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# 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 fi-nancial frictions. We find that accounting for financial market imperfections does not result in a uniform improvement in the accuracy of point forecasts during non-crisis times while the average quality of density forecast even deteriorates. In contrast, adding frictions in the housing market proves very helpful during the times of financial turmoil, overperforming both the frictionless benchmark and the alternative that incorporates financial frictions in the corporate sector. Moreover, we detect complementarities among the analyzed setups that can be exploited in the forecasting process.

*Keywords*: DSGE models; Financial frictions; Housing market
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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, 2013, 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, 2013). However, it has also been pointed out that the accuracy of DSGE model-based forecasts is rather poor in the absolute sense: they tend to be biased, not efficient and usually badly calibrated (Edge and Gurkaynak, 2010; 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. More recently, Del Negro and Schorfheide (2013) and Del Negro et al. (2013a) show that a similar extension to the Smets and Wouters (2007) model helps to forecast the US economy during the Great Recession, especially if the forecasts are conditioned on the available data on short-term interest rates and credit spreads. However, these two papers are silent about the effect of financial frictions on forecasts done in normal times. Moreover, and most importantly given our main findings, there is no evidence in the literature on the effect of including frictions in the housing market on the forecasting performance of DSGE models.

The aim of this paper is to investigate to what extent adding two popular types of 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 in either corporate or household sectors does not result in a uniform improvement in the accuracy of point forecasts for the main macroeconomic variables during normal, non-crisis times, while the average quality of density forecast even deteriorates. In contrast, the considered extensions to the benchmark DSGE model have been found relatively successful during the financial turmoil. This is particularly true for the variant featuring imperfections in the housing market: it clearly outperforms both the benchmark and the alternative that incorporates financial frictions in the corporate sector when only the period of and following the Great Recession is considered. Moreover, there seem to be interesting complementarities among the analyzed setups that can be exploited in the forecasting process. In particular, pooling the predictions from all three models usually results in point and density forecasts that are more accurate than those from the frictionless benchmark even during tranquil times, and the optimal weights on models exhibit substantial time variation.

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, and 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). As suggested by the results in Wolters (2014), this framework is particularly good at forecasting compared to other standard DSGE specifications, and hence constitutes a benchmark that is relatively difficult to beat.

The DSSW 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 a Taylor type rule.

Seven stochastic disturbances drive the model economy. 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 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, called entrepreneurs. They possess special skills in operating capital, 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, which implies that 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.[1]

## 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

[1]Our DSSW+FF extension differs from the one considered by Del Negro and Schorfheide (2013) and Del Negro et al. (2013a) in three respects. First, we estimate directly all three deep model parameters describing the financial sector (auditing costs $\chi$, as well as the steady-state survival rate of entrepreneurs $\nu$ and volatility of idiosyncratic risk $\sigma$ - see Appendix C) rather than their two implicit functions (the steady-state spread and the elasticity of external finance premium to leverage, with survival probability fixed). Second, we use not only spreads, but also loans as observables. Third, and related to the second point, we include not only riskiness shocks, but also shocks to the survival probability as e.g. in Christiano et al. (2010).

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 (2014), who finds that weighted forecasts of several standard (i.e. not including financial frictions) 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 broader empirical results surveyed in Timmermann (2006). Given these considerations and this paper's main focus, in what follows we report the results for the equally weighted pool. However, later on we will also touch upon the issue of more complicated weighting schemes.

### 2.5 Discussion

Before presenting the results of the forecasting contest, it is instructive to discuss why the two considered models with financial frictions might potentially generate more accurate forecasts than the baseline model. The first (economic) reason is that a richer specification might better describe the true data generating process (DGP). The second (econometric) reason is that the information set used in the estimation process is extended for two variables describing the financing conditions in the corporate sector (DSSW+FF) or four variables describing the situation in the housing sector (DSSW+HF). On the other hand, more sophisticated models contain a larger number of parameters that have to be estimated and hence might generate less accurate forecasts. This "estimation forecast error" would be especially high if the true DGP is better described by the (more parsimonious) baseline model.

# 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 16 quarters ahead (see Appendix D for technical details). 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 1990:1-1993:4 with models estimated on the sample spanning 1970:1-1989:4, the second set of forecasts is for the period 1990:2-1994:1 with models estimated on the sample 1970:1-1990:1 etc. Since our dataset ends in 2010:4, we can calculate forecast errors on the basis of 69 (for 16-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. The statistics are calculated for variables in levels rather than for growth rates, i.e. we compare the actual and forecasted cumulative 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 the log predictive scores (LPS) and probability integral transform (PIT) charts. The evaluation sample is split into two different periods, which we call the "tranquil period" and "crisis period". The former covers the years before the recent financial crisis, which, according to the NBER business cycle dating, started in 2007:4, whereas the latter includes observations from 2007:4 to 2010:4. This means that the "tranquil period" forecasts are evaluated on the basis of 56 (for 16-quarter ahead forecasts) to 71 (1-quarter ahead forecasts) observations while those covering the "crisis period" are based on 13 observations for all forecast horizons.

## 3.1 Point forecasts

We begin our forecasting contest by analyzing the MFEs calculated over the "tranquil period". The results presented in Table 1 show that the baseline model is biased, which confirms the findings from the previous studies (see e.g. Edge and Gurkaynak, 2010; Kolasa et al., 2012). In particular, the DSSW model underpredicts consumption and overpredicts investment. The potential reason is that the theoretical model imposes the common stochastic trend restriction on *per capita* output, consumption and investment, which is not consistent with the observed rising and declining trends for the shares of consumption and investment in output, respectively. The second result is that the DSSW model-based forecasts for prices tend to be too high. One of the explanations is that the average quarterly inflation rate stood at 1.36% in the period 1970:1-1989:4, which is much more than 0.58% observed in the period 1990:1-2007:3. The forecasts for the interest rate obtained from the benchmark model are also too high, which might be explained by the "risk free interest rate puzzle" (see Canzoneri et al., 2007, for a detailed discussion), i.e. the tendency of representative agent models to overestimate the steady state interest rate.

A simple way to remove the above-mentioned biases would be to apply a smooth statistical (e.g. Hodrick-Prescott) filter before running the estimation.[2] This would mean, however, that the forecast comparison would be based on the 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 imposed by the DSGE model. As a result, they can give a distorted picture on the usefulness for forecasting of particular mechanisms included in theoretical models, which is our paper's main focus. For this reason, we do not use any of these methods in our forecasting contest.[3]

[2]Indeed, according to our unreported (but available upon request) results, if we deal with variables that are detrended, the obtained forecasts are unbiased.

[3]An alternative that would be consistent with our empirical strategy would be to change the benchmark model structure in a way that helps to overcome the forecast bias. For example, as recently shown by Del Negro and Schorfheide (2013), adding a time-varying inflation target and using data on long-term inflation expectations can improve the quality of forecasts for inflation. However, since our focus is on the effect of adding financial frictions to the commonly used frictionless benchmark, we decided to keep its structure unchanged.

The results in Table 1 for the remaining models show that, in general, adding financial frictions does not help a lot during the "tranquil period". However, there are some interesting results for the individual variables. In particular, for both models with frictions there is no significant bias in the short-term investment forecasts and the DSSW+HF model generates unbiased forecasts for the interest rate. The latter result could be related to the fact that the DSSW+HF model explicitly differentiates between the deposit and borrowing rates for households. Next, it can also be seen that the baseline model and the DSSW+HF extension are to some degree complementary as the biases for output, investment, hours and prices are of the opposite sign. This explains why for these variables the equally weighted pool is an attractive option.

Turning to the "crisis period", the results reported in Table 2 show that all models were unable to predict the scale of the decline in the economic activity during the Great Recession. However, the size of the bias for the real sector variables is about twice lower for the DSSW+HF specification than for the other two models. The potential reason for the relatively good performance of this model variant is that the information set used in its estimation includes variables describing the housing sector, which is where the recent crisis originated. In contrast, the two additional observables used to estimate the DSSW+FF model occurred to be less helpful. As regards the nominal variables, the DSSW+FF extension seems to outperform its two competitors. In particular, it is the only model that generates unbiased forecasts for prices, which is consistent with the findings of Del Negro et al. (2013a).

We continue our investigation by comparing the second moments of the forecast errors. In Tables 3 and 4 we report the RMSFEs for the "tranquil" and "crisis" periods, respectively. In the case of the DSSW model we report the RMSFE values, whereas the remaining numbers are expressed as ratios so that values below unity indicate that a given model outperforms the benchmark. Moreover, to provide a rough gauge of whether the RMSFE ratios are significantly different from unity, we report the results of the Diebold and Mariano (1995) test.

Overall, the numbers in Table 3 show that in the pre-crisis period adding financial frictions does not lead to any systematic improvement in the accuracy of point forecasts. On the one hand, the RMSFE ratios are significantly below unity for wages (both extensions), hours (only DSSW+FF), investment and the interest rate (only DSSW+HF). On the other hand, there is a significant deterioration in the quality of forecasts for consumption (both models), the interest rate (DSSW+FF), output and prices (DSSW+HF).

In this context at least two features of the DSSW+FF model-based forecasts warrant a more detailed discussion. First, this extension produces most accurate longer-term investment forecasts, but worst (even though not significantly so) predictions of this variable up to one year ahead. 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 investment adjustment cost curvature are clearly the lowest for the DSSW+FF setup.[4] This suggests that the additional frictions introduced by the financial accelerator framework of Bernanke et al. (1999) to large extent substitute for this standard rigidity in a way that improves long-term forecasts of investment. However, since the Bernanke et al. frictions operate mainly on medium-term frequencies, the low costs of adjusting investment in the DSSW+FF variant make this variable very volatile over shorter horizons, which deteriorates point (and, as we will see later, even more density) forecasts.

Second, the DSSW+FF model clearly outperforms both the benchmark and the DSSW+HF alternative in forecasting labor market variables. By looking at the posterior estimates reported in Appendix C, one can note that adding financial frictions increases the estimated value of the Frisch elasticity more than four times. However, and what we do not report due to space constraints, it is the DSSW+FF extension in which the contribution of labor supply shocks to fluctuations in hours worked decreases substantially, bringing the unconditional standard deviation of this variable closer to the data. In other words, the internal propagation mechanisms included in the DSSW+FF variant substitute for exogenous sources of movements in total hours, making this macrocategory easier to forecast.

Another important result that one can find in Table 3 is that for all variables but consumption the RMSFE ratios obtained for the equally weighted pool tend to be below unity and in many cases significantly so. Moreover, in a few instances the RMSFEs from the pool are lower than those produced by any of the models, which points to the existence of complementarities among the three considered variants.

Given that the recent revival of interest in DSGE models with financial frictions was to a large degree a response to the recent crisis, it might be expected that their forecasting performance should be especially good during the "crisis period". This is exactly the case for the DSSW+HF model, which clearly outperforms the benchmark for all variables but prices. As shown in Table 4, the improvement in the accuracy of forecasts is sizable

[4] It is also worth mentioning that the (full sample) posterior mean standard deviation of investment specific technology shocks in the DSSW+FF variant is about ten times lower than in the DSSW benchmark (our priors on the volatility of shocks are very diffuse). This result is consistent with Justiniano et al. (2011) who argue that this type of shocks often proxy for financial frictions.

economically, varying between 15% and 35% for output, consumption and investment and standing at over 50% for hours over shorter horizons. As regards the DSSW+FF model, the results are more mixed: there is some gain for consumption, prices and wages, but at the expense of a deterioration in the accuracy of forecasts for investment, hours and the interest rate. Finally, it can be noted that almost all ratios for the equally weighted pool are once again below unity. This time, however, the pool ranks best only on very few occasions, which suggests that the degree of complementarity between the three alternative models during the crisis was not as pronounced as documented on the pre-crisis sample.

The general conclusion that can be drawn from the comparison of point forecasts can be summarized as follows. Allowing for financial market imperfections does not consistently improve the accuracy of point forecasts during the "tranquil period". However, in the "crisis period", the performance of the model with frictions in the housing market is much better than that of the other two models. The potential explanation is that the information set of the DSSW+HF model includes the time series describing the situation in the housing sector that was very important during the recent crisis.

## 3.2 Density forecasts

We complement the discussion of point forecasts accuracy with an evaluation of density forecasts. The aim is to check to what extent the analyzed forecasts provide a realistic description of actual uncertainty.

Let $p(Y_{t+h}|t,i)$ and $p(y_{t+h}|t,i)$ be the predictive density and predictive score of an $h$-step ahead forecast formulated at time $t$ using model $M_i$. We follow Adolfson et al. (2007) and assume that $p(Y_{t+h}|t,i)$ is Gaussian, the moments of which can be approximated using the sample of draws from the predictive density.[5] This enables us to compute the average log predictive score (LPS) of $h$-step ahead forecasts from model $M_i$ as:

$$S_{i,h} = \frac{1}{R}\sum_{t=P+1}^{P+R} \ln p(y_{t+h}|t,i). \tag{1}$$

where $P+1$ is the moment in which the first forecast is formulated and $R$ stand for the number of $h$-step ahead forecasting rounds. In the case of the weighted forecast, we follow

[5]The alternative option, proposed e.g. by Geweke and Amisano (2014), is to use the fact that $p(Y_{t+h}|t,i,\theta)$ is Gaussian and integrate out the parameters $\theta$ numerically to calculate $p(Y_{t+h}|t,M_i)$. The results obtained with this more computationally demanding method are broadly the same as in our baseline case.

Geweke and Amisano (2011) and calculate the predictive score as:

$$S_{w,h} = \sum_{i=1}^{n} w_i p(y_{t+h}|t, i) \tag{2}$$

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

In Tables 5 and 6 we report the average values of the LPSs for the "tranquil" and "crisis" subsamples, respectively. We focus on each of the seven macroeconomic variables separately, as well as on their joint distribution. The numbers for the DSSW model represent the average values of the LPSs, whereas the remaining numbers are expressed as differences so that positive values indicate that a given scheme overperforms the benchmark. To provide a rough gauge of whether these differences are significantly different from zero, we report the results of the Amisano and Giacomini (2007) test.

In general, our results show that during the pre-crisis period adding financial frictions in most cases leads to a deterioration in the accuracy of density forecasts. The LPS differences are significantly negative for output, consumption, investment (both models), the interest rate (DSSW+FF), hours and prices (DSSW+HF). Also the performance of the equally weighted pool tends to be worse than that of the baseline model. This is confirmed by the relevant statistics for all 7 variables: for the shortest horizon the DSSW model is significantly more accurate than its two competitors. There are also some exceptions: the LPS differences are significantly positive for wages (both models), hours (only DSSW+FF) or the interest rate (only DSSW+HF).

To examine where these differences in the LPSs across the models come from, we note that a well calibrated density forecast should be unbiased (null MFE) and effective (adequate width of the predictive density). A convenient way of illustrating to what extent these two criteria are met are the histograms of PITs, which we present in Figure 1 for the one-quarter ahead forecasts over the "tranquil period". More specifically, as advocated by Diebold et al. (1998) and recently employed to evaluate DSGE models by Herbst and Schorfheide (2012), we divide the unit interval into 10 subintervals and look if the fraction of PITs in each of them is close to 10%. If PITs are equally distributed across the 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 PITs suggest that, apart from the bias that we have already discussed while analyzing the accuracy of point forecasts, there is an additional problem with the excessive width of the predictive densities generated by the baseline model. Adding financial frictions usually makes this problem worse. For most variables and horizons, the density forecasts from the extended models are more diffuse that those from the benchmark.[6] This is especially evident for short-term investment forecasts from the DSSW+FF model and predictions for prices from the DSSW+HF model.

Turning to the LPS statistics for the "crisis period" reported in Table 6, the strongest result is that the quality of density forecasts from the DSSW+HF model are visibly better than from the baseline for all variables but prices. This is confirmed by the significantly positive LPS differences for the joint distribution of seven standard macrocategories. As regards the DSSW+FF model, the results are not so positive. There is even a significant deterioration of forecasts quality for the 7-variables case at short-run horizons. It can be also noticed that the equally weighted pool tends to underperform the DSSW+HF model.

To sum up, allowing for financial market imperfections usually deteriorates the accuracy of density forecasts in "tranquil periods". The reason is that this kind of extension increases the width of the already excessively diffuse predictive density. However, on the positive side, adding frictions in the housing market helps to boost the quality of density forecasts during the crisis times.

### 3.3 Time variation in optimal pools

The results discussed above show that the accuracy of forecasts from the analyzed models in the "tranquil" and "crisis" subsamples are visibly different. A natural question hence arises whether there is a significant time variation in the relative forecasting performance of the three investigated models. We address this issue by calculating time-varying weights that would optimize the *ex-post* forecasting performance in a rolling three-year windows. In particular, we compute the weights that would (i) minimize the RMSFE and (ii) maximize the LPS (see eq. (2)) of the weighted one-step ahead forecasts.[7]

The evolution of the weights that optimize the RMSFEs and LPSs are presented in Figures 2 and 3, respectively. Several interesting conclusions can be ventured. First of all, the "optimal" weights exhibit substantial time variation, especially for point forecasts. Another interesting finding is that the RMSFE and LPS optimizing weights might be substantially different from each other. This is especially visible for investment, for which the share of the benchmark DSSW model is close to null if one is interested in maximizing

[6] This pattern can be observed not only for one-quarter ahead forecasts, but also for longer horizons.

[7] A similar analysis has recently been proposed by Del Negro et al. (2013b), who calculate the time-varying LPS-maximizing weights for the Smets and Wouters (2007) model and its Bernanke et al. (1999) extension. Their main finding is that during financial turmoil the weight attributed to the model incorporating financial frictions is much higher than in normal times.

the LPS and almost 100% for most periods if one's focus is on the quality of point forecasts. Moreover, it can be seen that models with financial frictions are consistently outperform the baseline in forecasting hours and wages, whereas the DSSW+HF model is found to be the best in forecasting the interest rate. In contrast, the baseline was found to be relatively good in forecasting output, consumption and prices, especially in the 1990s. The last and most important conclusion is that the DSSW+HF performed visibly better than the other two models during the recent crisis: the weights attributed to this variant are close to 100% for all variables but prices, which confirms our earlier findings.

# 4 Conclusions

In this paper we have compared the quality of point and density forecasts from a richly-specified DSGE model and its two extensions that introduce financial frictions into the corporate and household sectors. We have found that accounting for financial frictions does not result in an overall improvement in the quality of forecasts during normal times, but does offer statistically and economically significant gains in forecast efficiency during the financial turmoil. In this respect, the model variant featuring the housing market has proved particularly successful, beating both the benchmark and the alternative that incorporates financial imperfections in the corporate sector.

These findings suggest that developing models with housing sector should provide a better guidance during the turbulent times. However, our results also indicate that maintaining all three model variants can be warranted. This recommendation is supported by a relatively good performance of pooled forecasts and substantial time variation of weights that optimize the forecast errors or predictive densities.

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# Tables and Figures

Table 1: Mean Forecast Errors for 1990:1-2007:3 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | | | | **Output** | | | |
| DSSW | -0.22*** | -0.39*** | -0.62** | -0.57 | -0.34 | 0.33 | 1.11 |
| DSSW+FF | -0.11* | -0.16 | -0.18 | 0.02 | 0.32 | 1.06** | 1.84*** |
| DSSW+HF | 0.20** | 0.54*** | 1.29*** | 2.06*** | 2.86*** | 4.44*** | 6.02*** |
| Pool | -0.04 | 0.00 | 0.16 | 0.50 | 0.95* | 1.94*** | 2.99*** |
| | | | | **Consumption** | | | |
| DSSW | 0.19** | 0.50*** | 1.29*** | 2.27*** | 3.28*** | 5.13*** | 6.64*** |
| DSSW+FF | 0.35*** | 0.85*** | 1.93*** | 3.04*** | 4.11*** | 6.02*** | 7.57*** |
| DSSW+HF | 0.45*** | 1.10*** | 2.52*** | 3.88*** | 5.11*** | 7.17*** | 8.85*** |
| Pool | 0.33*** | 0.82*** | 1.91*** | 3.06*** | 4.17*** | 6.11*** | 7.69*** |
| | | | | **Investment** | | | |
| DSSW | -0.64*** | -1.62*** | -3.85*** | -5.50*** | -6.24*** | -5.84*** | -3.93** |
| DSSW+FF | -0.34 | -0.86 | -1.83 | -2.08 | -1.74 | -0.15 | 1.85 |
| DSSW+HF | 0.05 | 0.14 | 0.58 | 1.83 | 3.80** | 8.58*** | 13.32*** |
| Pool | -0.31** | -0.78** | -1.70** | -1.92* | -1.39 | 0.86 | 3.75** |
| | | | | **Hours** | | | |
| DSSW | -0.35*** | -0.64*** | -1.02*** | -1.14*** | -1.06** | -0.70 | -0.30 |
| DSSW+FF | -0.21*** | -0.33** | -0.45* | -0.35 | -0.16 | 0.32 | 0.78 |
| DSSW+HF | 0.02 | 0.18 | 0.62* | 1.01** | 1.40** | 2.10*** | 2.67 |
| Pool | -0.18** | -0.26** | -0.28 | -0.16 | 0.06 | 0.57 | 1.05 |
| | | | | **Prices** | | | |
| DSSW | 0.00 | -0.03 | -0.26** | -0.76*** | -1.43*** | -3.07*** | -4.96*** |
| DSSW+FF | 0.03 | 0.05 | -0.02 | -0.30 | -0.74 | -2.10*** | -4.03*** |
| DSSW+HF | 0.13*** | 0.35*** | 0.93*** | 1.51*** | 2.14*** | 3.47*** | 4.71*** |
| Pool | 0.05** | 0.12** | 0.22* | 0.15 | -0.01 | -0.57 | -1.43** |
| | | | | **Wages** | | | |
| DSSW | -0.28*** | -0.68*** | -1.51*** | -2.21*** | -2.62*** | -3.02*** | -3.02*** |
| DSSW+FF | -0.16** | -0.38** | -0.84*** | -1.29*** | -1.62*** | -2.13*** | -2.41*** |
| DSSW+HF | -0.20*** | -0.46*** | -1.01*** | -1.47*** | -1.70*** | -1.75*** | -1.30* |
| Pool | -0.21*** | -0.51*** | -1.12*** | -1.65*** | -1.98*** | -2.30*** | -2.24*** |
| | | | | **Interest rate** | | | |
| DSSW | 0.03 | -0.02 | -0.37 | -0.94** | -1.49*** | -2.22*** | -2.51*** |
| DSSW+FF | -0.30** | -0.59** | -1.21*** | -1.84*** | -2.35*** | -3.02*** | -3.38*** |
| DSSW+HF | -0.16* | -0.19 | -0.14 | -0.11 | -0.05 | 0.09 | 0.26 |
| Pool | -0.14 | -0.27 | -0.57* | -0.96** | -1.30*** | -1.71*** | -1.87*** |

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 in percent, annualized.

Table 2: Mean Forecast Errors for 2007:4-2010:4 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | **Output** | | | | | | |
| DSSW | -0.71** | -1.70*** | -3.37** | -4.99*** | -6.83*** | -8.73*** | -9.64*** |
| DSSW+FF | -0.98*** | -2.16*** | -3.49*** | -4.43*** | -5.63*** | -7.24*** | -8.19*** |
| DSSW+HF | 0.17 | -0.02 | -0.86 | -2.13 | -3.95*** | -5.65*** | -5.96*** |
| Pool | -0.51** | -1.30** | -2.58** | -3.85** | -5.47*** | -7.21*** | -7.93*** |
| | **Consumption** | | | | | | |
| DSSW | -0.58* | -1.30** | -2.33* | -3.07** | -3.96*** | -4.72*** | -4.82*** |
| DSSW+FF | -0.42 | -0.92 | -1.73 | -2.59* | -3.68*** | -4.51*** | -4.36** |
| DSSW+HF | -0.24 | -0.61 | -1.30 | -1.65 | -1.97 | -1.49 | -0.98 |
| Pool | -0.41 | -0.95 | -1.78 | -2.44* | -3.21*** | -3.57*** | -3.38** |
| | **Investment** | | | | | | |
| DSSW | -1.87** | -5.06** | -12.05*** | -19.80*** | -28.15*** | -34.41*** | -35.86*** |
| DSSW+FF | -4.23*** | -8.92*** | -15.12*** | -19.23*** | -22.79*** | -26.21*** | -27.87*** |
| DSSW+HF | -0.38 | -2.34 | -7.60** | -14.51*** | -21.11*** | -23.74*** | -21.84*** |
| Pool | -2.16*** | -5.44*** | -11.59*** | -17.84*** | -24.02*** | -28.12*** | -28.52*** |
| | **Hours** | | | | | | |
| DSSW | -0.90*** | -2.08*** | -4.08*** | -5.65*** | -6.82*** | -7.43*** | -7.53*** |
| DSSW+FF | -1.42*** | -3.04*** | -4.75*** | -5.39*** | -5.76*** | -6.16*** | -6.56*** |
| DSSW+HF | 0.06 | -0.27 | -1.52** | -2.94** | -4.46*** | -5.71*** | -5.86*** |
| Pool | -0.75*** | -1.80*** | -3.45*** | -4.66*** | -5.68*** | -6.43*** | -6.65*** |
| | **Prices** | | | | | | |
| DSSW | -0.09 | -0.30** | -0.95*** | -1.54*** | -2.03*** | -2.67*** | -3.21*** |
| DSSW+FF | 0.03 | 0.02 | -0.21 | -0.49 | -0.79 | -0.70 | 0.45 |
| DSSW+HF | 0.46*** | 1.19*** | 2.68** | 3.45* | 2.08 | -2.06* | -1.88 |
| Pool | 0.14*** | 0.30*** | 0.51 | 0.48 | -0.25 | -1.81** | -1.54 |
| | **Wages** | | | | | | |
| DSSW | -0.22 | -0.54 | -1.50*** | -2.22*** | -3.53*** | -5.69*** | -7.04*** |
| DSSW+FF | -0.14 | -0.24 | -0.68 | -1.00* | -2.01*** | -3.75*** | -4.61*** |
| DSSW+HF | 0.20 | 0.27 | -0.30 | -1.04 | -2.46*** | -4.39*** | -5.16*** |
| Pool | -0.05 | -0.17 | -0.83 | -1.42** | -2.67*** | -4.61*** | -5.60*** |
| | **Interest rate** | | | | | | |
| DSSW | -0.42** | -0.93** | -2.12*** | -3.01*** | -3.75*** | -4.50*** | -4.85*** |
| DSSW+FF | 0.60 | 0.25 | -1.50* | -2.83*** | -3.80*** | -4.51*** | -4.67*** |
| DSSW+HF | -0.34 | -0.37 | -0.36 | -0.72 | -2.07* | -4.25*** | -4.20*** |
| Pool | -0.05 | -0.35 | -1.32* | -2.19** | -3.21*** | -4.42*** | -4.57*** |

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 in percent, annualized.

Table 3: Root Mean Squared Forecast Errors for 1990:1-2007:3 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | **Output** | | | | | | |
| DSSW | 0.63 | 0.95 | 1.55 | 1.98 | 2.28 | 2.91 | 3.52 |
| DSSW+FF | 0.95 | 0.90 | 0.83* | 0.80* | 0.81 | 0.84* | 0.85** |
| DSSW+HF | 1.04 | 1.17 | 1.37 | 1.54* | 1.70** | 1.85*** | 1.94*** |
| Pool | 0.92** | 0.88* | 0.89 | 0.96 | 1.03 | 1.13 | 1.19 |
| | **Consumption** | | | | | | |
| DSSW | 0.57 | 1.04 | 2.09 | 3.16 | 4.21 | 6.08 | 7.61 |
| DSSW+FF | 1.19*** | 1.30*** | 1.31*** | 1.27*** | 1.21*** | 1.13*** | 1.10*** |
| DSSW+HF | 1.20*** | 1.32*** | 1.40*** | 1.38*** | 1.34*** | 1.27** | 1.23** |
| Pool | 1.10** | 1.16*** | 1.19*** | 1.18*** | 1.15*** | 1.11*** | 1.09*** |
| | **Investment** | | | | | | |
| DSSW | 1.49 | 2.73 | 5.38 | 7.55 | 8.60 | 8.85 | 7.52 |
| DSSW+FF | 1.09 | 1.13 | 1.02 | 0.89 | 0.80 | 0.72 | 0.77 |
| DSSW+HF | 0.90** | 0.84** | 0.80* | 0.85 | 0.95 | 1.35 | 2.11*** |
| Pool | 0.92*** | 0.87*** | 0.79*** | 0.75*** | 0.71*** | 0.74 | 0.96 |
| | **Hours** | | | | | | |
| DSSW | 0.58 | 0.95 | 1.60 | 2.00 | 2.26 | 2.77 | 3.19 |
| DSSW+FF | 0.92 | 0.84 | 0.76** | 0.68** | 0.64** | 0.64** | 0.68** |
| DSSW+HF | 1.01 | 1.03 | 1.05 | 1.14 | 1.21 | 1.23 | 1.22 |
| Pool | 0.87*** | 0.78*** | 0.74*** | 0.76** | 0.80 | 0.85 | 0.89 |
| | **Prices** | | | | | | |
| DSSW | 0.21 | 0.40 | 0.78 | 1.36 | 2.09 | 3.86 | 5.95 |
| DSSW+FF | 1.04 | 1.10 | 1.18 | 1.12 | 1.05 | 0.95 | 0.90 |
| DSSW+HF | 1.24*** | 1.46*** | 1.71*** | 1.61*** | 1.45** | 1.24 | 1.11 |
| Pool | 1.02 | 1.02 | 0.93 | 0.79 | 0.69* | 0.59** | 0.53*** |
| | **Wages** | | | | | | |
| DSSW | 0.79 | 1.31 | 2.18 | 2.95 | 3.44 | 4.05 | 4.22 |
| DSSW+FF | 0.95*** | 0.90*** | 0.82*** | 0.78*** | 0.77*** | 0.80*** | 0.84*** |
| DSSW+HF | 0.92** | 0.89*** | 0.83*** | 0.80*** | 0.79*** | 0.78*** | 0.76*** |
| Pool | 0.95*** | 0.92*** | 0.87*** | 0.85*** | 0.84*** | 0.85*** | 0.85*** |
| | **Interest rate** | | | | | | |
| DSSW | 0.57 | 1.04 | 1.73 | 2.16 | 2.47 | 2.83 | 2.96 |
| DSSW+FF | 1.20 | 1.18 | 1.20 | 1.25** | 1.28*** | 1.30*** | 1.33*** |
| DSSW+HF | 0.83** | 0.79*** | 0.78*** | 0.79 | 0.83 | 0.93 | 0.99 |
| Pool | 0.90 | 0.91 | 0.92 | 0.92 | 0.93 | 0.95 | 0.94 |

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. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Diebold-Mariano test, where the long-run variance is calculated 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 in percent, annualized.

Table 4: Root Mean Squared Forecast Errors for 2007:4-2010:4 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | **Output** | | | | | | |
| DSSW | 1.03 | 2.30 | 4.41 | 6.02 | 7.32 | 9.08 | 10.13 |
| DSSW+FF | 1.16 | 1.10 | 0.97 | 0.88** | 0.84*** | 0.83*** | 0.86*** |
| DSSW+HF | 0.75 | 0.68 | 0.67 | 0.66** | 0.65*** | 0.68*** | 0.67*** |
| Pool | 0.82 | 0.82 | 0.83* | 0.82** | 0.82*** | 0.84*** | 0.84*** |
| | **Consumption** | | | | | | |
| DSSW | 1.08 | 2.15 | 3.54 | 4.24 | 4.61 | 5.29 | 5.73 |
| DSSW+FF | 0.93* | 0.92* | 0.92** | 0.94* | 0.93** | 0.95* | 0.95** |
| DSSW+HF | 0.81 | 0.82 | 0.86 | 0.84 | 0.79* | 0.57** | 0.50** |
| Pool | 0.90 | 0.90* | 0.91* | 0.91** | 0.88*** | 0.81*** | 0.79** |
| | **Investment** | | | | | | |
| DSSW | 3.19 | 7.19 | 15.15 | 23.01 | 29.91 | 36.22 | 38.37 |
| DSSW+FF | 1.55** | 1.39** | 1.13 | 0.94 | 0.84*** | 0.79*** | 0.81*** |
| DSSW+HF | 0.85 | 0.75* | 0.72** | 0.73** | 0.75** | 0.75*** | 0.70*** |
| Pool | 1.02 | 0.98 | 0.92 | 0.88* | 0.86*** | 0.84*** | 0.83*** |
| | **Hours** | | | | | | |
| DSSW | 1.03 | 2.32 | 4.65 | 6.37 | 7.46 | 8.07 | 8.20 |
| DSSW+FF | 1.67 | 1.50 | 1.18 | 0.98 | 0.88*** | 0.84*** | 0.87** |
| DSSW+HF | 0.48*** | 0.41*** | 0.49** | 0.60** | 0.68*** | 0.81*** | 0.83*** |
| Pool | 0.90 | 0.88 | 0.85* | 0.84** | 0.85*** | 0.88*** | 0.90*** |
| | **Prices** | | | | | | |
| DSSW | 0.24 | 0.45 | 1.19 | 1.86 | 2.46 | 3.16 | 3.77 |
| DSSW+FF | 0.89 | 0.62 | 0.57** | 0.56* | 0.66 | 0.87 | 0.91 |
| DSSW+HF | 2.24*** | 3.04*** | 3.08* | 2.95 | 2.20 | 1.13 | 1.43 |
| Pool | 1.06 | 0.96 | 0.90 | 0.78 | 0.63* | 0.81 | 0.96 |
| | **Wages** | | | | | | |
| DSSW | 0.92 | 1.38 | 2.20 | 2.68 | 3.60 | 5.79 | 7.13 |
| DSSW+FF | 0.93* | 0.89** | 0.75** | 0.71*** | 0.64*** | 0.67*** | 0.67*** |
| DSSW+HF | 0.89** | 0.87 | 0.80 | 0.79** | 0.74*** | 0.78*** | 0.74*** |
| Pool | 0.91*** | 0.86** | 0.80** | 0.80*** | 0.78*** | 0.81*** | 0.80*** |
| | **Interest rate** | | | | | | |
| DSSW | 0.72 | 1.23 | 2.34 | 3.27 | 4.00 | 4.68 | 5.03 |
| DSSW+FF | 2.01** | 1.47* | 1.01 | 1.01 | 1.03 | 1.03 | 0.98 |
| DSSW+HF | 0.91 | 0.88 | 0.93 | 0.94 | 0.86 | 0.99 | 0.95 |
| Pool | 1.10 | 0.98 | 0.88 | 0.87 | 0.89 | 1.00 | 0.97 |

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. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Diebold-Mariano test, where the long-run variance is calculated 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 in percent, annualized.

Table 5: Average log predictive scores for 1990:1-2007:3 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | **Output** | | | | | | |
| DSSW | -1.06 | -1.51 | -2.00 | -2.26 | -2.42 | -2.65 | -2.81 |
| DSSW+FF | -0.07*** | -0.09*** | -0.03 | 0.02 | 0.05 | 0.07* | 0.08** |
| DSSW+HF | -0.08** | -0.14** | -0.22** | -0.30** | -0.39** | -0.52*** | -0.66*** |
| Pool | -0.04* | -0.06** | -0.06 | -0.06 | -0.06 | -0.08 | -0.11** |
| | **Consumption** | | | | | | |
| DSSW | -0.89 | -1.45 | -2.11 | -2.56 | -2.94 | -3.53 | -3.94 |
| DSSW+FF | -0.14*** | -0.24*** | -0.45*** | -0.63*** | -0.72*** | -0.68*** | -0.52*** |
| DSSW+HF | -0.17*** | -0.29*** | -0.44*** | -0.54*** | -0.59*** | -0.60** | -0.59* |
| Pool | -0.09*** | -0.15*** | -0.22*** | -0.26*** | -0.26*** | -0.22** | -0.19* |
| | **Investment** | | | | | | |
| DSSW | -1.91 | -2.54 | -3.18 | -3.51 | -3.65 | -3.75 | -3.74 |
| DSSW+FF | -0.52*** | -0.43*** | -0.21*** | -0.05 | 0.03 | 0.09 | 0.06 |
| DSSW+HF | -0.04** | -0.05 | -0.04 | -0.06 | -0.11 | -0.28*** | -0.47*** |
| Pool | -0.15*** | -0.13*** | -0.07* | -0.02 | -0.01 | -0.04 | -0.10* |
| | **Hours** | | | | | | |
| DSSW | -1.15 | -1.57 | -2.01 | -2.22 | -2.34 | -2.50 | -2.62 |
| DSSW+FF | 0.04** | 0.05 | 0.16*** | 0.27*** | 0.33*** | 0.38*** | 0.38*** |
| DSSW+HF | -0.07*** | -0.10** | -0.10 | -0.13 | -0.17 | -0.18 | -0.20 |
| Pool | -0.01 | 0.00 | 0.04 | 0.08 | 0.10* | 0.12* | 0.12 |
| | **Prices** | | | | | | |
| DSSW | -0.04 | -0.72 | -1.41 | -1.86 | -2.21 | -2.76 | -3.22 |
| DSSW+FF | -0.02 | -0.03 | -0.07 | -0.08 | -0.07 | -0.01 | 0.09 |
| DSSW+HF | -0.40*** | -0.53*** | -0.69*** | -0.73*** | -0.71*** | -0.64*** | -0.53*** |
| Pool | -0.11*** | -0.15*** | -0.19*** | -0.20*** | -0.19*** | -0.14* | -0.06 |
| | **Wages** | | | | | | |
| DSSW | -1.22 | -1.69 | -2.22 | -2.54 | -2.71 | -2.87 | -2.89 |
| DSSW+FF | 0.09*** | 0.10** | 0.15** | 0.20** | 0.21** | 0.15 | 0.06 |
| DSSW+HF | 0.12** | 0.12*** | 0.20*** | 0.25*** | 0.27*** | 0.29*** | 0.26*** |
| Pool | 0.10** | 0.09*** | 0.13*** | 0.17*** | 0.18*** | 0.17*** | 0.13** |
| | **Interest rate** | | | | | | |
| DSSW | -1.28 | -1.66 | -2.03 | -2.22 | -2.33 | -2.46 | -2.50 |
| DSSW+FF | -0.04 | -0.06 | -0.13 | -0.19*** | -0.23*** | -0.27*** | -0.30*** |
| DSSW+HF | 0.19*** | 0.21*** | 0.16*** | 0.08 | 0.01 | -0.13 | -0.24** |
| Pool | 0.06*** | 0.07** | 0.04 | -0.01 | -0.04 | -0.09*** | -0.14*** |
| | **7 variables** | | | | | | |
| DSSW | -7.07 | -10.26 | -13.83 | -16.09 | -17.77 | -20.41 | -22.37 |
| DSSW+FF | -0.59*** | -0.55** | -0.45 | -0.54 | -0.68 | -0.82 | -0.98 |
| DSSW+HF | -0.51*** | -0.89*** | -1.29 | -1.69 | -2.01 | -2.55 | -2.96** |
| Pool | -0.22*** | -0.33 | -0.34 | -0.38** | -0.44*** | -0.47*** | -0.48*** |

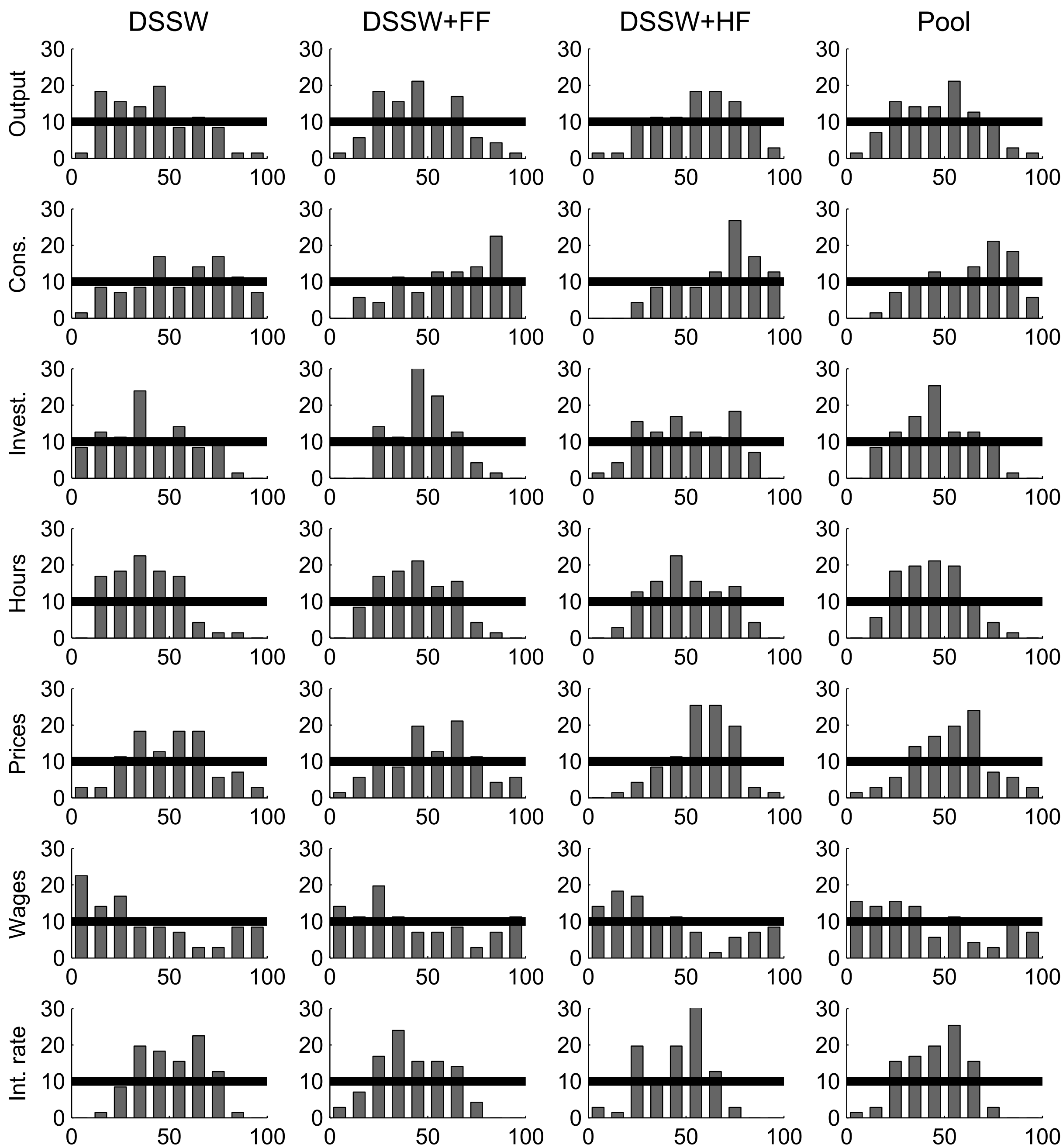
Notes: For the DSSW model LPSs are reported in levels, whereas for the remaining models they appear as the differences so that the values above zero indicate that a given model has a higher LPS than the benchmark. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Amisano and Giacomini (2007) test, where the long-run variance is calculated 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 in percent, annualized.

Table 6: Average log predictive scores for 2007:4-2010:4 period

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ | $H=16$ |
|---|---|---|---|---|---|---|---|
| | **Output** | | | | | | |
| DSSW | -1.55 | -2.85 | -4.02 | -4.45 | -4.67 | -4.75 | -4.63 |
| DSSW+FF | -0.08 | 0.28 | 0.73 | 0.89* | 0.92*** | 0.76*** | 0.50*** |
| DSSW+HF | 0.35 | 0.97 | 1.45 | 1.59* | 1.64*** | 1.40*** | 1.19*** |
| Pool | 0.22 | 0.74 | 1.14 | 1.21* | 1.15** | 0.90*** | 0.70*** |
| | **Consumption** | | | | | | |
| DSSW | -1.88 | -3.07 | -3.71 | -3.57 | -3.41 | -3.33 | -3.31 |
| DSSW+FF | 0.25 | 0.44 | 0.36** | 0.11** | 0.06 | -0.02 | 0.02 |
| DSSW+HF | 0.56 | 1.00 | 1.07 | 0.81 | 0.67* | 0.69* | 0.60* |
| Pool | 0.46 | 0.91 | 0.90 | 0.57* | 0.39* | 0.38** | 0.32** |
| | **Investment** | | | | | | |
| DSSW | -2.88 | -4.06 | -5.27 | -6.29 | -7.13 | -7.58 | -7.40 |
| DSSW+FF | -0.16 | 0.14 | 0.56 | 1.08 | 1.52*** | 1.61*** | 1.21*** |
| DSSW+HF | 0.46 | 0.93 | 1.38* | 1.89* | 2.42** | 2.84*** | 2.72*** |
| Pool | 0.28 | 0.62 | 0.99 | 1.46* | 1.89** | 2.17*** | 2.03*** |
| | **Hours** | | | | | | |
| DSSW | -1.45 | -2.52 | -4.04 | -4.87 | -5.15 | -4.77 | -4.33 |
| DSSW+FF | -0.80 | -1.12 | -1.07 | -0.82 | -0.72 | -0.87* | -1.28** |
| DSSW+HF | 0.30** | 0.87** | 1.73** | 2.05** | 1.97** | 1.24*** | 0.72*** |
| Pool | 0.04 | 0.40 | 1.14 | 1.44** | 1.37** | 0.67*** | 0.21*** |
| | **Prices** | | | | | | |
| DSSW | -0.06 | -0.73 | -1.60 | -2.05 | -2.33 | -2.61 | -2.82 |
| DSSW+FF | 0.06 | 0.18* | 0.30** | 0.31** | 0.24 | 0.02 | -0.08 |
| DSSW+HF | -0.73*** | -0.98*** | -1.07*** | -0.97*** | -0.74*** | -0.70*** | -0.87*** |
| Pool | -0.11 | -0.13* | -0.07 | -0.04 | -0.06 | -0.16** | -0.24*** |
| | **Wages** | | | | | | |
| DSSW | -1.41 | -1.74 | -2.21 | -2.42 | -2.71 | -3.36 | -3.73 |
| DSSW+FF | 0.14 | 0.07 | 0.13 | 0.11 | 0.23*** | 0.53*** | 0.71*** |
| DSSW+HF | 0.20*** | 0.15 | 0.20 | 0.20*** | 0.28*** | 0.38*** | 0.56*** |
| Pool | 0.15** | 0.10** | 0.13* | 0.12*** | 0.18*** | 0.34*** | 0.47*** |
| | **Interest rate** | | | | | | |
| DSSW | -1.25 | -1.67 | -2.27 | -2.75 | -3.11 | -3.42 | -3.55 |
| DSSW+FF | -0.59** | -0.37* | -0.02 | 0.05 | 0.09 | 0.19*** | 0.34*** |
| DSSW+HF | 0.15*** | 0.13* | 0.07 | 0.19 | 0.42 | 0.43* | 0.55*** |
| Pool | -0.07 | -0.03 | 0.06 | 0.15 | 0.24* | 0.25** | 0.34*** |
| | **7 variables** | | | | | | |
| DSSW | -9.72 | -14.86 | -20.27 | -22.91 | -24.73 | -25.61 | -25.21 |
| DSSW+FF | -0.89*** | -1.20** | -1.03 | -0.14 | 1.30 | 1.74 | 0.83 |
| DSSW+HF | 0.63*** | 1.53*** | 2.46 | 2.88 | 3.51 | 3.46 | 3.12** |
| Pool | 0.65*** | 1.50 | 2.74 | 3.26** | 3.56*** | 3.25*** | 2.83*** |

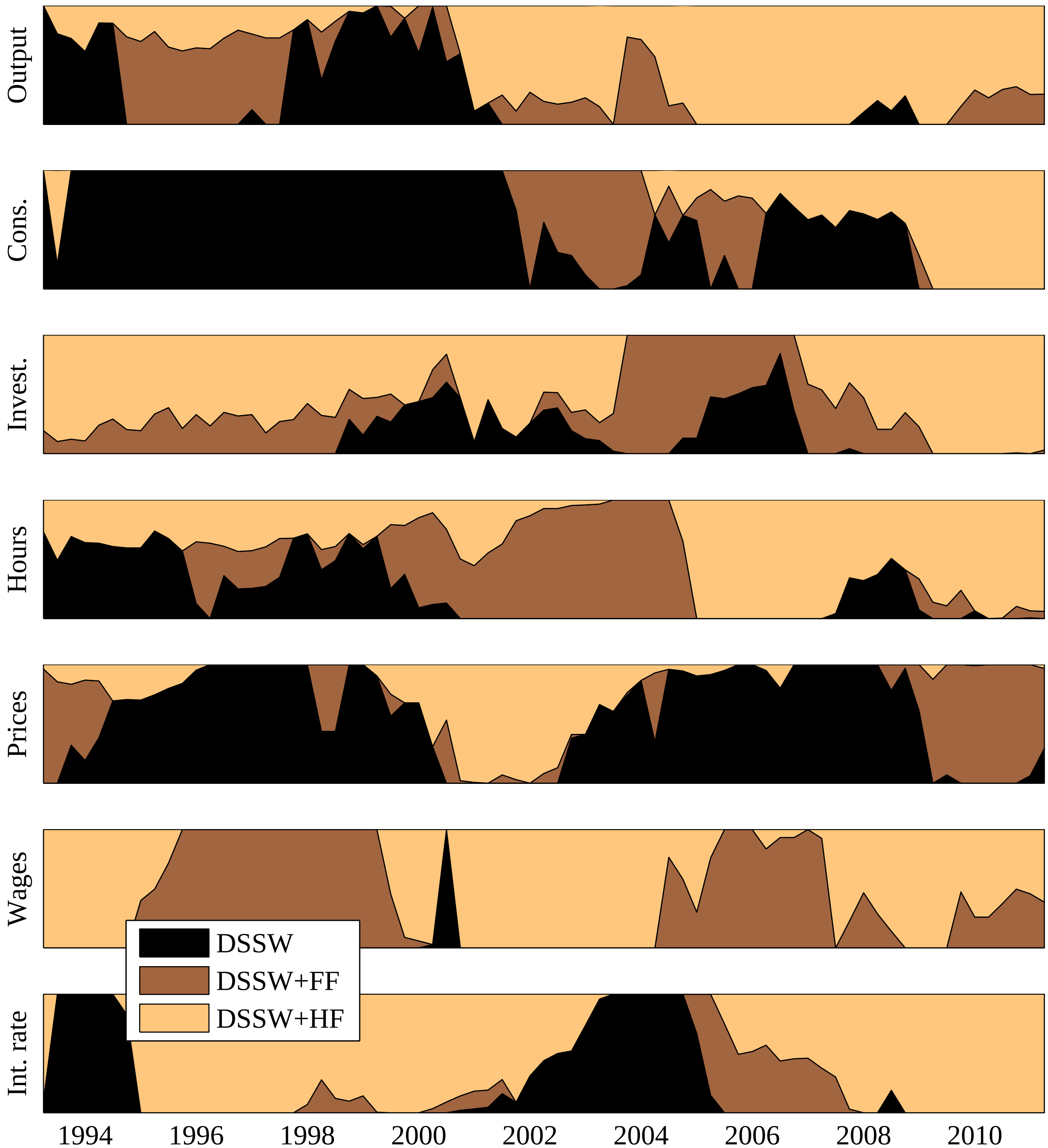
Notes: For the DSSW model LPSs are reported in levels, whereas for the remaining models they appear as the differences so that the values above zero indicate that a given model has a higher LPS than the benchmark. Asterisks ***, ** and * denote, respectively, the 1%, 5% and 10% significance levels of the Amisano and Giacomini (2007) test, where the long-run variance is calculated 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 in percent, annualized.

Figure 1: Density forecasts: PIT histograms for one-quarter horizon and period 1990:1-2007:3



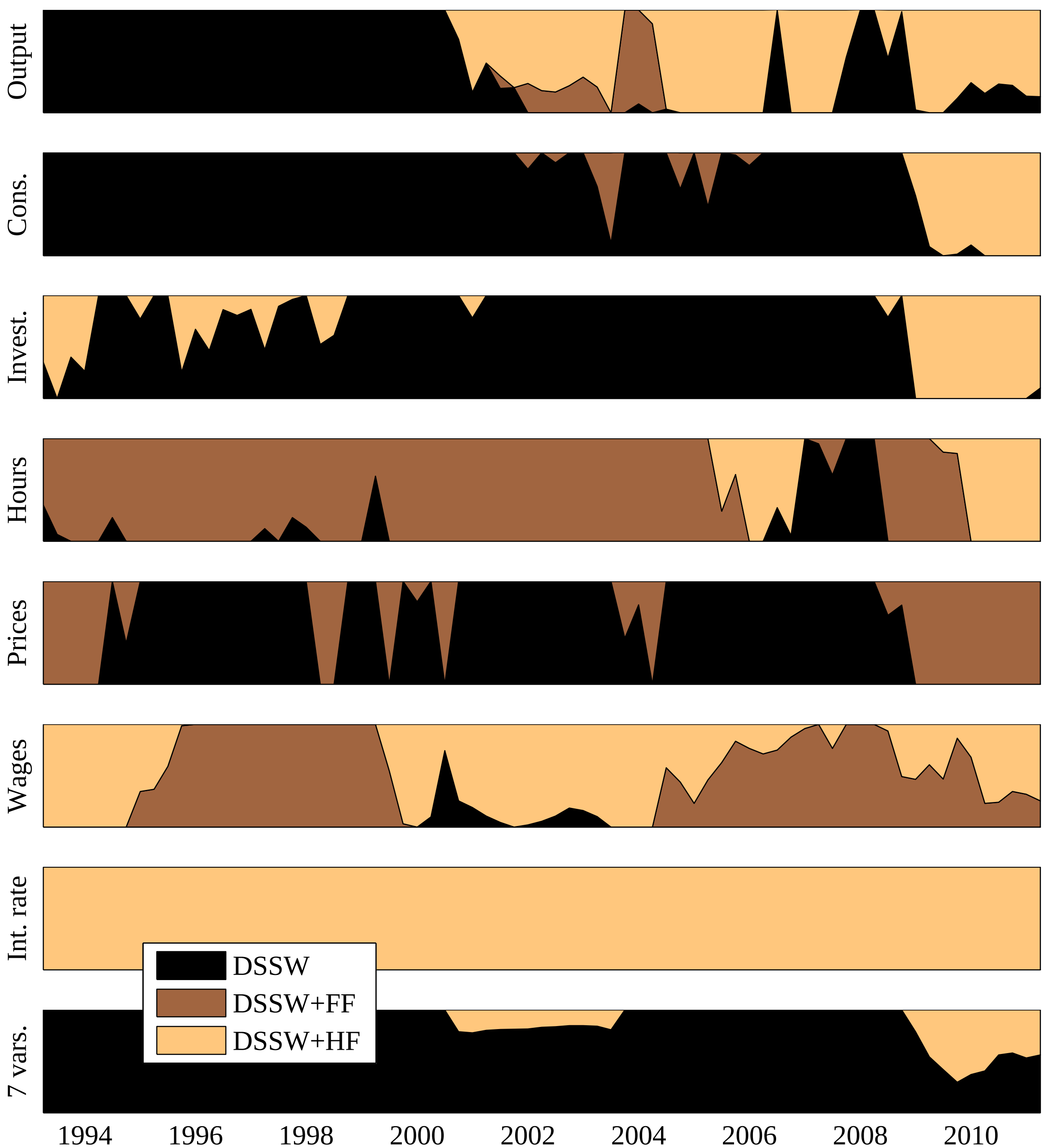

Notes: Bars represent the fraction of realized observations falling into the particular deciles of density forecasts. The theoretical value of 10% for a perfectly calibrated model is represented by a solid line.

Figure 2: Rolling weights minimizing 1-step ahead RMSFE




Notes: The weights are calculated for three-year windows.

Figure 3: Rolling weights maximizing 1-step ahead LPS




Notes: The weights are calculated for three-year windows.

# 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, $\Lambda_t$ is marginal utility, $P_t$ is the aggregate price level, $\pi_t$ is inflation, $Q_t$ is the real price of capital, $R_t$ is the policy rate, $\Delta_t$ 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 $\mu_t$, disutility of labor $\phi_t$, 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

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

Optimal contract

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

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

$$R^d_t = \frac{\tilde{\omega}_t R^e_t Q_{t-1} P_{t-1} \bar{K}_{t-1}}{D_{t-1}} \tag{A.26}$$

The law of motion for net worth in the economy

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

The aggregate resource constraint

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

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 $R^d_t$, and two auxiliary functions $F_{1,t}$ and $F_{2,t}$. The cumulative density function of idiosyncratic risk $\omega$ 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 $\nu_t$ and the volatility of idiosyncratic risk $\sigma_t$. 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

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

Demand for impatient households' labor

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

Total labor supply

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

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 $C_t$, $\Lambda_t$, $W_t$, $\tilde{W}_t$, $\tilde{L}_t$ and $\beta$. 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 $\Theta_t$. 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 $\mu_t^o$, 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 |
|---|---|---|
| $\phi$ | 0.8 | Steady-state weight on leisure in utility |
| $\lambda_w$ | 0.3 | Steady-state wage markup |
| $\delta$ | 0.025 | Capital depreciation rate |
| $\delta_o$ | 0.005 | Housing depreciation rate |
| $\lambda_l$ | 0.3 | Elasticity of substitution between labor of patient and impatient HHs |

Table C.2: Prior assumptions - structural parameters

| Parameter | Type | Mean | Std. | Description |
|---|---|---|---|---|
| $\alpha$ | beta | 0.33 | 0.05 | Capital share |
| $\zeta_p$ | beta | 0.6 | 0.2 | Calvo probability for prices |
| $\iota_p$ | 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 |
| $\nu_l$ | gamma | 2 | 0.75 | Inv. Frisch elasticity of labor supply |
| $\zeta_w$ | beta | 0.6 | 0.2 | Calvo probability for wages |
| $\iota_w$ | beta | 0.5 | 0.2 | Wage indexation |
| $r^*$ | gamma | 2 | 1 | Steady state real interest rate (annualized) |
| $\psi_1$ | gamma | 1.5 | 0.4 | Weight on inflation in Taylor rule |
| $\psi_2$ | gamma | 0.2 | 0.1 | Weight on output in Taylor rule |
| $\rho_R$ | beta | 0.5 | 0.2 | Interest rate smoothing |
| $\pi^*$ | normal | 3.01 | 1.5 | Steady state inflation (annualized) |
| $\gamma$ | gamma | 2 | 1 | Steady-state growth rate of technology (annualized) |
| $\lambda_f$ | 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 |
| $\nu$ | beta | 0.975 | 0.001 | Steady-state survival rate of entrepreneurs |
| $\chi$ | beta | 0.12 | 0.01 | Auditing costs |
| $\sigma$ | 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 | 0.215 | 0.01 | Steady-state weight of housing in utility |
| $\beta^i$ | beta | 0.97 | 0.01 | Impatient HHs' discount factor |
| $m$ | normal | 0.75 | 0.01 | Steady-state loan-to-value ratio |
| $S_o$" | gamma | 4 | 1.5 | Residential investment adjustment cost curvature |
| $\lambda_d$ | gamma | 0.006 | 0.001 | Steady-state spread on loans to impatient HHs |
| $n_p$ | beta | 0.38 | 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 $\alpha$ is 0.27.

Table C.3: Prior assumptions - shocks

| Parameter | Type | Mean | Std. | Description |
|---|---|---|---|---|
| $\rho_z$ | beta | 0.2 | 0.1 | Persistence of productivity shock |
| $\rho_\phi$ | beta | 0.6 | 0.2 | Persistence of labor supply shock |
| $\rho_{\lambda_f}$ | beta | 0.6 | 0.2 | Persistence of price markup shock |
| $\rho_\mu$ | beta | 0.8 | 0.05 | Persistence of investment shock |
| $\rho_b$ | beta | 0.6 | 0.2 | Persistence of intertemporal utility shock |
| $\rho_g$ | beta | 0.8 | 0.05 | Persistence of government spending shock |
| $\rho_\nu$ | beta | 0.8 | 0.2 | Persistence of entrepreneurs' survival shock |
| $\rho_\sigma$ | beta | 0.8 | 0.2 | Persistence of idiosyncratic risk volatility shock |
| $\rho_a$ | beta | 0.6 | 0.2 | Persistence of housing demand shock |
| $\rho_m$ | beta | 0.6 | 0.2 | Persistence of loan-to-value shock |
| $\rho_{\mu_o}$ | beta | 0.8 | 0.05 | Persistence of residential investment shock |
| $\rho_{\lambda_d}$ | beta | 0.6 | 0.2 | Persistence of spread shock |
| $\sigma_z$ | inv. gamma | 0.5 | inf | Volatility of productivity shock |
| $\sigma_\phi$ | inv. gamma | 2 | inf | Volatility of labor supply shock |
| $\sigma_{\lambda_f}$ | inv. gamma | 0.5 | inf | Volatility of price markup shock |
| $\sigma_\mu$ | inv. gamma | 0.5 | inf | Volatility of investment shock |
| $\sigma_b$ | inv. gamma | 0.5 | inf | Volatility of intertemporal utility shock |
| $\sigma_g$ | inv. gamma | 0.5 | inf | Volatility of government spending shock |
| $\sigma_R$ | inv. gamma | 0.25 | inf | Volatility of interest rate shock |
| $\sigma_\nu$ | inv. gamma | 0.5 | inf | Volatility of entrepreneurs' survival shock |
| $\sigma_\sigma$ | inv. gamma | 0.5 | inf | Volatility of idiosyncratic risk volatility shock |
| $\sigma_a$ | inv. gamma | 0.5 | inf | Volatility of housing demand shock |
| $\sigma_m$ | inv. gamma | 0.5 | inf | Volatility of loan-to-value shock |
| $\sigma_{\mu_o}$ | inv. gamma | 0.5 | inf | Volatility of residential investment shock |
| $\sigma_{\lambda_d}$ | inv. gamma | 0.5 | inf | Volatility of spread shock |

## C.2 Posterior estimates

All estimations are done with Dynare, version 4.2.4 (Adjemian et al., 2011). The posterior distributions are obtained with the Metropolis-Hastings algorithm. For each subsample, we create 500,000 draws, of which the first 400,000 draws are discarded. Table C.4 reports the characteristics of the marginal posterior distributions for some key parameters describing nominal and real rigidities, obtained from the full sample estimation.

Table C.4: Posterior estimates - selected structural parameters

| Parameter | DSSW | | | DSSW+FF | | | DSSW+HF | | |
|---|---|---|---|---|---|---|---|---|---|
| | mean | 5% | 95% | mean | 5% | 95% | mean | 5% | 95% |
| $\zeta_p$ | 0.85 | 0.75 | 0.93 | 0.93 | 0.91 | 0.95 | 0.72 | 0.66 | 0.77 |
| $\iota_p$ | 0.20 | 0.01 | 0.53 | 0.50 | 0.36 | 0.64 | 0.26 | 0.08 | 0.44 |
| $S$" | 7.11 | 4.82 | 9.68 | 0.27 | 0.19 | 0.35 | 5.12 | 3.25 | 6.95 |
| $h$ | 0.72 | 0.65 | 0.79 | 0.77 | 0.71 | 0.84 | 0.83 | 0.75 | 0.90 |
| $\nu_l$ | 2.07 | 1.15 | 2.98 | 0.48 | 0.25 | 0.70 | 0.50 | 0.23 | 0.77 |
| $\zeta_w$ | 0.36 | 0.20 | 0.52 | 0.40 | 0.31 | 0.49 | 0.67 | 0.59 | 0.74 |
| $\iota_w$ | 0.15 | 0.05 | 0.25 | 0.18 | 0.09 | 0.28 | 0.24 | 0.12 | 0.36 |

# D Forecasts

To generate forecasts we take each 20th draw from the final 100,000 parameter draws produced by the Metropolis-Hastings algorithm, which gives us 5,000 draws from the posterior distribution. For each of them, we draw seven shock trajectories to generate the predictions for the seven macrovariables of interest. The thus obtained 35,000 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.