might explain why our results differ from the ones in Kolasa and Rubaszek (2015b). Finally, in the SWBGG model the parameter measuring the elasticity of external finance premium with respect to the leverage position of firms, \( \kappa \), is estimated in the range \([0.053,0.065]\) over the sample 2003Q3-2018Q1. Therefore, the presence of financial frictions is always empirically relevant since a model without financial frictions features of value of zero for \( \kappa \). This also helps explaining the results of the Fluctuation test.
3.2.2 Density Forecast Evaluation

The forecast evaluation is completed with an assessment of the density forecasts to provide a realistic pattern of the actual uncertainty. This kind of analysis has recently become popular in forecasting exercises involving DSGE-based models (Herbst and Schorfheide, 2012; Kolasa et al., 2012; Del Negro and Schorfheide, 2013; Wolters, 2015). However, the evaluation of the density forecasts is less straightforward than the evaluation and the comparison of RMSFEs. As discussed in Wolters (2015), the true density is never observed. Notwithstanding this, the researcher can compare the distribution of observed data with density forecasts to investigate whether forecasts explain the actual uncertainty. There are different ways of examining the accuracy of density forecasts for DSGE model forecasting. We evaluate and rank the density forecasts using the log predictive density scores (LPDS) (as in Adolfson et al., 2007; Christoffel et al., 2010; Marcellino and Rychalovska, 2014, among others). We can define $f_{t+h,t,i}$ as a prediction of the density $Y_{t+h}$, conditional on information up to date $t$. Meanwhile, $y_{t+h}$ is the realization of $Y_{t+h}$, and the $h$-step ahead density forecasts are available from a starting date $T_s$ based on a total number of $T$ observations. The average log score is given by the following formula:

$$A S_{i,h} = \frac{1}{T - h - T_s + 1} \sum_{t=T_s}^{T-h} \ln f_{t+h,t,i}(y_{t+h}),$$  \hspace{1cm} (1)

A higher value for the LPDS suggests a more accurate density forecast. We implement a nonparametric kernel estimator for the density and distribution function of the forecasts. As discussed in Chiu et al. (2017), this estimator helps the researcher to account for any potential non-linearities in the forecast distribution and, in addition, it is able to allow better performance at the tails of the predictive density, where the Great Recession would reasonably fall.

Table 7 presents the LPDS of the SWBF and SWBGG models relative to SW for the period 2003-2008. A positive number indicates an improvement over the SW model. For output growth, wage, consumption, investment and hours, the SW model is always better than the SWBF and SWBGG models. For inflation, the SWBF/SWBGG models produce the best performance in the longer horizon. The SWBGG model outperforms the SW model also for predicting FFR. Table 8 presents the LPDS of the SWBF and SWBGG models relative to SW for the period 2009-2016. According to the LPDS, for output growth the SWBGG model clearly outperforms the SW model at any horizon, while the SWBF model predicts better at horizons 1, 4, and 12. For inflation, both SWBF and SWBGG models outperform the SW one with the exception of
horizon. Meanwhile, for FFR, consumption, investment, hours and wage, the SW is always outperformed by the other two models.

This result is in line with the findings of the point forecast reported in Table 6. Our results, especially for inflation, are in line with other findings in forecasting DSGE with financial frictions as shown in Del Negro and Schorfheide (2013), Kolasa and Rubaszek (2015a) and Galvao et al. (2016). In addition, in Tables 9 and 10, we report the log predictive density score for the models estimated with fixed parameters. In both samples, we provide evidence on how the SW model outperforms the models with financial frictions, showing how the models with updated parameters are preferred in a forecasting evaluation since they may produce more reliable forecasting evaluation. These results which also show how density forecasts are worse in case of fixed parameters models are due to the sample used in the estimation analysis. The models are estimated since 1973 including high volatility periods such as the 70s and the 80s, before the Great Moderation. In case of turbulent periods (as it was after the oil price shock or the Great Recession), updating parameters allows the researcher improving forecast accuracy.

4 Conclusion

This paper analyses the forecasting performance of DSGE models with and without financial frictions using US real-time data. It presents two different comparisons. First, it investigates whether updating parameters estimation as new data become available provides better forecast versus a fixed-parameters estimation. This analysis aims at disentangling the role of parameters instabilities in affecting point forecasts in DSGE models. The paper then compares the forecasting performance of two DSGE models with different types of financial frictions versus a standard medium-scale DSGE model à la Smets and Wouters (2007).

The forecast analysis based on RMSFE and LPDS shows that updating models parameters yields to lower forecast errors compared to the fixed scheme model. This result can be explained by the fact that the rolling estimation of parameters exhibits a considerable degree of variation in all the three DSGE models over the sample starting from 1973Q2-2003Q1 and ending in 2018Q1. As far as the second comparison is concerned, in the first sample (2003Q2-2008Q4) there is a weak evidence in favor of financial frictions; meanwhile in the second sample (2009Q1-2018Q1) there is a clear evidence in favor of financial frictions in terms of forecasting accuracy. We implement an additional forecast analysis by means of the Fluctuation test as in Giacomini
and Rossi (2010), which reveals that for both GDP growth and inflation models with financial frictions outperform the SW model. In particular, adding financial frictions to a standard medium-scale DSGE model helps to improve the forecasting performance of output growth and overall also of inflation.

This exercise turns out to be useful also for policy-making since updating parameter estimates with real-time data is a more appropriate forecasting exercise due to the estimated instabilities in the parameters. In addition, omitting financial variables would severely decrease the forecasting performance of DSGE models. This would lead eventually to the design of appropriate model features which take into account the underlying driving forces of business cycle fluctuations.
Linearized equations

**SW model**

Euler equation
\[ c_t = \left( 1 - \frac{\beta}{\gamma} \right) c_{t-1} + \left( 1 - \frac{\beta}{\gamma} \right) E_t c_{t+1} + \frac{\gamma}{\beta} \left( \pi_{t+1} \right) \pi_t + \frac{\pi_t}{\beta} \left( E_t \pi_{t+1} \right) \left( 1 - \beta \gamma^{-1} \right) \left( 1 - \beta \right) \left( 1 - \beta \gamma^{-1} \right) \]

Flexible wages
\[ w_t = \left( 1 - \frac{\beta}{\gamma} \right) w_{t-1} + \left( 1 - \frac{\beta}{\gamma} \right) E_t w_{t+1} + \pi_t \]

Utilization rate
\[ u_t = \frac{1 - \omega}{\omega} x_t^b \]

Wage mark-up
\[ \mu_w = w_t - \left( \frac{1 - \beta}{\gamma} \right) \left( 1 - \beta \right) \left( 1 - \beta \gamma^{-1} \right) \left( 1 - \beta \right) \left( 1 - \beta \gamma^{-1} \right) \]

Production function
\[ y_t = \phi_t \left( k_{t-1} + w_t \right) + \left( 1 - \alpha \right) \ell_t + x_t^b \]

Utilization rate
\[ u_t = \frac{1 - \omega}{\omega} x_t^b \]

**SWBF model**

Credit spread
\[ r_t^{sp} = r_{t+1} - \left( 1 - \beta \right) \left( 1 - \beta \gamma^{-1} \right) \]

Balance sheet
\[ q_t + k_t = l e c_t + n_t \]

Leverage
\[ l e c_t = n_t + \omega \left( q_t \right) \]

Gain of having net worth
\[ \eta_t = \frac{\pi_t}{\beta} \left( E_t \pi_{t+1} - \pi_t + x_t + E_t n_t \right) \]

Growth rate of net worth
\[ x_t = \frac{\eta_t}{\pi_t} + r_t \left( 1 - l e c_t \right) \]

Gain of expanding assets
\[ \eta_t = \frac{\pi_t}{\beta} \left( E_t \pi_{t+1} - \pi_t + x_t + E_t \pi_{t+1} \right) + \frac{\pi_t}{\beta} \left( x_t - r_t \right) \]

Growth rate in assets
\[ x_t = \frac{\eta_t}{\pi_t} + \omega \left( q_t + k_t \right) \]

Net worth
\[ n_t = n_t^b + n_t \]

Net worth of existing bankers
\[ n_t^b = n_t^b - z_t + x_t \]

Net worth of new bankers
\[ n_t^b = \xi \left( \psi + k_t \right) \]

Price of capital
\[ x_{t+1} = \frac{1}{\pi_t} \left( h_t + x_{t+1} \right) + \frac{1}{\pi_t} \left( 1 - x_{t+1} \right) \]

**SWBGG Model**

Spread
\[ E_t r_{t+1} = \pi_t + E P r \]

External finance premium
\[ E P r = \omega \left( \pi_t + k_{t+1} - n_{t+1} \right) \]

Net worth
\[ n_t = n_t^b + \omega \left( q_t + k_t \right) \]

\[ \left( k_t + q_t - 1 \right) \pi_t + \left( \frac{1}{\pi_t} - 1 \right) \]

\[ \left( k_t + q_t - 1 \right) \pi_t + \left( \frac{1}{\pi_t} - 1 \right) \]

Table 1: Linearized equations. All variables are log-linearized around their steady state balanced growth path and starred variables represent steady state values. The parameters are: \( h \) the degree of habits in consumption; \( \sigma_c \) the coefficient of relative risk aversion; \( \gamma \) the steady state growth rate; \( \beta \) the discount factor; \( \xi \) the Calvo probability of not adjusting nominal wages; \( \ell \) the degree of wage indexation; \( e^w \) the curvature of the Kimball aggregator in the labor market; \( \alpha \) the output elasticity to capital; \( \psi \) the elasticity of the capital utilization adjustment cost; \( t_p \) the indexation parameter; \( \xi_p \) the degree of price stickiness; \( e^h \) the curvature of Kimball aggregator in the goods market; \( \varphi \) the elasticity of investment adjustment costs; \( \delta \) the depreciation rate of capital; \( \rho_r, \rho_d, \rho_p \) and \( \rho_{\Delta p} \) the responsiveness of the nominal interest rate to inflation, to the output gap and to changes in the output gap, respectively; \( c_t \) and \( s_t \) are the steady state share of consumption and investment; \( \omega \) the survival rate of banks; \( \phi \) fraction of capital that can be diverted; and \( \xi \) the start-up transfer. The shocks are: \( e_t^h \), TFP; \( e_t^c \), price mark-up; \( e_t^r \), wage mark-up; \( e_t^x \), investment-specific technology; \( e_t^b \), risk premium; \( e_t^e \), exogenous spending; \( e_t^m \), monetary policy; and \( e_t^l \), net worth shock in the SWBF and SWBGG models.
<table>
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<tr>
<th>Parameter</th>
<th>Value</th>
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<td>η_p</td>
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<tr>
<td>Kimball aggregator in the labor market</td>
<td>η_w</td>
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<tr>
<td>Gross mark-up in the labor market</td>
<td>λ_w</td>
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<tr>
<td>Government share of output</td>
<td>Ψ/Y</td>
</tr>
<tr>
<td>Survival rate of financial intermediaries/firms (SWBF/SWBGG)</td>
<td>ϖ</td>
</tr>
<tr>
<td>Fraction of divertable assets (SWBF)</td>
<td>φ</td>
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<td>Fraction of assets given to new bankers (SWBF)</td>
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<td>Firm’s leverage ratio (SWBGG)</td>
<td>k_<em>/n_</em></td>
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Table 2: Calibration

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<th>Wage</th>
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<th>Hours</th>
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Table 3: Relative Root Mean Square Forecast Error (RMSFE), computed as a ratio between the RMSFE of the model with fixed parameters and the RMSFE of the model updated each quarter. Hence values greater than one indicate that the updated model has a lower RMSFE than the one with fixed parameters. Forecasting evaluation period: 2003Q3-2008Q4. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test (one-sided alternative).
<table>
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<tr>
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<th>FFR</th>
<th>Wage</th>
<th>Consumption</th>
<th>Investment</th>
<th>Hours</th>
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<td>0.89</td>
<td>0.97</td>
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</table>

Table 4: Relative Root Mean Square Forecast Error (RMSFE), computed as a ratio between the RMSFE of the model with fixed parameters and the RMSFE of the model updated each quarter. Hence values greater than one indicate that the updated model has a lower RMSFE than the one with fixed parameters. Forecasting evaluation period: 2009Q1-2018Q1. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test (one-sided alternative).

<table>
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<tr>
<th>Horizon</th>
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<th>FFR</th>
<th>Wage</th>
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Table 5: Root Mean Square Forecast Error (RMSFE) are computed as a ratio between the RMSFE of the SWBF/SWBGG model and the RMSFE of the SW model. Hence values greater than one indicate that the SW model has a lower RMSFE than the alternative model featuring financial frictions. Forecasting evaluation period: 2003Q2-2008Q4. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark - West test.
Table 6: Root Mean Square Forecast Error (RMSFE) are computed as a ratio between the RMSFE of the SWBF/SWBGG model and the RMSFE of the SW model. Hence values greater than one indicate that the SW model has a lower RMSFE than the alternative model featuring financial frictions. Forecasting evaluation period: 2009Q1-2018Q1. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Clark-West test.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Model</th>
<th>Output</th>
<th>Inflation</th>
<th>FFR</th>
<th>Wage</th>
<th>Consumption</th>
<th>Investment</th>
<th>Hours</th>
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Table 7: Percentage improvement in the log predictive scores (LPS) for the period 2003Q2-2008Q4 of the SWBF/SWBGG model over the SW model with updated parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

<table>
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<th>FFR</th>
<th>Wage</th>
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<th>Hours</th>
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Table 8: Percentage improvement in the log predictive scores (LPS) for the period 2009Q1-2018Q1 of the SWBF/SWBGG model over the SW model with updated parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

<table>
<thead>
<tr>
<th>Horizon</th>
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<th>Output</th>
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<th>FFR</th>
<th>Wage</th>
<th>Consumption</th>
<th>Investment</th>
<th>Hours</th>
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Table 8: Percentage improvement in the log predictive scores (LPS) for the period 2009Q1-2018Q1 of the SWBF/SWBGG model over the SW model with updated parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).
Table 9: Percentage improvement in the log predictive scores (LPS) for the period 2003Q2-2008Q4 of the SWBF/SWBGG model over the SW model with fixed parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Model</th>
<th>Output</th>
<th>Inflation</th>
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<th>Wage</th>
<th>Consump.</th>
<th>Invest.</th>
<th>Hours</th>
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Table 10: Percentage improvement in the log predictive scores (LPS) for the period 2009Q1-2018Q1 of the SWBF/SWBGG model over the SW model with fixed parameters. A positive number indicates an improvement over the SW model. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the test by Amisano and Giacomini (2007).

<table>
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</table>
References


Online Appendix

A Data sources and transformations

This section discusses the sources of the observables used in the estimation and their transformation. The source of macroeconomic data, except the short term interest rate, used to estimate the models is the Real-Time Data Set for Macroeconomics (RTDSM) maintained by the Federal Reserve Bank of Philadelphia. GDP is the Real Gross domestic product (ROUT-PUT), consumption is the Real personal consumption expenditures (RCON), investment is the Real gross private domestic non-residential investment (RINVBF), hours is the aggregate weekly hours (HOURS), wages is the nominal wage and salary disbursements (WSD), and inflation is calculated using the Price index for gross domestic product (P). The short term interest rate, not subject to revisions, is the Federal Funds Rate downloaded from the ALFRED database of the Federal Reserve Bank of St. Louis. Net worth of banks is downloaded from the FRED database and it is computed as the difference between total assets of all commercial banks (TLAACBW027SBOG) and total liabilities of all commercial banks (TLBACBM027SBOG). The spread in the SWBGG model is computed as the annualized Moody’s Seasoned Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield at Constant Maturity, as in Del Negro and Schorfheide (2013). Data are transformed as in Smets and Wouters (2007). In particular, GDP, consumption, investment and net worth are transformed in real per-capita terms by the civilian population. Real wages are computed by dividing compensation per hour by the Price level. As shown in the measurement equations, the observable variables of GDP, consumption, investment, wages and net worth are expressed in first differences. Hours worked are multiplied by civilian employment, expressed in per capita terms and demeaned. The inflation rate is computed as a quarter-on-quarter difference of the log of the GDP deflator. The fed funds rate is expressed in quarterly terms. Remaining variables are expressed in 100 times log. All series are seasonally adjusted. Data on spreads are also extracted from the ALFRED database of the Federal Reserve Bank of St. Louis. Our variables are built as described in Kolasz and Rubaszek (2015a).

The following set of measurement equations shows the link between the observable variables
in the dataset and the endogenous variables of the DSGE model:

\[
\begin{bmatrix}
\Delta Y^o_t \\
\Delta C^o_t \\
\Delta I^o_t \\
\Delta W^o_t \\
L^o_t \\
\pi^o_t \\
\gamma^{n,o}_t \\
\Delta N^o_t \\
EP^o_t
\end{bmatrix}
= \begin{bmatrix}
\bar{\gamma} \\
\bar{\gamma} \\
\bar{\gamma} \\
\bar{\gamma} \\
\bar{\gamma} \\
\bar{\gamma} \\
\bar{\gamma}^N \\
\bar{\gamma}^N \\
\bar{EP}
\end{bmatrix}
\begin{bmatrix}
y_t - y_{t-1} \\
c_t - c_{t-1} \\
i_t - i_{t-1} \\
w_t - w_{t-1} \\
l_t \\
\pi_t \\
r_t \\
n_t - n_{t-1} \\
EP_t
\end{bmatrix},
\] (2)

where \(\bar{\gamma} = 100(\gamma - 1)\) is the common quarterly trend growth rate of GDP, consumption, investment and wages; \(\bar{l}\) is the steady-state hours of work; \(\bar{\pi}\) is the steady-state quarterly inflation rate; and \(\bar{r}^m\) is the steady-state quarterly nominal interest rate; \(\bar{\gamma}^N = 100(\gamma^N - 1)\) is the quarterly trend growth rate of net worth of financial intermediaries in the SWBF model, as in Gelain and Ilbas (2017); and \(\bar{EP}\) is the steady-state quarterly credit spread.
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