Forecasting with DSGE models with financial frictions

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Abstract

This paper compares the quality of forecasts from DSGE models with and without financial frictions. We find that adding frictions affecting firms tends to improve the quality of point forecasts while the opposite is true if frictions are introduced into the household sector. However, neither of these modifications offers a cure for bias and rather badly calibrated density forecasts. Still, there are complementarities among the analyzed setups that can be exploited in the forecasting process, especially in the periods of sharp contraction in economic activity.

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1 Introduction

During the last decade, dynamic stochastic general equilibrium (DSGE) models have become the workhorse framework in both academic and policy circles. Following advances in Bayesian estimation methods, these models started to be used not only for business cycle and policy analyses, but also for forecasting (see Del Negro and Schorfheide, 2012, for a review). A number of papers have evaluated the accuracy of point forecasts generated by DSGE models and found that they are at least competitive in comparison to time series models or even professional forecasters (see e.g. Smets and Wouters, 2003; Adolfson et al., 2007; Rubaszek and Skrzypczynski, 2008; Edge et al., 2010; Edge and Gurkaynak, 2010; Kolasa et al., 2012; Wieland and Wolters, 2012). However, it has also been pointed out that the accuracy of DSGE model-based forecasts is rather poor in the absolute sense: the correlation of realizations and forecasts tends to be low and in some cases even negative. Moreover, a few recent studies have indicated that density forecasts obtained from DSGE models are usually badly calibrated (Herbst and Schorfheide, 2012; Kolasa et al., 2012). Finally, yet another weakness of DSGE models was exposed during the recent crisis as their predictions were clearly at odds with the observed output collapse.

One of the reasons for these failures could be that a standard DSGE setup assumes frictionless financial markets and, importantly in the context of the recent financial crisis, does not include housing. A growing body of literature has responded to this deficiency by adding financial frictions to the standard framework, usually building upon concepts proposed before the crisis. This trend has also affected the structure of models developed by central banks and other policy-making institutions (Gerke et al., 2013). However, the literature on the effect of these modeling developments on the forecasting performance of DSGE models is very incomplete as, if anything, the contributing papers only report marginal likelihoods for the considered alternative specifications. One of very few exceptions is Christiano et al. (2011), who demonstrate that augmenting a medium-sized

DSGE model of the Swedish economy with frictions á la Bernanke et al. (1999) increases the accuracy of point forecasts. It is not clear, however, if the reported differences are statistically significant and density forecasts are not discussed at all.

In this paper we investigate to what extent adding financial frictions can contribute to an improvement in the quality of DSGE model-based forecasts. To this end, we consider two extensions to the benchmark New Keynesian setup, exemplified by the work of Del Negro et al. (2007), both of which can be considered the state of the art for modeling frictions affecting respectively non-financial firms and households. More specifically, the first addition introduces frictions between firms and banks using the financial accelerator setup developed by Bernanke et al. (1999). The second extension follows Iacoviello (2005) and incorporates housing and collateral constraints into the household sector. We next analyze the performance of point and density forecasts generated by the three variants of the model, as well as by their equally weighted pool.

We find that accounting for financial frictions affecting firms tends to improve the quality of point forecasts while the opposite is true for the extension with household sector financial frictions. Overall, neither of these modifications to the standard DSGE framework offers a spectacular remedy for the deficiencies pointed out by the earlier literature. In particular, the augmented models still generate point forecasts that can be considered poor in the absolute sense and rather badly calibrated density forecasts. However, there seem to be interesting complementarities among the analyzed setups that can be exploited in the forecasting process as pooling the predictions from all models usually results in better point and density forecasts. These gains can be particularly substantial in the periods of sharp contraction in economic activity, like the one observed during the recent financial crisis.

The rest of this paper proceeds as follows. Section 2 presents the models. The results of the forecasting contest are discussed in section 3. The last section concludes. The detailed equations of the models, the description of the data and estimation issues are reported in the Appendix.

2 The DSGE models

In this section we briefly describe the models that are used in our forecasting competition: a baseline New Keynesian setup, its two extensions incorporating financial frictions, as well as the pool of the models. A full list of models equations is presented in Appendix A.

2.1 Baseline New Keynesian model (DSSW)

Our baseline New Keynesian DSGE model is identical to that documented by Del Negro et al. (2007), which is essentially a slightly modified version of the microfounded setup developed by Christiano et al. (2005) and estimated with Bayesian methods by Smets and Wouters (2003). The model features a standard set of nominal and real rigidities that have been found crucial for ensuring a reasonable data fit. These include: consumption habits, investment adjustment costs, time-varying capacity utilization, as well as wage and price stickiness with indexation. Government spending is exogenous and financed by lump sum taxes, while the monetary policy is conducted according to the Taylor rule.

The model economy is driven by seven stochastic disturbances. Labor augmenting technology is assumed to be a unit-root process and hence generates a common trend in output, consumption, investment, capital and real wages. The remaining shocks are stationary and disturb the rate of time preference, relative price of investment, disutility of labor, price markup, government purchases and monetary policy.

The DSSW model is estimated with seven key macroeconomic time series: output, consumption, investment, labor, real wages, inflation and the short-term interest rate. The trending variables are expressed in growth rates.

2.2 Financial frictions in the corporate sector (DSSW+FF)

The first extension of the baseline model introduces financial frictions into the corporate sector. We use the financial accelerator framework developed by Bernanke et al. (1999), except that, following Christiano et al. (2003), the financial contract is specified in nominal terms. Our choice of the model specification is based on the results of Brzoza-Brzezina et al. (2013), who indicate that this way of modeling frictions in financing firm investments fits the US data better than the popular alternative based on collateral constraints as in Kiyotaki and Moore (1997). The main features of the DSSW+FF extension are as follows.

Unlike in the baseline DSSW setup, capital is managed by an additional type of agents – entrepreneurs. They possess special skills in operating capital and hence find it optimal to borrow additional funds over net worth to finance their operations. Management of capital is risky as entrepreneurs are hit by idiosyncratic shocks after they have signed a debt contract with a bank. Depending on the shock draw, an entrepreneur may have or not enough resources to repay the loan. In the latter case, she declares default and the bank seizes all her assets, having paid a proportional auditing cost. Since entrepreneurs are assumed to be risk neutral and banks are owned by risk averse households, the optimal contract between these two parties isolates the latter from any aggregate risk. As regards the banking sector, it is assumed to be competitive with free entry, which implies that each bank breaks even in every period. Given that entrepreneurs are defined on a continuum and hence the idiosyncratic risk can be fully diversified, the premium charged by banks over the risk-free rate is just a compensation for auditing costs.

Compared to the baseline DSSW setup, there are two additional stochastic shocks in the DSSW+FF model, affecting the standard deviation of idiosyncratic risk faced by entrepreneurs and their survival rate. Including these shocks allows us to use two additional time series while taking the model to the data. These are the growth rate of loans to firms and the spread on loans to firms.

2.3 Financial frictions in the household sector (DSSW+HF)

The second extension of the baseline DSSW model incorporates financial frictions affecting households. It is based on Iacoviello (2005), who uses the Kiyotaki and Moore (1997) framework to model collateral constraints in the housing market. Following Gerali et al. (2010), we also allow for monopolistic competition in the banking sector, which results in the spread between the interbank and loan rates. The main characteristics of the DSSW+HF extension are summarized below.

In contrast to the DSSW benchmark, the household sector is not homogeneous, but populated by two types of agents that differ in their rate of time preference. Impatient households discount the future more heavily, hence are natural borrowers. Their borrowing is constrained by the value of their housing stock, where the constraint is assumed to be binding in every period. Apart from serving as a collateral, housing also provides utility for both types of agents. The financial intermediation between patient and impatient households is conducted by imperfectly competitive banks, which accept deposits at the policy rate and offer loans at a rate reflecting their monopolistic power.

The DSSW+HF extension adds four new shocks to the DSSW setup. These concern the housing weight in utility, loan-to-value ratio, relative price of residential investment and markups in the banking sector. The corresponding four new variables used in estimation are: residential investment, mortgage loans, house prices and the spread on mortgage loans. The first three variables are expressed in growth rates.

2.4 Equally weighted pool

The last competitor in our contest is the equally weighted pool of all three model-based forecasts, which we analyze just to check whether there are complementarities among the analyzed setups that can be exploited in the forecasting process. A related question is investigated by Wolters (2010), who finds that weighted forecasts of several standard (i.e.

not including financial fricitons) DSGE models tend to be more accurate than forecasts from individual models. His results also show that a simple pool of forecasts tends to outperform forecasts obtained with more sophisticated weighting methods, which is in line with the broader characterization of empirical results surveyed in Timmermann (2006). Given these considerations and this paper's main foucs, in what follows we report the results only for the equally weighted pool.

3 Forecasts comparison

In this section we compare the quality of forecasts from the DSSW, DSSW+FF and DSSW+HF models, as well as their equally weighted pool. Our investigation proceeds in four steps.

First, we collect the following quarterly data describing the functioning of the US economy in the period between 1970:1 and 2010:4: output, consumption, corporate investment, residential investment, labor, wages, house prices, inflation, the interest rate, loans to firms, spread on loans to firms, mortgage loans and spread on mortgage loans. The detailed description of the data definitions and sources is provided in Appendix B.

Second, we estimate all three DSGE models with standard Bayesian methods, where the estimation details are outlined in Appendix C.

Third, we generate point and density forecasts for horizons up to 24 quarters ahead. The forecasting scheme is recursive and the evaluation sample spans from 1990:1 to 2010:4. More specifically, the first set of forecasts is generated for the period 1990:1-1995:4 with models estimated on the sample spanning 1970:1-1989:4, the second set of forecasts is for the period 1990:2-1996:1 with models estimated on the sample 1970:1-1990:1 etc. Since our dataset ends in 2010:4, the forecasts are evaluated on the basis of 61 (for 24-quarter ahead forecasts) to 84 (1-quarter ahead forecasts) observations.

Finally, we assess the quality of forecasts for the seven US macroeconomic time series that show up in all three model variants: output, consumption, investment, hours worked, inflation, wages and the interest rate. Given that the maximum forecast horizon is relatively long, the statistics are calculated for variables in levels rather than for growth rates. While assessing the quality of forecasts, both frequentist and Bayesian statistical methods are used. In particular, we evaluate point forecasts with the mean forecast error (MFE) and root mean squared forecast error (RMSFE) statistics, while the quality of density forecasts is assessed using log predictive scores (LPS) and probability integral transform charts.

3.1 Point forecasts

We begin our forecasting contest by analyzing the mean forecast errors. The results presented in Table 1 show that all models overpredict investment and underpredict consumption, where the size of this bias is most pronounced for the DSSW model. This indicates that adding financial frictions to a canonical New Keynesian setup helps in accounting for the observed differences in the average growth rates of GDP components. This result, however, does not translate into better forecasts for output: the MFEs from the DSSW model are comparable, and for longer horizons even smaller in absolute value, than those from either of the two extensions.

A significant bias can also be detected for labor market variables, as well as for medium and long-term forecasts of inflation and the interest rate. In particular, the latter tend to be too high for all three models, where the source of the bias is twofold: the models overpredict both the future level of inflation and the real interest rate.

In comparison to other related studies (see Del Negro and Schorfheide, 2012, for a review), the systematic bias of DSGE model-based forecasts found in our analysis can be explained by the fact that we evaluate the predictions for levels of variables, some of which are non-stationary, rather than for growth rates. The main reasons for the bias seem to be the following. First, the realization of stochastic trends was different in the estimation and evaluation samples. For instance, the average quarterly growth rate of output stood at 0.37% in the period 1970:1-1989:4 and was equal to 0.31% over the period 1990:1-2010:4. The difference is even more visible for inflation: the respective quarterly averages over the two subsamples amount to 1.36% and 0.55%, respectively. The second reason for the biased forecasts is related to the common stochastic trend restriction imposed by the theoretical model on per capita output, consumption, investment and real wages, which is not consistent with the data over the evaluation sample. In particular, the shares of consumption and investment in output exhibit positive and negative trends, respectively. Third, too high interest rate forecasts are due to the "risk free interest rate puzzle" (see Canzoneri et al., 2007, for a detailed discussion), i.e. the tendency of representative agent models to overpredict the steady state interest rate. Our results show that adding financial frictions somewhat alleviates, but does not resolve these problems.

A simple way to remove the bias would be to apply a smooth statistical (e.g. Hodrick-Prescott) filter before running the estimation. This would mean, however, that the forecast comparison would concern cyclical components that are not observed by forecasters in real time. A more flexible alternative has been recently proposed by Canova (2012). In his framework, the non-model based component is designed such that it can endogenously capture those aspects of the data that the theoretical model has problems to explain. Yet another option would be to relax some of the cross equation restrictions imposed by the model structure (see e.g. Ireland, 2004; Cayen et al., 2009) or to use them only as a prior for an atheoretical time series model (Del Negro and Schorfheide, 2004). Clearly, all these approaches generate departures from the restrictions that are model dependent. As a result, they can give a distorted picture on the usefulness for forecasting of particular mechanisms included in the theoretical model, which is our paper's focus. For this reason, we do not use any of these methods in our forecasting contest.

We continue our investigation by comparing the second moments of the forecast errors. In Table 2 we report the RMSFEs for the DSSW model, whereas the remaining numbers are expressed as ratios so that values below unity indicate that a given model outperforms the DSSW benchmark. Moreover, to provide a rough gauge of whether the RMSFE ratios are significantly different from unity, we report the results of the Diebold-Mariano test (Diebold and Mariano, 1995).

Overall, the RMSFE statistic show that adding financial frictions in the corporate sector helps in reducing RMSFEs for all variables at longer horizons, whereas the results for shorter horizons are mixed. On the other hand, allowing for financial frictions in the household sector tends to increase RMSFEs for all variables but consumption and investment. At least two features of the DSSW+FF model-based forecasts warrant a more detailed discussion. First, this extension produces most accurate medium and long-term investment forecasts, but worst (even though not significantly so) predictions of this variable up to one year ahead. Second, the DSSW+FF model clearly outperforms both the benchmark and the DSSW+HF alternative in forecasting labor market variables. To understand why this happens, it is useful to look at how the parameters describing investment and labor market rigidities differ between the model variants. As can be seen in Appendix C, the posterior estimates of both investment adjustment cost curvature and wage stickiness are clearly lowest in the DSSW+FF setup. This suggests that the additional frictions introduced by the financial accelerator framework of Bernanke et al. (1999) to some extent substitute for these two standard rigidities in a way that improves forecasts of labor market variables, as well as medium and long term investment forecasts. On the other hand, since the Bernanke et al. frictions operate mainly on medium-term frequencies, low costs of adjusting investment in the DSSW+FF variant make this variable very volatile over short forecast horizons,[1] which deteriorates short-run point (and, as we

[1]The autocorrelation of log change in investment in our evaluation sample is 0.71, while the correlation of one step ahead forecasts from the DSSW+FF variant with the last available observation is just 0.32.

will see later, even more density) forecasts.

Finally, we note that for all variables and horizons the RMSFE ratios obtained for the equally weighted pool tend to be below unity and in many cases significantly so. Moreover, in many instances the RMSFEs from the pool are lower than those produced by any of the models. This is particularly true for the short term forecasts of the following three key macroeconomic variables: output, prices and the interest rate.

Given that the recent revival of interest in DSGE models with financial frictions was to a large degree a response to the Great Recession, we also look at the relative performance of the investigated models during this episode, which according to the NBER's business cycle dating took place from 2007:4 to 2009:2. In Table 3 we show the RMSFEs for this subsample. Given that each statistic is calculated on the basis of only seven observations, we do not report the results of the Diebold-Mariano test. The comparison with Table 2 reveals that for output, consumption and investment the RMSFEs over the crisis period are about twice higher than those calculated over the entire evaluation sample. For the remaining variables, the RMSFEs are also larger during the crisis, but the difference is not very pronounced. Overall, the relative performance of the alternative models during the crisis can be considered very similar to that observed over the whole sample. The only exceptions are the substantial improvement of forecasts from the DSSW+FF variant for prices and wages and the deterioration of the DSSW+HF model-based forecasts for consumption and hours.

The general conclusions that can be drawn from the comparison of point forecasts are threefold. First, allowing for financial market imperfections somewhat attenuates the problem of forecast bias, especially for GDP components. Second, adding financial frictions in the corporate sector tends to improve the accuracy of point forecasts measured by the RMSFEs, while the opposite is usually true for the version with frictions affecting households. According to this statistics, the pool of models is an attractive option. Third, the relative accuracy of point forecasts from the investigated models during the recent crisis and over the entire evaluation sample are broadly the same.

3.2 Density forecasts

We complement the discussion of point forecasts accuracy with an evaluation of density forecasts. Our aim is to check to what extent the analyzed forecasts provide a realistic description of actual uncertainty. More specifically, we evaluate the relative performance of the models by comparing their predictive scores and discuss the absolute performance by using the probability integral transforms.

Let us define the predictive density of an h-step ahead forecast formulated at time t from model M_i as:

$$p(Y_{t+h}|\Omega_t, M_i) = \int p(Y_{t+h}|\Omega_t, M_i, \theta_i)p(\theta_i|\Omega_t, M_i)d\theta_i \qquad (1)$$

where θ_i is the vector of model parameters. In the empirical application, for each individual model, we follow Adolfson et al. (2007) and assume that $p(Y_{t+h}|\Omega_t, M_i)$ is a multivariate normal density, and estimate the mean vector and the covariance matrix from the predictive sample.[2] In the case of the pool, we follow Geweke and Amisano (2011b) and calculate the predictive density as:

$$\sum_{i=1}^{n} w_i p(Y_{t+h}|\Omega_t, M_i) \qquad (2)$$

where w_i are weights that satisfy $w_i \geq 0$ and $\sum w_i = 1$.

We compare the relative density forecasts from the competing models using the Kullback-Leibler Information Criterion (KLIC), which measures the distance between the true den-

[2]The alternative option, proposed e.g. by Geweke and Amisano (2011a), is to use the fact that $p(Y_{t+h}|\Omega_t, M_i, \theta_i)$ is Gaussian and integrate out the parameters numerically to calculate $p(Y_{t+h}|\Omega_t, M_i)$. The results obtained with this more computationally demanding method are broadly the same as in our baseline case.

sity $p(Y_{t+h}|\Omega_t)$ and the density forecast from model M_i as:

$$KLIC_{i,t,h} = E(\ln p(Y_{t+h}|\Omega_t) - \ln p(Y_{t+h}|\Omega_t, M_i)) \tag{3}$$

The average of sample information is:

$$\widehat{KLIC}_{i,h} = \frac{1}{R_h} \sum_{t=P}^{T-h} (\ln p(y_{t+h}|\Omega_t) - \ln p(y_{t+h}|\Omega_t, M_i)), \tag{4}$$

where y_t denotes the realization of Y_t, T and P stand for full sample and in-sample length, and $R_h = T - P - h + 1$ is the number of h-step ahead predictions. The value of $\widehat{KLIC}_{i,h}$ is the difference between the average log (unobservable) true density of realizations and the average log predictive score (LPS) of the h-step ahead forecasts from model M_i:

$$S_{i,h} = \frac{1}{R_h} \sum_{t=P}^{T-h} \ln p(y_{t+h}|\Omega_t, M_i) \tag{5}$$

and thus:

$$\widehat{KLIC}_{i,h} - \widehat{KLIC}_{i,h} = S_{i,h} - S_{j,h}. \tag{6}$$

The null of equal accuracy of density forecasts from models M_i and M_j:

$$H_0 : KLIC_{i,t,h} - KLIC_{j,t,h} = 0 \tag{7}$$

can be tested using the KLIC type of tests that compare LPSs from both models (Mitchell and Hall, 2005; Mitchell and Wallis, 2011), e.g. the Diebold-Mariano type of test proposed by Amisano and Giacomini (2007).

In Table 4 we report the average values of the LPSs for the DSSW model, whereas the remaining numbers are expressed as differences so that values above zero indicate that a given model outperforms the DSSW benchmark. To provide a rough gauge of whether these differences are significantly different from zero, we report the results of the Amisano-Giacomini test.

Our results show that adding financial frictions in the corporate sector improves significantly the quality of longer term density forecasts for output, investment and wages. However, at the same time, this extension decreases the performance of short term forecasts for investment, consumption and prices. If we compare the joint forecast density for all seven variables under investigation, the conclusion is that the DSSW+FF model is significantly worse than the benchmark for short horizons. As regards the DSSW+HF variant, a significant improvement can be observed for consumption, while the forecast quality deteriorates for prices and the interest rate. A comparison of the joint forecast density for all seven variables shows that the DSSW model-based predictions are better calibrated than those from the DSSW+HF variant for one quarter ahead, and worse for the longest horizons. Finally, it is worth noting that, as in the RMSFE analysis, pooling helps to improve the quality of density forecasts: in most cases the LPS differences are positive. In particular, for the seven variables case and horizons above one year, they are significantly greater than zero.

As in the case of RMSFEs, we also discuss the relative accuracy of density forecasts during the recent financial crisis. The LPS statistics for this subsample are reported in Table 5. Given that the estimates are based on only seven observations, we do not report the results of the Amisano-Giacomini test. Similarly to point forecasts, the quality of density forecasts substantially deteriorated during the recession. The difference between the LPSs calculated for the crisis period and their full sample counterparts is particularly large for output, consumption and investment. It is worth noting, however, that the performance of financial friction models relative to the DSSW benchmark is better during the crisis than over the entire evaluation period. In particular, and in contrast to the full sample results, the DSSW+HF model turns out to be very efficient in forecasting output, investment and hours worked. Finally, pooling the forecasts works very well during the crisis, which is especially visible if one compares the LPSs for all seven variables. Overall, the results for the recent crisis episode confirm our claim that the three models are quite complementary to each other.

The next examine where these differences in the LPSs across the models come from. For a well calibrated density forecast, one would expect that it is unbiased (null MFE) and effective (RMSFE equal to the average standard deviation of the predictive density, SDPD). We have already looked at the first issue while analyzing the quality of point forecasts. It can be noticed that there is a visible relationship between the MFEs and LPSs: the higher the bias, the lower the LPSs. As regards the second issue, we address it in Table 6, which reports the SDPDs for the DSSW model, while the remaining numbers are expressed as ratios so that values above unity indicate that the density forecast from a given model is more diffuse than that from the DSSW benchmark. The comparison of numbers in Tables 2 and 6 indicates that for the DSSW model the SDPDs are usually comparable to the RMSFEs, except for short-term forecasts of inflation and the interest rate. This means that for this model the main problem is not the width of the predictive densities, but the bias. The general conclusion for the DSSW+FF model is broadly similar. The main difference relates to investment: adding financial frictions in the corporate sector almost doubles the SDPD for short-term horizons, which leads to a significant fall in the LPS (see Table 4). As discussed in the previous section, this result can be traced back to low estimates of investment adjustment costs. Finally, the SDPDs from the DSSW+HF model are visibly larger than those from the benchmark model, and hence the forecasts are too diffuse. On the other hand, this feature becomes an advantage during the crisis, with the model's predictive density being more consistent with the output collapse observed during this period.

In the last step, we evaluate the quality of density forecasts with the probability integral transform (PIT), which for an h-step ahead forecast from model M_i is defined as:

$$PIT_{i,t,h} = \int_{-\infty}^{y_{t+h}} p(Y_{t+h}|\Omega_t, M_i) dY_{t+h} \tag{8}$$

If a density forecast is well calibrated, $PIT_{i,t,h}$ should be independently and uniformly distributed on the interval (0,1). Diebold et al. (1998) advocate a variety of graphical approaches to forecast analysis using this statistics. In this paper, we use a visualization that has been recently used for evaluation of DSGE models by Herbst and Schorfheide (2012), i.e. we divide the unit interval into 10 subintervals and check if the fraction of PITs in each of them is close to 10%.

Figure 1 shows the histograms of PITs for four quarter ahead forecasts. The interpretation of these histograms is as follows. If PITs are equally distributed across bins, a density forecast is well calibrated. If PITs are concentrated in the lower (upper) bins, a model tends to overpredict (underpredict) a given variable. Finally, if PITs are concentrated in the middle (outer) bins, a density forecast is too diffuse (tight). Overall, the figure confirms our earlier findings about an upward bias of forecasts generated from the investigated models for all variables but consumption, whose density forecasts look relatively well calibrated except for the DSSW+FF model.

Overall, the general conclusions that can be drawn from the comparison of density forecasts are twofold. First, density forecasts from the three analyzed models are generally poorly calibrated. The main source of this result can be traced back to a significant bias, which was detected for most horizons and all analyzed variables. The width of the predictive density does not seem to be a serious problem for the DSSW and DSSW+FF models, but is too high in the case of the DSSW+HF variant. Second, the comparison of the log predictive scores across the models, variables and forecast horizons indicates that no model dominates the other. The DSSW+FF model is found to be relatively good in forecasting output and wages, the DSSW+HF variant is quite successful in forecasting consumption and investment and also generates best density forecasts for real variables during the recent crisis, whereas the baseline DSSW model performs best for hours and inflation. Given these complementarities, there are clear gains from pooling forecasts from all three models.

4 Conclusions

In this paper we have compared point and density forecasts from a richly-specified DSGE model and from its two extensions that introduce financial frictions into the corporate and household sectors. We have found that the main problem of the three models is a significant and sizable bias of their forecasts. Another important finding is that adding financial frictions in the corporate sector using the Bernanke et al. (1999) setup tends to improve the accuracy of point forecasts, and, though to a lesser extent, the quality of density forecasts. On the other hand, allowing for financial frictions in the household sector á la Iacoviello (2005) tends to deteriorate the accuracy of point forecasts and makes the density forecasts too diffuse. This setup, however, generated relatively good density predictions of real variables during the recent financial crisis. Finally, we have also shown that pooling forecasts from all three models is an attractive option, especially for density forecasts.

We believe that the above findings contribute to the current discussion on the usefulness of DSGE models with financial frictions in forecasting and policy oriented analyses. Our results indicate that while none of the two considered extensions offer a spectacular improvement in the quality of DSGE model-based forecasts, especially in the absolute sense, adding them to the suite of models does bring some benefits. In particular, as suggested by a relatively good performance of pooled forecasts and additional insights from the financial crisis episode, there seems to be sufficient complementarity between the three setups that justifies their use in the forecasting process. However, our results also clearly point to the problem of bias in forecasts from DSGE models. This suggests that modeling long-run trends within this framework deserves more attention than it has so far received in the literature.

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Table 1: Mean Forecast Errors (MFE)

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
				Output				
DSSW	-0.34***	-0.67***	-1.21***	-1.53***	-1.73**	-1.67*	-1.34	-0.37
DSSW+FF	-0.36***	-0.65***	-1.04***	-1.34***	-1.60**	-1.77**	-1.73	-1.30
DSSW+HF	-0.13	-0.35**	-0.90**	-1.47***	-2.05***	-2.60***	-2.74**	-2.62*
				Consumption				
DSSW	0.03	0.14	0.56	1.18*	1.80**	3.06***	4.13***	6.06***
DSSW+FF	0.09	0.22	0.57	0.99	1.42	2.50**	3.56***	5.55***
DSSW+HF	0.02	0.08	0.29	0.60	0.96	1.95**	2.87***	4.40***
				Investment				
DSSW	-0.85***	-2.18***	-5.23***	-8.03***	-10.3***	-11.5***	-10.7***	-6.93*
DSSW+FF	-0.89**	-1.69*	-2.87*	-3.74*	-4.35*	-4.47	-4.15	-3.12
DSSW+HF	-0.43***	-1.32***	-3.40***	-5.24***	-6.78***	-6.93***	-5.91*	-4.11
				Hours				
DSSW	-0.49***	-0.95***	-1.70***	-2.15***	-2.38***	-2.35***	-2.15**	-1.94
DSSW+FF	-0.55***	-0.99***	-1.59***	-2.04***	-2.36***	-2.67***	-2.85***	-3.24***
DSSW+HF	-0.23***	-0.56***	-1.29***	-2.00***	-2.63***	-3.20***	-3.44***	-3.97***
				Prices				
DSSW	-0.01	-0.07	-0.37***	-0.87***	-1.49***	-2.89***	-4.40***	-7.70***
DSSW+FF	-0.07**	-0.20***	-0.53***	-0.86***	-1.23***	-2.10***	-3.00***	-5.08***
DSSW+HF	0.05**	0.10*	0.11	-0.13	-0.64*	-2.15***	-3.87***	-7.27***
				Wages				
DSSW	-0.27***	-0.65***	-1.50***	-2.17***	-2.73***	-3.44***	-3.73***	-3.31***
DSSW+FF	-0.22***	-0.45***	-0.86***	-1.20***	-1.56***	-2.16***	-2.53***	-2.45***
DSSW+HF	-0.12**	-0.34***	-0.98***	-1.70***	-2.49***	-3.75***	-4.43***	-4.42***
				Interest rate				
DSSW	-0.01	-0.13	-0.61*	-1.22***	-1.80***	-2.52***	-2.82***	-3.19***
DSSW+FF	0.04	-0.29*	-0.98***	-1.47***	-1.83***	-2.28***	-2.49***	-2.89***
DSSW+HF	-0.34***	-0.58***	-1.04***	-1.60***	-2.23***	-3.17***	-3.61***	-3.97***

Notes: A positive value indicates that forecasts are on average below the actual values. Asterisks ***, **and *denote the rejection of the null that the MFE is equal to zero at the 1%, 5% and 10% significance levels, respectively. The test statistics are corrected for autocorrelation of forecast errors with the Newey-West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Table 2: Root Mean Squared Forecast Errors (RMSFE)

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
	Output							
DSSW	0.73	1.27	2.27	3.05	3.68	4.69	5.48	6.38
DSSW+FF	0.99	0.96	0.91**	0.89**	0.89***	0.90***	0.89***	0.89***
DSSW+HF	0.98	0.98	1.00	1.05	1.07**	1.09**	1.05	1.01
Pool	0.95*	0.94**	0.94**	0.96**	0.97**	0.98	0.96	0.94
	Consumption							
DSSW	0.67	1.24	2.27	3.19	4.07	5.69	7.04	9.08
DSSW+FF	1.01	1.03	1.05	1.04	1.01	0.97	0.94**	0.90***
DSSW+HF	1.01	1.00	0.95	0.90	0.85*	0.80***	0.78***	0.74***
Pool	0.97**	0.97**	0.96**	0.94**	0.93**	0.91***	0.89***	0.88***
	Investment							
DSSW	1.85	3.75	7.78	11.6	14.6	17.5	18.3	18.1
DSSW+FF	1.39	1.28	1.06	0.92	0.84**	0.77**	0.77**	0.84**
DSSW+HF	0.95	0.89*	0.86**	0.87**	0.88***	0.87**	0.87**	0.89
Pool	1.03	0.98	0.92***	0.89***	0.87***	0.86***	0.86**	0.89**
	Hours							
DSSW	0.81	1.31	2.16	2.85	3.41	4.35	4.84	4.98
DSSW+FF	0.91***	0.85***	0.78***	0.77***	0.77***	0.82***	0.86**	0.89**
DSSW+HF	1.02	0.98	0.91*	0.92*	0.95	1.06*	1.13***	1.16***
Pool	0.96***	0.92***	0.88***	0.88***	0.89***	0.95***	0.99	1.01
	Prices							
DSSW	0.21	0.38	0.78	1.33	1.99	3.51	5.26	9.27
DSSW+FF	1.15	1.26	1.26*	1.13	1.04	0.97	0.92*	0.89***
DSSW+HF	1.06	1.11	1.13	1.07	1.03	1.05	1.07	1.03
Pool	0.97	0.95	0.89	0.86	0.86	0.87	0.87	0.85
	Wages							
DSSW	0.81	1.31	2.16	2.85	3.41	4.35	4.84	4.98
DSSW+FF	0.91***	0.85***	0.78***	0.77***	0.77***	0.82***	0.86**	0.89**
DSSW+HF	1.02	0.98	0.91*	0.92*	0.95	1.06**	1.13***	1.16***
Pool	0.96***	0.92***	0.88***	0.88***	0.89***	0.95***	0.99	1.01
	Interest rate							
DSSW	0.62	1.10	1.83	2.32	2.71	3.14	3.32	3.63
DSSW+FF	1.00	0.90	0.95	0.95	0.93	0.87**	0.87***	0.96**
DSSW+HF	1.19*	1.10	1.00	0.99	1.04	1.20**	1.32***	1.35***
Pool	0.99	0.96	0.95	0.94**	0.95*	0.99	1.04	1.07**

Notes: For the DSSW model the RMSFEs are reported in levels, whereas for the remaining models they appear as the ratios so that the values below unity indicate that a given model has a lower RMSE than the benchmark. To provide a rough guidance of whether the ratios are different from unity, we use the Diebold-Mariano test, where the long-run variance is calculated with the Newey-West method. Asterisks ***, **and *denote the 1%, 5% and 10% significance levels, respectively. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Table 3: Root Mean Squared Forecast Errors for 2007:4-2009:2 period

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
	Output							
DSSW	1.34	3.01	5.33	6.30	6.62	8.72	9.43	7.63
DSSW+FF	1.09	1.02	0.93	0.92	0.93	0.90	0.89	0.95
DSSW+HH	0.91	0.90	0.97	1.03	1.07	1.07	1.05	1.02
Pool	0.98	0.97	0.96	0.98	1.00	0.99	0.98	0.99
	Consumption							
DSSW	1.43	2.88	4.36	4.42	4.04	5.10	5.12	2.82
DSSW+FF	0.97	0.98	1.02	1.07	1.17	1.14	0.98	0.83
DSSW+HH	1.07	1.07	1.08	1.10	1.11	1.03	0.97	0.89
Pool	1.01	1.02	1.03	1.05	1.09	1.05	0.98	0.89
	Investment							
DSSW	3.60	8.84	16.72	21.42	24.47	29.55	29.90	24.92
DSSW+FF	1.66	1.24	0.89	0.80	0.75	0.68	0.69	0.78
DSSW+HH	0.75	0.80	0.86	0.86	0.89	0.86	0.80	0.72
Pool	1.09	1.00	0.91	0.88	0.87	0.84	0.83	0.83
	Hours							
DSSW	1.13	1.19	2.43	3.05	3.74	6.19	7.27	6.16
DSSW+FF	0.87	0.79	0.71	0.69	0.69	0.70	0.75	0.83
DSSW+HH	1.15	1.09	1.09	1.11	1.12	1.12	1.13	1.24
Pool	1.00	0.94	0.92	0.93	0.93	0.94	0.96	1.02
	Prices							
DSSW	0.32	0.42	0.82	0.99	1.44	1.64	1.99	3.08
DSSW+FF	0.87	0.67	0.38	0.59	0.47	0.38	0.46	0.63
DSSW+HH	0.98	0.95	0.77	0.68	0.86	1.30	1.32	1.32
Pool	0.89	0.72	0.59	0.59	0.67	0.80	0.86	0.79
	Wages							
DSSW	1.13	1.19	2.43	3.05	3.74	6.19	7.27	6.16
DSSW+FF	0.87	0.79	0.71	0.69	0.69	0.70	0.75	0.83
DSSW+HH	1.15	1.09	1.09	1.11	1.12	1.12	1.13	1.24
Pool	1.00	0.94	0.92	0.93	0.93	0.94	0.96	1.02
	Interest rate							
DSSW	0.99	1.65	2.75	3.33	3.67	4.01	4.35	4.57
DSSW+FF	1.07	0.82	0.92	0.93	0.85	0.82	0.91	0.95
DSSW+HH	1.21	1.10	0.98	1.02	1.10	1.27	1.28	1.32
Pool	0.95	0.95	0.97	0.98	0.98	1.03	1.06	1.09

Notes: For the DSSW model the RMSFEs are reported in levels, whereas for the remaining models they appear as the ratios so that the values below unity indicate that a given model has a lower RMSE than the benchmark. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Table 4: Average log predictive scores (LPS)

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
	Output							
DSSW	-1.15	-1.73	-2.32	-2.62	-2.79	-3.02	-3.16	-3.29
DSSW+FF	-0.06*	0.00	0.08	0.09**	0.08**	0.06*	0.07**	0.09**
DSSW+HF	-0.05	-0.02	-0.03	-0.08	-0.11	-0.16	-0.18	-0.24**
Pool	-0.02	0.02	0.07	0.06	0.03	0.01	0.01	-0.02
	Consumption							
DSSW	-1.05	-1.70	-2.33	-2.68	-2.96	-3.41	-3.73	-4.07
DSSW+FF	0.01	0.00	-0.16	-0.26***	-0.28**	-0.17	0.01	0.29***
DSSW+HF	-0.01	0.01	0.07	0.15*	0.26***	0.47***	0.61***	0.75***
Pool	0.02	0.04*	0.03*	0.05*	0.10***	0.23***	0.35***	0.50***
	Investment							
DSSW	-2.06	-2.77	-3.51	-3.96	-4.23	-4.42	-4.43	-4.35
DSSW+FF	-0.49***	-0.34***	-0.12	0.02	0.13	0.21**	0.19***	0.04
DSSW+HF	0.04	0.08	0.12	0.17	0.21	0.21	0.15	-0.02
Pool	-0.10	-0.03	0.06	0.14	0.21	0.26*	0.26	0.14
	Hours							
DSSW	-1.23	-1.74	-2.37	-2.68	-2.84	-2.94	-2.99	-3.07
DSSW+FF	-0.03	-0.06	-0.07	-0.13	-0.20	-0.25	-0.24	-0.24
DSSW+HF	-0.05	-0.02	0.01	-0.02	-0.09	-0.24	-0.33**	-0.45***
Pool	-0.01	0.02	0.11	0.13	0.10	0.02	-0.04	-0.11***
	Prices							
DSSW	-0.04	-0.70	-1.41	-1.85	-2.18	-2.68	-3.06	-3.71
DSSW+FF	-0.14***	-0.12**	-0.07	-0.02	0.00	0.02	0.05	0.15*
DSSW+HF	-0.13***	-0.19***	-0.27***	-0.31***	-0.32***	-0.33***	-0.32***	-0.18
Pool	-0.07***	-0.09***	-0.09***	-0.09***	-0.08**	-0.08**	-0.05	0.04
	Wages							
DSSW	-1.23	-1.69	-2.21	-2.49	-2.68	-2.94	-3.03	-3.03
DSSW+FF	0.11**	0.12***	0.21***	0.25***	0.26***	0.23***	0.17**	0.07
DSSW+HF	0.00	0.03	0.07	0.07	0.06	0.00	-0.07**	-0.13***
Pool	0.08***	0.07***	0.11***	0.13***	0.13***	0.10**	0.05	-0.01
	Interest rate							
DSSW	-1.29	-1.67	-2.07	-2.29	-2.44	-2.60	-2.66	-2.76
DSSW+FF	-0.05**	-0.05	-0.04	0.00	0.06	0.14	0.15*	0.09
DSSW+HF	-0.05	-0.04	-0.03	-0.05	-0.10	-0.23***	-0.34***	-0.37***
Pool	-0.03**	-0.02	-0.01	0.00	0.01	0.00	-0.03	-0.06*
	7 variables							
DSSW	-7.50	-11.0	-14.8	-17.1	-18.8	-21.1	-22.7	-25.0
DSSW+FF	-0.67***	-0.50**	-0.28	-0.24	-0.17	-0.11	-0.13	-0.29
DSSW+HF	-0.37***	-0.39***	-0.31	-0.12	0.17	0.80	1.42**	2.47***
Pool	-0.18***	-0.08	0.19	0.37**	0.59***	0.96***	1.30***	2.01***

Notes: For the DSSW model LPSs are reported in levels, whereas for the remaining models they appear as the differences so that the values above zero indicate that a given model has a higher LPS than the benchmark. To provide a rough guidance of whether the differences are different from zero, we use the Amisano and Giacomini (2007) test, where the long-run variance is calculated with the Newey-West method. Asterisks ***, **and *denote the 1%, 5% and 10% significance levels, respectively. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Table 5: Average log predictive scores for 2007:4-2009:2 period

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
	Output							
DSSW	-2.12	-4.07	-5.17	-4.64	-4.13	-4.47	-4.26	-3.49
DSSW+FF	0.13	0.57	0.68	0.26	0.04	0.12	0.14	0.04
DSSW+HF	0.41	1.14	1.39	0.92	0.57	0.66	0.51	-0.04
Pool	0.27	0.84	1.05	0.65	0.33	0.39	0.32	0.01
	Consumption							
DSSW	-3.00	-4.93	-4.97	-3.75	-3.06	-3.25	-3.11	-2.75
DSSW+FF	0.28	0.43	-0.33	-0.70	-0.80	-0.70	-0.07	0.13
DSSW+HF	-0.11	-0.15	-0.03	0.01	-0.02	0.14	0.08	-0.23
Pool	0.10	0.22	-0.03	-0.10	-0.16	-0.03	0.05	-0.02
	Investment							
DSSW	-3.28	-5.01	-5.84	-5.82	-5.80	-6.05	-5.74	-4.92
DSSW+FF	-0.26	0.25	0.74	0.69	0.74	0.96	0.71	0.30
DSSW+HF	0.84	1.30	1.29	1.17	1.07	1.28	1.14	0.54
Pool	0.46	0.89	0.94	0.91	0.83	1.04	0.89	0.41
	Hours							
DSSW	-1.45	-2.81	-4.12	-3.87	-3.66	-3.57	-3.42	-3.24
DSSW+FF	-0.47	-0.85	-0.51	-0.50	-0.62	-0.39	-0.35	-0.38
DSSW+HF	0.16	0.67	1.09	0.75	0.46	0.24	0.07	-0.17
Pool	0.00	0.33	0.76	0.49	0.29	0.17	0.07	-0.11
	Prices							
DSSW	-0.28	-0.71	-1.40	-1.72	-2.02	-2.33	-2.57	-2.97
DSSW+FF	0.04	0.07	0.24	0.15	0.16	0.04	-0.05	-0.17
DSSW+HF	0.02	-0.07	-0.11	-0.22	-0.27	-0.39	-0.45	-0.51
Pool	0.07	0.01	0.06	-0.01	-0.02	-0.10	-0.15	-0.20
	Wages							
DSSW	-1.76	-1.62	-2.32	-2.54	-2.75	-3.53	-3.81	-3.29
DSSW+FF	0.35	0.09	0.30	0.33	0.35	0.62	0.66	0.23
DSSW+HF	-0.23	-0.10	-0.08	-0.10	-0.10	0.05	0.04	-0.25
Pool	0.17	0.01	0.10	0.10	0.11	0.27	0.28	0.01
	Interest rate							
DSSW	-1.43	-1.92	-2.52	-2.77	-2.90	-3.02	-3.17	-3.24
DSSW+FF	-0.05	0.12	0.16	0.22	0.35	0.41	0.35	0.32
DSSW+HF	-0.17	-0.12	0.01	0.01	-0.05	-0.25	-0.19	-0.19
Pool	-0.03	0.03	0.07	0.09	0.13	0.11	0.09	0.07
	7 variables							
DSSW	-12.5	-18.4	-22.0	-20.6	-20.2	-20.9	-21.1	-21.0
DSSW+FF	-0.75	0.05	1.60	1.06	1.07	1.36	1.60	0.55
DSSW+HF	0.10	0.27	-0.33	-0.89	-0.92	-0.84	-0.35	-0.17
Pool	0.38	1.13	1.42	0.65	0.63	0.83	1.02	0.43

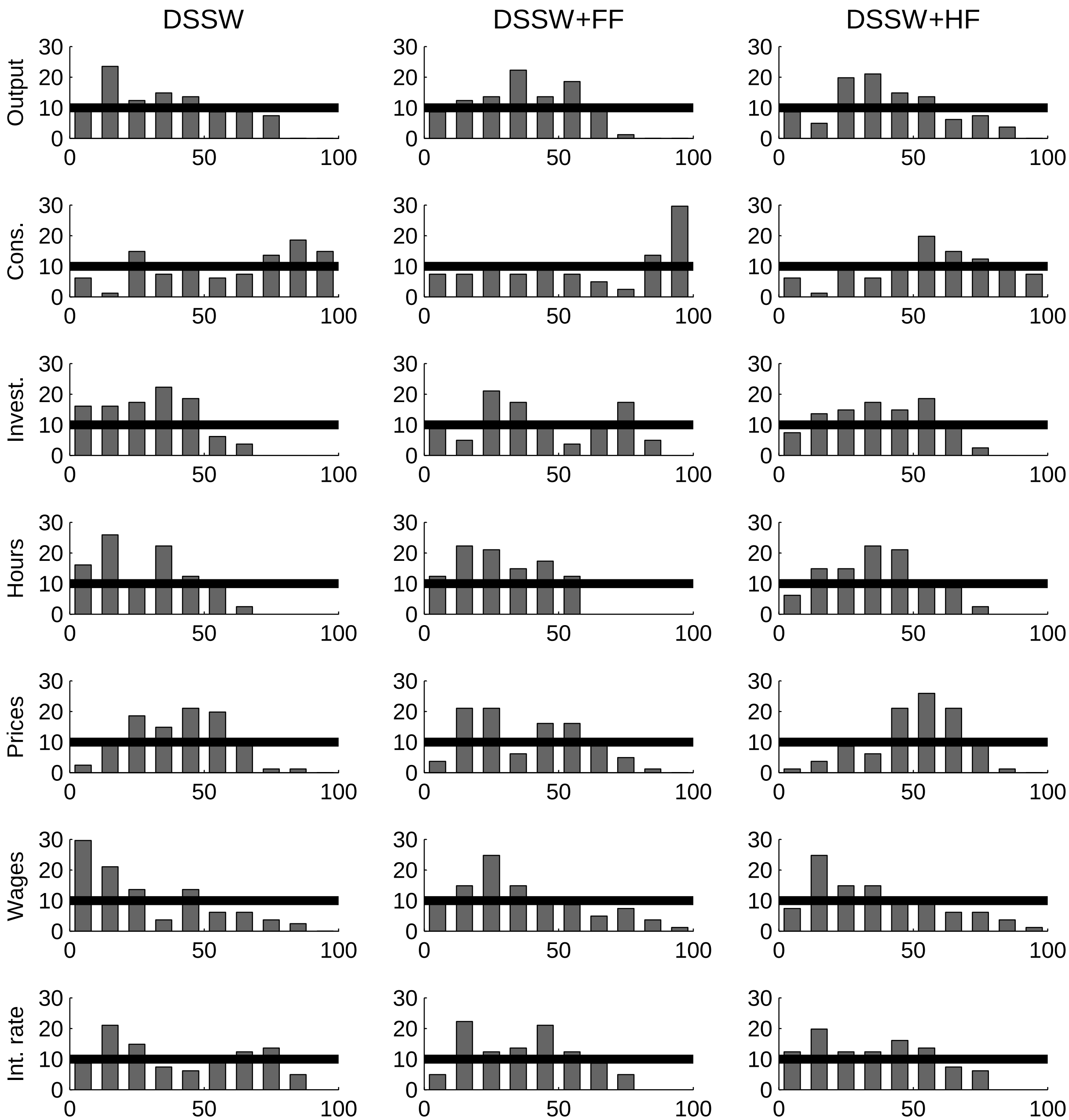
Notes: For the DSSW model LPSs are reported in levels, whereas for the remaining models they appear as the differences so that the values above zero indicate that a given model has a higher LPS than the benchmark. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Table 6: Average standard deviation of predictive density (SDPD)

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$	$H=24$
	Output							
DSSW	0.88	1.39	2.26	2.98	3.59	4.52	5.24	6.34
DSSW+FF	1.20	1.18	1.07	1.00	0.97	0.95	0.95	0.98
DSSW+HF	1.19	1.24	1.34	1.42	1.48	1.59	1.66	1.75
	Consumption							
DSSW	0.70	1.17	1.90	2.47	2.93	3.66	4.26	5.34
DSSW+FF	0.98	0.93	0.87	0.85	0.84	0.87	0.90	0.95
DSSW+HF	1.04	1.02	1.06	1.12	1.19	1.30	1.36	1.43
	Investment							
DSSW	2.08	4.00	7.43	10.0	11.8	13.9	14.9	16.1
DSSW+FF	1.98	1.60	1.21	1.05	0.96	0.89	0.87	0.87
DSSW+HF	1.07	1.11	1.17	1.24	1.30	1.42	1.49	1.59
	Hours							
DSSW	1.08	1.59	2.31	2.86	3.29	3.89	4.28	4.75
DSSW+FF	0.97	0.97	0.93	0.88	0.86	0.84	0.83	0.84
DSSW+HF	1.17	1.25	1.42	1.57	1.70	1.91	2.08	2.34
	Prices							
DSSW	0.34	0.69	1.40	2.06	2.69	3.90	5.09	7.47
DSSW+FF	1.16	1.07	0.98	0.97	0.99	1.04	1.09	1.19
DSSW+HF	1.19	1.27	1.41	1.52	1.62	1.78	1.90	2.04
	Wages							
DSSW	0.67	1.23	2.10	2.70	3.13	3.76	4.26	5.13
DSSW+FF	1.25	1.15	1.04	1.01	1.01	1.04	1.07	1.11
DSSW+HF	1.08	1.13	1.20	1.24	1.26	1.25	1.21	1.16
	Interest rate							
DSSW	1.29	1.74	2.26	2.54	2.69	2.83	2.89	2.98
DSSW+FF	1.07	1.13	1.17	1.18	1.18	1.19	1.21	1.24
DSSW+HF	0.99	0.97	1.03	1.13	1.23	1.38	1.48	1.57

Notes: For the DSSW model the SDPDs are reported in levels, whereas for the remaining models they appear as the ratios so that the values above unity indicate that a given model has a more diffuse predictive density than the benchmark. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Figure 1: Density forecasts: PIT histograms for four-quarter horizon



Notes: Bars represent the fraction of realized observations falling into the particular deciles of density forecasts. The theoretical value of 10% for a well calibrated model is represented by a solid line. All histograms are for variables in log-levels multiplied by 100, except for the interest rate that is expressed as annual percent.

Appendix

A Model equations

This section lays out the full systems of equations that make up each of the models used in our forecasting competition.

A.1 DSSW model

Marginal utility

$$\Lambda_t = \frac{b_t}{C_t - hC_{t-1}} - \beta h E_t \left\{ \frac{b_{t+1}}{C_{t+1} - hC_t} \right\} \tag{A.1}$$

Euler equation for households

$$\beta E_t \left\{ \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R_t}{\pi_{t+1}} \right\} = 1 \tag{A.2}$$

Wage of reoptimizing households

$$E_t \left\{ \sum_{s=0}^{\infty} \zeta_w^s \beta^s \left[\frac{\tilde{W}_t}{P_{t+s}} \left(\frac{P_{t+s-1} Z_{t+s-1}}{P_{t-1} Z_{t-1}} \right)^{\iota_w} (\pi^* e^{\gamma})^{s(1-\iota_w)} - (1+\lambda_w) \frac{\phi_{t+s} \tilde{L}_{t+s}^{\nu_l}}{\Lambda_{t+s}} \right] \Lambda_{t+s} \tilde{L}_{t+s} \right\} = 0 \tag{A.3}$$

Labor of reoptimizing households

$$\tilde{L}_{t+s} = \left[\frac{\tilde{W}_t}{W_{t+s}} \left(\frac{P_{t+s-1} Z_{t+s-1}}{P_{t-1} Z_{t-1}} \right)^{\iota_w} (\pi^* e^{\gamma})^{s(1-\iota_w)} \right]^{-\frac{1+\lambda_w}{\lambda_w}} L_{t+s} \tag{A.4}$$

Aggregate wage

$$W_t = \left[\zeta_w \left(W_{t-1} (\pi_{t-1} e^{z_{t-1}})^{\iota_w} (\pi^* e^{\gamma})^{1-\iota_w} \right)^{-\frac{1}{\lambda_w}} + (1-\zeta_w) \tilde{W}_t^{-\frac{1}{\lambda_w}} \right]^{-\lambda_w} \tag{A.5}$$

Capital stock

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + \mu_t \left(1 - S\left(\frac{I_t}{I_{t-1}} \right) \right) I_t \tag{A.6}$$

Capital services

$$K_t = u_t \bar{K}_{t-1} \tag{A.7}$$

Investment demand

$$1 = \mu_t \left(1 - S\left(\frac{I_t}{I_{t-1}}\right) - I_t S'\left(\frac{I_t}{I_{t-1}}\right)\right) Q_t + \beta E_t \left\{\frac{\Lambda_{t+1}}{\Lambda_t}\mu_{t+1}\frac{I_{t+1}^2}{I_t}S'\left(\frac{I_{t+1}}{I_t}\right)Q_{t+1}\right\} \quad \text{(A.8)}$$

Rate of return on capital

$$R_t^e = \frac{u_t R_t^k - a(u_t)P_t + (1-\delta)Q_t P_t}{Q_{t-1}P_{t-1}} \quad \text{(A.9)}$$

Optimal capital holdings

$$1 = \beta E_t \left\{\frac{\Lambda_{t+1}}{\Lambda_t}\frac{R_{t+1}^e}{\pi_{t+1}}\right\} \quad \text{(A.10)}$$

Optimal capacity utilization

$$a'(u_t) = \frac{R_t^k}{P_t} \quad \text{(A.11)}$$

Marginal cost

$$MC_t = Z_t^{\alpha-1}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_t^k}{\alpha}\right)^{\alpha} \quad \text{(A.12)}$$

Price set by reoptimizing firms

$$E_t\left\{\sum_{s=0}^{\infty}\zeta_p^s\beta^s\frac{\Lambda_{t+s}}{P_{t+s}}\left[\tilde{P}_t\left(\frac{P_{t+s-1}}{P_{t-1}}\right)^{\iota_p}\pi^{*s(1-\iota_p)} - (1+\lambda_{f,t+s})MC_{t+s}\right]\tilde{Y}_{t+s}\right\} = 0 \quad \text{(A.13)}$$

Output of reoptimizing firms

$$\tilde{Y}_{t+s} = \left[\frac{\tilde{P}_t}{P_{t+s}}\left(\frac{P_{t+s-1}}{P_{t-1}}\right)^{\iota_p}\pi^{*s(1-\iota_p)}\right]^{-\frac{1+\lambda_{f,t+s}}{\lambda_{f,t+s}}} Y_{t+s} \quad \text{(A.14)}$$

Aggregate price level

$$P_t = \left[\zeta_p\left(P_{t-1}(\pi_{t-1})^{\iota_p}(\pi^*)^{1-\iota_p}\right)^{-\frac{1}{\lambda_{f,t}}} + (1-\zeta_p)\tilde{P}_t^{-\frac{1}{\lambda_{f,t}}}\right]^{-\lambda_{f,t}} \quad \text{(A.15)}$$

Taylor rule

$$\frac{R_t}{R^*} = \left(\frac{R_{t-1}}{R^*}\right)^{\rho_R}\left[\left(\frac{\pi_t}{\pi^*}\right)^{\psi_1}\left(\frac{Y_t}{Y_t^*}\right)^{\psi_2}\right]^{1-\rho_R} e^{\epsilon_{R,t}} \quad \text{(A.16)}$$

Aggregate resource constraint

$$\frac{1}{g_t}Y_t \quad = \quad C_t + I_t + a(u_t)\overline{K}_{t-1} \tag{A.17}$$

Labor market clearing

$$L_t = \left(\frac{1-\alpha}{\alpha}\right)^{\alpha}\left(\frac{R_t^k}{W_t}\right)^{\alpha}\frac{Y_t}{Z_t^{1-\alpha}}\Delta_t \tag{A.18}$$

Capital market clearing

$$K_t = \left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}\left(\frac{W_t}{R_t^k}\right)^{1-\alpha}\frac{Y_t}{Z_t^{1-\alpha}}\Delta_t \tag{A.19}$$

Price dispersion

$$\Delta_t = (1-\zeta_p)\left(\frac{\tilde{P}_t}{P_t}\right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}} + \zeta_p\left(\frac{(\pi_{t-1})^{\iota_p}(\pi^*)^{1-\iota_p}}{\pi_t}\right)^{-\frac{1+\lambda_{f,t}}{\lambda_{f,t}}}\Delta_{t-1} \tag{A.20}$$

In the equations above, the notation is as in Del Negro et al. (2007). In particular, Y_t is output, C_t is consumption, I_t is investment, L_t is labor, $\bar{K}_t$ is capital, K_t is capital services, u_t is the capital utilization rate, MC_t is marginal cost, W_t is wage, R_t^k is the rental rate on capital, R_t^e is the rate of return on capital, Λ_t is marginal utility, P_t is the aggregate price level, π_t is inflation, Q_t is the real price of capital, R_t is the policy rate, Δ_t is price dispersion, Z_t is technology. Tildas indicate choices made by reoptimizing agents in the Calvo scheme, while stars denote the steady-state values. $a(\bullet)$ and $S(\bullet)$ are twice differentiable functions. The parameters of the model are described in section C.1.

The model is driven by seven stochastic disturbances: the growth rate of technology $z_t \equiv log(Z_t/Z_{t-1})$, time preference b_t, the relative price of investment μ_t, disutility of labor ϕ_t, price markup $\lambda_{f,t}$, government purchases g_t, and the monetary policy $\epsilon_{R,t}$. Except for the monetary policy shock, that is assumed to be white noise, all shocks follow independent first-order autoregressive processes. The following model variables are treated as observable in estimation: the growth rate of output $\Delta \log Y_t$, the growth rate of consumption $\Delta \log C_t$, the growth rate of investment $\Delta \log I_t$, employment $\log L_t$, the growth rate of real wages $\Delta \log(W_t/P_t)$, inflation $\Delta \log P_t$, and the short-term interest rate R_t.

A.2 DSSW+FF model

Entrepreneurial debt

$$D_t = Q_t P_t \bar{K}_t - N_t \tag{A.21}$$

Zero profit condition for the banking sector

$$R_t^e Q_{t-1} P_{t-1} \bar{K}_{t-1} \left[\tilde{\omega}_t (1 - F_{1,t}) + (1-\chi) F_{2,t}\right] = R_{t-1} D_{t-1} \tag{A.22}$$

Optimal contract

$$E_t \left\{ \begin{array}{c} \frac{R_{t+1}^e}{R_t} \left[1 - \tilde{\omega}_{t+1}(1 - F_{1,t+1}) - F_{2,t+1}\right] + \\ + \frac{1 - F_{1,t+1}}{1 - F_{1,t+1} - \chi \tilde{\omega}_{t+1} F'_{1,t+1}} \left(\frac{R_{t+1}^e}{R_t} \left[\tilde{\omega}_{t+1}(1 - F_{1,t+1}) + (1-\chi) F_{2,t+1}\right] - 1 \right) \end{array} \right\} = 0 \tag{A.23}$$

Auxiliary functions

$$F_{1,t} = \int_0^{\tilde{\omega}_t} dF(\omega) \tag{A.24}$$

$$F_{2,t} = \int_0^{\tilde{\omega}_t} \omega dF(\omega) \tag{A.25}$$

The rate of interest paid to the bank by non-defaulting entrepreneurs

$$R_t^d = \frac{\tilde{\omega}_t R_t^e Q_{t-1} P_{t-1} \bar{K}_{t-1}}{D_{t-1}} \tag{A.26}$$

The law of motion for net worth in the economy

$$N_t = \nu_t \left(R_t^e Q_{t-1} P_{t-1} \bar{K}_{t-1} - R_{t-1} D_{t-1} - \chi R_t^e Q_{t-1} P_{t-1} \bar{K}_{t-1} F_{2,t} \right) + W_t^e \tag{A.27}$$

The aggregate resource constraint

$$\frac{1}{g_t} Y_t = C_t + I_t + a(u_t) \bar{K}_{t-1} + \mu F_{2,t} R_t^e Q_{t-1} \bar{K}_{t-1} \pi_t^{-1} \tag{A.28}$$

Equations (A.23) and (A.28) in the DSSW+FF model replace equations (A.10) and (A.17) of the benchmark model. All remaining equations are the same as in the DSSW variant. The new variables are: entrepreneurial debt D_t and net worth N_t, the cutoff value of idiosyncratic shock determining entrepreneurs' solvency $\tilde{\omega}_t$, the contractual (non-default) interest rate on loans to entrepreneurs R_t^d, and two auxiliary functions $F_{1,t}$ and $F_{2,t}$. The cumulative density function of idiosyncratic risk ω is denoted by $F(\omega)$. All new parameters are described in section C.1.

The DSSW+FF model includes two additional stochastic shocks, which affect the survival rate of entrepreneurs ν_t and the volatility of idiosyncratic risk σ_t. Both are assumed to follow a first-order autoregressive process. The two additional variables used in estimation are the growth rate of nominal loans to firms $\Delta \log D_t$ and the spread on loans to firms $R_t^d - R_t$.

A.3 DSSW+HF model

Housing demand by patient households

$$\frac{a_t}{O_t^p} + \beta^p (1-\delta_o) E_t \left\{ \Lambda_{t+1}^p Q_{t+1}^o \right\} = Q_t^o \Lambda_t^p \tag{A.29}$$

Impatient households' budget constraint

$$P_t C_t^i + R_{t-1}^i D_{t-1}^i + T_t^i + P_t Q_t^o (O_t^i - (1-\delta_o) O_{t-1}^i) = W_t^i L_t^i + D_t^i \tag{A.30}$$

Euler equation for impatient households'

$$\beta^i E_t \left\{ \frac{\Lambda_{t+1}^i}{\pi_{t+1}} R_t^i \right\} + \Theta_t R_t^i = \Lambda_t^i \tag{A.31}$$

Housing demand by impatient households

$$\frac{a_t}{O_t^i} + \beta (1-\delta_o) E_t^i \left\{ Q_{t+1}^o \Lambda_{t+1}^i \right\} + \Theta_t m_t (1-\delta_o) E_t \left\{ \pi_{t+1} Q_{t+1}^o \right\} = Q_t^o \Lambda_t^i \tag{A.32}$$

Collateral constraint

$$R_t^i D_t^i = m_t (1-\delta_o) E_t \left\{ P_{t+1} Q_{t+1}^o O_t^i \right\} \tag{A.33}$$

Housing accumulation

$$O_t = (1-\delta_o) O_{t-1} + \mu_t^o \left(1 - S_o \left(\frac{I_t^o}{I_{t-1}^o} \right) \right) I_t^o \tag{A.34}$$

Residential investment demand

$$1 = \mu_t^o \left(1 - S_o \left(\frac{I_t^o}{I_{t-1}^o} \right) - I_t^o S_o' \left(\frac{I_t^o}{I_{t-1}^o} \right) \right) Q_t^o + \beta E_t \left\{ \frac{\Lambda_{t+1}^p}{\Lambda_t^p} \mu_{t+1}^o \frac{I_{t+1}^{o2}}{I_t^o} S_o' \left(\frac{I_{t+1}^o}{I_t^o} \right) Q_{t+1}^o \right\} \tag{A.35}$$

Lending rate

$$R_t^i = (1 + \lambda_{d,t}) R_t \tag{A.36}$$

Demand for patient households' labor

$$L_t^p = n_p \left(\frac{W_t^p}{W_t} \right)^{-\frac{1+\lambda_l}{\lambda_l}} L_t \tag{A.37}$$

Demand for impatient households' labor

$$L_t^i = (1 - n_p) \left(\frac{W_t^i}{W_t} \right)^{-\frac{1+\lambda_l}{\lambda_l}} L_t \tag{A.38}$$

Total labor supply

$$L_t = \left[n_p^{\frac{\lambda_l}{1+\lambda_l}} \left(L_t^p \right)^{\frac{1}{1+\lambda_l}} + (1 - n_p)^{\frac{\lambda_l}{1+\lambda_l}} \left(L_t^i \right)^{\frac{1}{1+\lambda_l}} \right]^{1+\lambda_l} \tag{A.39}$$

Housing market clearing

$$O_t = n_p O_t^p + (1 - n_p) O_t^i \tag{A.40}$$

Aggregate resource constraint

$$\frac{1}{g_t} Y_t = n_p C_t^p + (1 - n_p) C_t^i + I_t + I_t^o + a(u_t) \bar{K}_{t-1} \tag{A.41}$$

In comparison to the DSSW model, (A.28) replaces (A.17) and all other equations defining the equilibrium are the same, except that a superscript p should be added to C_t, Λ_t, W_t, $\tilde{W}_t$, $\tilde{L}_t$ and β. The following equations have their "clones" for impatient households: (A.3), (A.4) and (A.5). The new variables showing up in the DSSW+HF model are: housing stock O_t, real house prices Q_t^o, residential investment I_t^o, loans to impatient households D_t^i, the interest rate on loans to impatient households R_t^i and the Lagrange multiplier on the collateral constraint Θ_t. Subscripts p and i denote patient and impatient households, respectively. The new parameters are described in section C.1.

There are four new stochastic disturbances, all assumed to follow a first-order autoregressive process. They are the shocks to housing preferences a_t, the relative price of residential investment μ_t^o, the loan-to-value ratio m_t, and the lending-deposit rate spread $\lambda_{d,t}$. Compared to the DSSW model, the vector of observable variables also includes the growth rate of residential investment $\Delta \log I_t^o$, the growth rate of mortgage loans $\Delta \log D_t^i$, the growth rate of nominal house prices $\Delta \log Q_t^o + \log \pi_t$ and the spread on mortgage loans $R_t^i - R_t$.

B Data

We use the following US time series to estimate our models.

Ouptut: Real gross domestic product, chained index. Source: Bureau of Economic Analysis.

Consumption: Nominal personal consumption expenditures, deflated by the implicit GDP deflator. Source: Bureau of Economic Analysis.

Investment: Nominal gross private fixed domestic investment (only nonresidential for DSSW+HF), deflated by the implicit GDP deflator. Source: Bureau of Economic Analysis.

Residential investment: Nominal gross private fixed domestic residential investment, deflated by the implicit GDP deflator. Source: Bureau of Economic Analysis.

Labor: Average weekly hours in the non-farm business sector, multiplied with the civilian employment (16 years and over), and divided by the population level (16 years and over). Source: Bureau of Labor Statistics.

Wages: Nominal compensation of employees in the non-farm business sector, deflated by the implicit GDP deflator. Source: Bureau of Labor Statistics and Bureau of Economic Analysis.

House prices: Price index of new single-family houses sold, including value of lot. Source: Census Bureau.

Inflation: Implicit GDP deflator. Source: Bureau of Economic Analysis.

Interest rate: Federal funds rate. Source: Federal Reserve Board.

Loans to firms: Credit market instruments liabilities of the non-farm non-financial business sector. Source: Federal Reserve Board.

Spread on loans to firms: Difference between the industrial BBB corporate bond yield, backcasted using BAA corporate bond yields, and the federal funds rate. Source: Bloomberg and Federal Reserve Board.

Mortgage loans: Home mortgages liabilities of the private domestic nonfinancial sectors, excluding state and local governments. Source: Federal Reserve Board.

Spread on mortgage loans: Difference between the effective interest rate on conventional single-family mortgages and the federal funds rate. Source: Federal Housing Finance Agency and Federal Reserve Board.

While estimating the models, we express the following variables in log-differences: output, consumption, investment, wages, house prices and loans. Note that, in the US data, debt to output ratios and real house prices exhibit secular trends. Since these processes are not explained in our models, we include an intercept in the measurement equations that link the data on loans and house prices to their model counterparts. These intercepts, denoted, respectively, as D_{adj} and $Q_{o,adj}$, are estimated with relatively loose priors (see section C.1).

C Estimation

C.1 Prior assumptions

Our calibration and prior assumptions, together with a short description of each parameter, are reported in Tables C.1, C.2 and C.3. For the DSSW model, they are identical as in Del Negro et al. (2007). As regards the DSSW+FF and DSSW+HF extensions, we center the priors on the additional parameters such that the models match some key steady state proportions of the US data. These include the residential and non-residential investment shares in GDP, debt-to-GDP ratios and interest rate spreads.

Table C.1: Calibrated parameters

Parameter	Value	Description
ϕ	0.8	Steady-state weight on leisure in utility
λ_w	0.3	Steady-state wage markup
δ	0.025	Capital depreciation rate
δ_o	0.005	Housing depreciation rate
λ_l	0.3	Elasticity of substitution between labor of patient and impatient HHs

Table C.2: Prior assumptions - structural parameters

Parameter	Type	Mean	Std.	Description
α	beta	0.33	0.05	Capital share
ζ_p	beta	0.6	0.2	Calvo probability for prices
ι_p	beta	0.5	0.2	Price indexation
S"	gamma	4	1.5	Investment adjustment cost curvature
h	beta	0.7	0.05	Habits in consumption
a"	gamma	0.2	0.1	Capacity utilization cost curvature
ν_l	gamma	2	0.75	Inv. Frisch elasticity of labor supply
ζ_w	beta	0.6	0.2	Calvo probability for wages
ι_w	beta	0.5	0.2	Wage indexation
r^*	gamma	2	1	Steady state real interest rate (annualized)
ψ_1	gamma	1.5	0.4	Weight on inflation in Taylor rule
ψ_2	gamma	0.2	0.1	Weight on output in Taylor rule
ρ_R	beta	0.5	0.2	Interest rate smoothing
π^*	normal	3.01	1.5	Steady state inflation (annualized)
γ	gamma	2	1	Steady-state growth rate of technology (annualized)
λ_f	gamma	0.15	0.1	Steady-state price markup
g^*	gamma	0.3	0.1	Steady-state government spending share
L_{adj}	normal	662	10	Steady-state hours worked
ν	beta	0.975	0.001	Steady-state survival rate of entrepreneurs
χ	beta	0.12	0.01	Auditing costs
σ	gamma	0.3	0.01	Steady-state standard deviation of idiosyncratic risk
D_{adj}	normal	0.5	0.1	Excess trend of real debt
a	gamma	0.2	0.01	Steady-state weight of housing in utility
β^i	beta	0.97	0.01	Impatient HHs' discount factor
m	normal	0.85	0.01	Steady-state loan-to-value ratio
S_o"	gamma	4	1.5	Residential investment adjustment cost curvature
λ_d	gamma	0.006	0.001	Steady-state spread on loans to impatient HHs
n_p	beta	0.2	0.01	Share of patient HHs
$Q_{o,adj}$	normal	0.2	0.1	Trend in real house prices

Notes: For the DSSW+HF model, the prior mean of α is 0.27.

Table C.3: Prior assumptions - shocks

Parameter	Type	Mean	Std.	Description
ρ_z	beta	0.2	0.1	Persistence of productivity shock
ρ_ϕ	beta	0.6	0.2	Persistence of labor supply shock
ρ_{λ_f}	beta	0.6	0.2	Persistence of price markup shock
ρ_μ	beta	0.8	0.05	Persistence of investment shock
ρ_b	beta	0.6	0.2	Persistence of intertemporal utility shock
ρ_g	beta	0.8	0.05	Persistence of government spending shock
ρ_ν	beta	0.8	0.2	Persistence of entrepreneurs' survival shock
ρ_σ	beta	0.8	0.2	Persistence of idiosyncratic risk volatility shock
ρ_a	beta	0.6	0.2	Persistence of housing demand shock
ρ_m	beta	0.6	0.2	Persistence of loan-to-value shock
ρ_{μ_o}	beta	0.8	0.05	Persistence of residential investment shock
ρ_{λ_d}	beta	0.6	0.2	Persistence of spread shock
σ_z	inv. gamma	0.5	inf	Volatility of productivity shock
σ_ϕ	inv. gamma	2	inf	Volatility of labor supply shock
σ_{λ_f}	inv. gamma	0.5	inf	Volatility of price markup shock
σ_μ	inv. gamma	0.5	inf	Volatility of investment shock
σ_b	inv. gamma	0.5	inf	Volatility of intertemporal utility shock
σ_g	inv. gamma	0.5	inf	Volatility of government spending shock
σ_R	inv. gamma	0.25	inf	Volatility of interest rate shock
σ_ν	inv. gamma	0.5	inf	Volatility of entrepreneurs' survival shock
σ_σ	inv. gamma	0.5	inf	Volatility of idiosyncratic risk volatility shock
σ_a	inv. gamma	0.5	inf	Volatility of housing demand shock
σ_m	inv. gamma	0.5	inf	Volatility of loan-to-value shock
σ_{μ_o}	inv. gamma	0.5	inf	Volatility of residential investment shock
σ_{λ_d}	inv. gamma	0.5	inf	Volatility of spread shock

C.2 Posterior estimates

All estimations are done with Dynare, version 4.2.4. The posterior distributions are obtained with the Metropolis-Hastings algorithm. For each subsample, we create 125,000 draws, of which the first 25,000 draws are discarded. The characteristics of the marginal posterior distributions, obtained from the full sample estimation, are reported in Tables C.4 and C.5.

Table C.4: Posterior estimates - structural parameters

Parameter	DSSW			DSSW-FF			DSSW-HF		
	mean	5%	95%	mean	5%	95%	mean	5%	95%
α	0.16	0.13	0.20	0.34	0.31	0.38	0.13	0.10	0.15
ζ_p	0.82	0.76	0.89	0.38	0.29	0.47	0.89	0.84	0.94
ι_p	0.33	0.06	0.58	0.36	0.09	0.64	0.09	0.01	0.16
S"	6.12	3.87	8.33	0.10	0.10	0.10	6.30	4.22	8.53
h	0.74	0.68	0.80	0.79	0.72	0.85	0.84	0.81	0.88
a"	0.22	0.07	0.37	0.50	0.29	0.70	0.27	0.10	0.42
ν_l	1.95	1.06	2.84	3.75	2.75	4.75	4.62	3.25	5.92
ζ_w	0.50	0.34	0.64	0.09	0.06	0.13	0.53	0.45	0.59
ι_w	0.06	0.01	0.10	0.26	0.11	0.41	0.09	0.02	0.16
r^*	1.41	0.65	2.11	1.46	0.79	2.09	1.87	1.33	2.43
ψ_1	1.89	1.47	2.31	2.22	2.00	2.45	1.29	1.20	1.40
ψ_2	0.09	0.02	0.16	0.19	0.14	0.24	0.01	0.00	0.01
ρ_R	0.77	0.73	0.82	0.49	0.40	0.59	0.70	0.66	0.73
π^*	4.43	3.22	5.57	2.80	0.95	4.54	1.83	0.01	3.23
γ	1.41	0.89	1.92	1.48	0.97	1.98	1.47	1.13	1.84
λ_f	0.28	0.12	0.43	0.19	0.08	0.30	0.57	0.35	0.82
g^*	0.25	0.14	0.36	0.31	0.24	0.40	0.18	0.10	0.24
L_{adj}	662.4	654.7	669.6	661.5	659.9	663.0	648.0	634.2	663.4
ν				0.98	0.98	0.98			
χ				0.13	0.11	0.14			
σ				0.29	0.27	0.30			
D_{adj}				0.24	0.16	0.32	0.65	0.49	0.78
a							0.19	0.17	0.21
β^i							0.98	0.97	0.99
m							0.79	0.79	0.80
S_o"							1.31	0.89	1.70
λ_d							0.01	0.00	0.01
n_p							0.21	0.19	0.22
$Q_{o,adj}$							0.14	0.08	0.21

Table C.5: Posterior estimates - shocks

Parameter	DSSW			DSSW-FF			DSSW-HF		
	mean	5%	95%	mean	5%	95%	mean	5%	95%
ρ_z	0.14	0.04	0.23	0.15	0.07	0.23	0.09	0.02	0.15
ρ_ϕ	0.90	0.83	0.98	0.98	0.96	0.99	0.99	0.99	0.99
ρ_{λ_f}	0.41	0.08	0.70	0.95	0.92	0.97	0.77	0.65	0.90
ρ_μ	0.76	0.69	0.83	0.88	0.83	0.93	0.84	0.79	0.89
ρ_b	0.43	0.19	0.65	0.47	0.30	0.63	0.34	0.21	0.47
ρ_g	0.93	0.90	0.96	0.94	0.93	0.96	0.96	0.94	0.98
ρ_ν				0.50	0.42	0.60			
ρ_σ				0.93	0.91	0.96			
ρ_a							0.92	0.89	0.94
ρ_m							0.97	0.95	0.99
ρ_{μ_o}							0.96	0.93	0.98
ρ_{λ_d}							0.85	0.79	0.91
σ_z	0.84	0.73	0.95	1.03	0.91	1.14	0.75	0.68	0.82
σ_ϕ	5.79	3.26	7.90	3.65	2.74	4.53	13.35	9.27	17.36
σ_{λ_f}	9.37	4.19	14.74	6.52	3.25	10.36	9.26	5.02	13.06
σ_μ	5.91	3.82	7.93	0.36	0.33	0.39	4.13	2.83	5.59
σ_b	2.83	2.13	3.51	3.33	2.32	4.33	4.08	3.03	4.99
σ_g	0.67	0.59	0.74	0.69	0.62	0.76	0.67	0.60	0.73
σ_R	0.33	0.28	0.37	0.46	0.38	0.53	0.29	0.26	0.32
σ_ν				0.75	0.66	0.83			
σ_σ				7.90	6.42	9.31			
σ_a							14.64	10.26	18.50
σ_m							1.68	1.52	1.85
σ_{μ_o}							2.09	1.79	2.47
σ_{λ_d}							40.12	31.50	48.11