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Forecasting using 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 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 actually deteriorates. In contrast, adding frictions in the housing market proves very helpful during times of financial turmoil, outperforming 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.

1. Introduction

Over 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 began to be used not only for business cycle and policy analyses, but also for forecasting (see Del Negro & 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 with time series models or even professional forecasters (see e.g. Adolfson, Lindé, & Villani, 2007; Edge & Gurkaynak, 2010; Edge, Kiley, & Laforte, 2010; Kolasa, Rubaszek, & Skrzypczynski, 2012; Rubaszek & Skrzypczynski, 2008; Smets & Wouters, 2003; Wieland & 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 and inefficient, and are usually calibrated badly (Edge & Gurkaynak, 2010; Herbst & 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 also, 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 the contributing papers only report marginal likelihoods for the considered alternative specifications, if anything.

One of very few exceptions is the study by Christiano, Trabandt, and Walentin (2011), who demonstrate that augmenting a medium-sized DSGE model of the Swedish economy with frictions á la Bernanke, Gertler, and Gilchrist (1999, chap. 21) increases the accuracy of point forecasts. It is not clear, however, whether the reported differences are statistically significant, and density forecasts are not

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discussed at all. More recently, Del Negro, Giannoni, and Schorfheide (2013) and Del Negro and Schorfheide (2013) 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 produced 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 the extent to which adding two popular types of financial frictions can improve 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, Schorfheide, Smets, and Wouters (2007), both of which can be considered the state of the art for modeling frictions which affect non-financial firms and households respectively. More specifically, the first addition introduces frictions between firms and banks using the financial accelerator setup developed by Bernanke et al. (1999, chap. 21). The second extension follows Iacoviello (2005) and incorporates housing and collateral constraints into the household sector. We next analyze the performances 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 the 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 the density forecasts actually deteriorates. In contrast, the extensions considered for the benchmark DSGE model have been found to be relatively successful during times of 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 the Great Recession and thereafter 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 a substantial degree of variation over time.

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. Finally, the detailed equations of the models, a description of the data and various 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 model 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, Eichenbaum, and Evans (2005) and estimated using Bayesian methods by Smets and Wouters (2003). As the results of Wolters (in press) suggest, this framework is particularly good at forecasting relative 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 to be crucial for ensuring a reasonable data fit. These include: consumption habits, investment adjustment costs, time-varying capacity utilization, and wage and price stickiness with indexation. Government spending is exogenous and is financed by lump sum taxes, while 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 using 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, chap. 21), except that, following Christiano, Motto, and Rostagno (2003), the financial contract is specified in nominal terms. Our choice of the model specification is based on the results of Brzoza-Brzezina, Kolasa, and Makarski (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 per 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 agent, called entrepreneurs. They possess special skills in operating capital, and hence find it optimal to borrow additional funds over their net worth to finance their operations. The 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 or may not have enough resources to repay the loan. In the latter case, she declares default and the bank seizes all of 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 diversified fully, 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 that affect the standard deviation of the 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 the work of Iacoviello (2005), who uses the Kiyotaki and Moore (1997) framework to model collateral constraints in the housing market. Following Gerali, Neri, Sessa, and Signoretti (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 is populated by two types of agents that differ in their rate of time preference. Impatient households discount the future more heavily, and 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.

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

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

2.5. Discussion

Before presenting the results of the forecasting contest, it is instructive to discuss why the two models with financial frictions considered might potentially generate more accurate forecasts than the baseline model. The first (economic) reason is that a richer specification might describe the true data generating process (DGP) better. 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 larger numbers of parameters that have to be estimated, and therefore might generate less accurate forecasts. This "estimation forecast error" would be especially high if the true DGP is described better by the (more parsimonious) baseline model.

3. Forecast comparison

In this section, we compare the quality of the forecasts from the DSSW, DSSW+FF and DSSW+HF models, as well as from 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. A detailed description of the data definitions and sources is provided in Appendix B. Second, we estimate all three DSGE models using 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 the period 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, then the second set of forecasts is for the period 1990:2–1994:1, with models estimated on the sample 1970:1–1990:1, and so on. Since our dataset ends in 2010:4, we can calculate forecast errors on the basis of between 69 (for 16-quarter-ahead forecasts) and 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. For 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 the "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 previous studies (see for example Edge & Gurkaynak, 2010; Kolasa et al., 2012). In particular, the DSSW model underpredicts consumption and overpredicts investment. A potential reason for this could be 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. A second result is that the DSSW model-based forecasts for prices tend to be too high. One explanation for this is that the average quarterly inflation rate stood at 1.36% in the period 1970:1–1989:4, which is much more than the 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, Cumby, & Diba, 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] However, this would mean that the forecast comparison would be based on the cyclical components that are not observed by forecasters in real time. A more flexible alternative was proposed recently by Canova (2012). In his framework, the non-model-based component is designed so as to be able to capture endogenously those aspects of the data that the theoretical model has problems in explaining. Yet another option would be to relax some of the cross-equation restrictions imposed by the model structure (see for example Cayen, Gosselin, & Kozicki, 2009; Ireland, 2004), or to use them only as a prior for an atheoretical time series model (Del Negro & Schorfheide, 2004). Clearly, all of these approaches generate departures from the restrictions imposed by the DSGE model. As a result, they can give a distorted picture of 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]

The results in Table 1 for the remaining models show that, in general, adding financial frictions does not help much 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 complementary to some extent, as the biases for output, investment, hours and prices are of the opposite sign. This explains why the equally weighted pool is an attractive option for these variables.

Turning to the "crisis period", the results reported in Table 2 show that none of the models were able to predict the scale of the decline in economic activity during the Great Recession. However, the size of the bias for the real sector variables with the DSSW+HF specification is about half the size of those with the other two models. One potential reason for the relatively good performance of this model variant is the fact that the information set used in its estimation includes variables that describe the housing sector, which is where the recent crisis originated. In contrast, the two additional observables used to estimate the DSSW+FF model turned out 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, Giannoni et al. (2013).

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

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

3 An alternative that would be consistent with our empirical strategy would be to change the benchmark model structure so as to overcome the forecast bias. For example, as was shown recently 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 inflation forecasts. 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.

Table 1
Mean forecast errors for the period 1990:1–2007:3.

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$
	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 the forecasts are below the actual values, on average. The test statistics are corrected for the autocorrelation of forecast errors using the Newey–West method. All statistics reported are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.
* Denotes the rejection of the null that the MFE is equal to zero at the 10% significance level.
** Denotes the rejection of the null that the MFE is equal to zero at the 5% significance level.
*** Denotes the rejection of the null that the MFE is equal to zero at the 1% significance level.

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 also report the results of the Diebold and Mariano (1995) test.

Overall, the numbers in Table 3 show that adding financial frictions does not lead to any systematic improvement in the accuracy of point forecasts in the pre-crisis period. 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 the most accurate longer-term investment forecasts, but the least accurate (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 the investment adjustment cost curvature are clearly the lowest for the DSSW+FF setup.[4] This suggests

[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 that in the DSSW benchmark (our priors on the volatility of shocks are very diffuse). This result is consistent with the findings of Justiniano, Primiceri, and Tambalotti (2011), who argue that these types of shocks often proxy for financial frictions.

Table 2
Mean forecast errors for the period 2007:4–2010:4.

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$
	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 the forecasts are below the actual values, on average. The test statistics are corrected for the autocorrelation of forecast errors using the Newey–West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.

* Denotes the rejection of the null that the MFE is equal to zero at the 10% significance level.

** Denotes the rejection of the null that the MFE is equal to zero at the 5% significance level.

*** Denotes the rejection of the null that the MFE is equal to zero at the 1% significance level.

that, to large extent, the additional frictions introduced by the financial accelerator framework of Bernanke et al. (1999, chap. 21) 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 lower costs of adjusting investment in the DSSW+FF variant make this variable very volatile over shorter horizons, leading to a deterioration in the point forecasts (and even more in the density forecasts, as we will see later).

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 more than quadruples the estimated value of the Frisch elasticity. However, while we do not report this here 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, significantly so in many cases. 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 variants considered.

Given that the recent revival of interest in DSGE models with financial frictions was largely a response to the

Table 3
Root mean squared forecast errors for the period 1990:1–2007:3.

	$H = 1$	$H = 2$	$H = 4$	$H = 6$	$H = 8$	$H = 12$	$H = 16$
	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 ratios, so that values below unity indicate that a given model has a lower RMSE than the benchmark. The long-run variance is calculated using the Newey–West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.

* Denotes significance of the Diebold–Mariano test at the 10% level.

** Denotes significance of the Diebold–Mariano test at the 5% level.

*** Denotes significance of the Diebold–Mariano test at the 1% level.

recent crisis, it might be expected that their forecasting performances 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 Table 4 shows, the improvement in the accuracy of forecasts is sizable 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 on only very few occasions, which suggests that the degree of complementarity between the three alternative models during the crisis was not as pronounced as that 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 those of the other two models. One potential explanation is that the information set of the DSSW+HF model includes the time series that describe the situation in the housing sector, which was very important during the recent crisis.

3.2. Density forecasts

We complement the discussion of point forecasting accuracy with an evaluation of density forecasts. The

Table 4
Root mean squared forecast errors for the period 2007:4–2010:4.

	$H = 1$	$H = 2$	$H = 4$	$H = 6$	$H = 8$	$H = 12$	$H = 16$
	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 ratios, so that values below unity indicate that a given model has a lower RMSE than the benchmark. The long-run variance is calculated using the Newey–West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.
* Denotes significance of the Diebold–Mariano test at the 10% level.
** Denotes significance of the Diebold–Mariano test at the 5% level.
*** Denotes significance of the Diebold–Mariano test at the 1% level.

aim is to determine the extent to which the analyzed forecasts provide a realistic description of the actual uncertainty.

Let $p(Y_{t+h}|t, i)$ and $p(y_{t+h}|t, i)$ be the predictive density and the 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, with moments 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 stands for the number of h-step-ahead forecasting rounds. In the case of the weighted forecast, we follow 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

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

Table 5
Average log predictive scores for the period 1990:1–2007:3.

	$H=1$	$H=2$	$H=4$	$H=6$	$H=8$	$H=12$	$H=16$
	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***
	Seven 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 differences, so that values above zero indicate that a given model has a higher LPS than the benchmark. The long-run variance is calculated using the Newey–West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.
* Denotes significance of the Amisano–Giacomini test at the 10% level.
** Denotes significance of the Amisano–Giacomini test at the 5% level.
*** Denotes significance of the Amisano–Giacomini test at the 1% level.

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 outperforms 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 leads to a deterioration in the accuracy of density forecasts in most cases. The LPS differences are significantly negative for output, consumption and investment (both models), as well as for the interest rate (DSSW+FF), hours and prices (DSSW+HF). In addition, 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 seven variables: the DSSW model is significantly more accurate than its two competitors for the shortest horizon. 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).

Table 6
Average log predictive scores for the period 2007:4–2010:4.

	$H = 1$	$H = 2$	$H = 4$	$H = 6$	$H = 8$	$H = 12$	$H = 16$
	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***
	Seven 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 differences, so that values above zero indicate that a given model has a higher LPS than the benchmark. The long-run variance is calculated using the Newey–West method. All reported statistics are for variables in log-levels multiplied by 100, except for the interest rate, which is expressed in percentages, annualized.
* Denotes significance of the Amisano–Giacomini test at the 10% level.
** Denotes significance of the Amisano–Giacomini test at the 5% level.
*** Denotes significance of the Amisano–Giacomini test at the 1% level.

To determine where these differences between the LPSs across 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 the extent to which these two criteria are met is the PIT histograms, which we present in Fig. 1 for the one-quarter-ahead forecasts over the "tranquil period". More specifically, as was advocated by Diebold, Gunther, and Tay (1998) and recently employed for evaluating DSGE models by Herbst and Schorfheide (2012), we divide the unit interval into 10 subintervals and check whether the fraction of PITs in each of them is close to 10%. If the PITs are distributed equally across the bins, a density forecast is calibrated well. If the PITs are concentrated in the lower (upper) bins, the model tends to overpredict (underpredict) a given variable. Finally, if the 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 when analyzing the accuracy of point forecasts, there is also 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

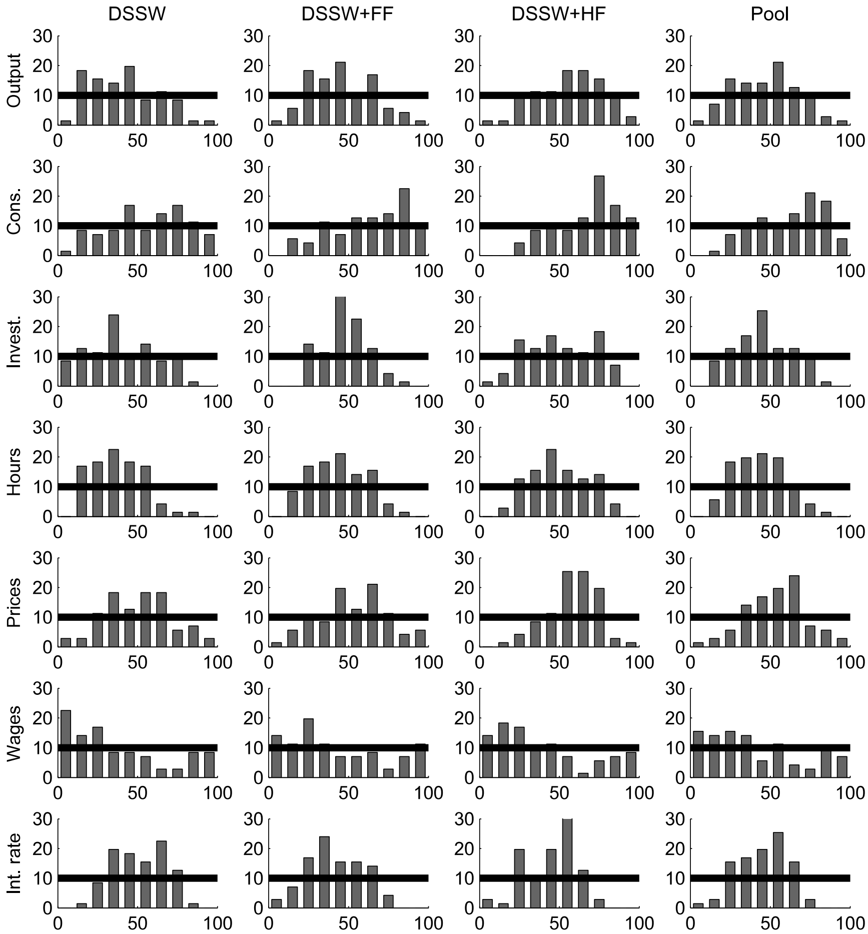

Fig. 1. Density forecasts: PIT histograms for the one-quarter horizon and the period 1990:1–2007:3. Notes: Bars represent the fractions of realized observations that fall into each individual decile of density forecasts. The theoretical value of 10% for a perfectly calibrated model is represented by a solid line.

horizons, the density forecasts from the extended models are more diffuse than 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 is visibly better than that 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. The results for the DSSW+FF model are not so positive. There is even a significant deterioration in forecast quality for the seven-variables case at short horizons. It can also be seen that the equally weighted pool tends to perform worse than the DSSW+HF model.

To sum up, allowing for financial market imperfections usually leads to a deterioration in the accuracy of density forecasts in "tranquil periods". The reason for this 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 crisis periods.

3.3. *Time variation in optimal pools*

The results discussed above show that the forecast accuracies of the analyzed models are visibly different in the "tranquil" and "crisis" subsamples. Hence, a natural question arises as to whether there is a significant degree of time variation in the relative forecasting performances of the three models investigated. We address this issue by calculating time-varying weights that would optimize the *ex-post* forecasting performance in 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]

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

[7] A similar analysis was proposed recently by Del Negro, Hasegawa, and Schorfheide (2013), who calculated the time-varying LPS-maximizing

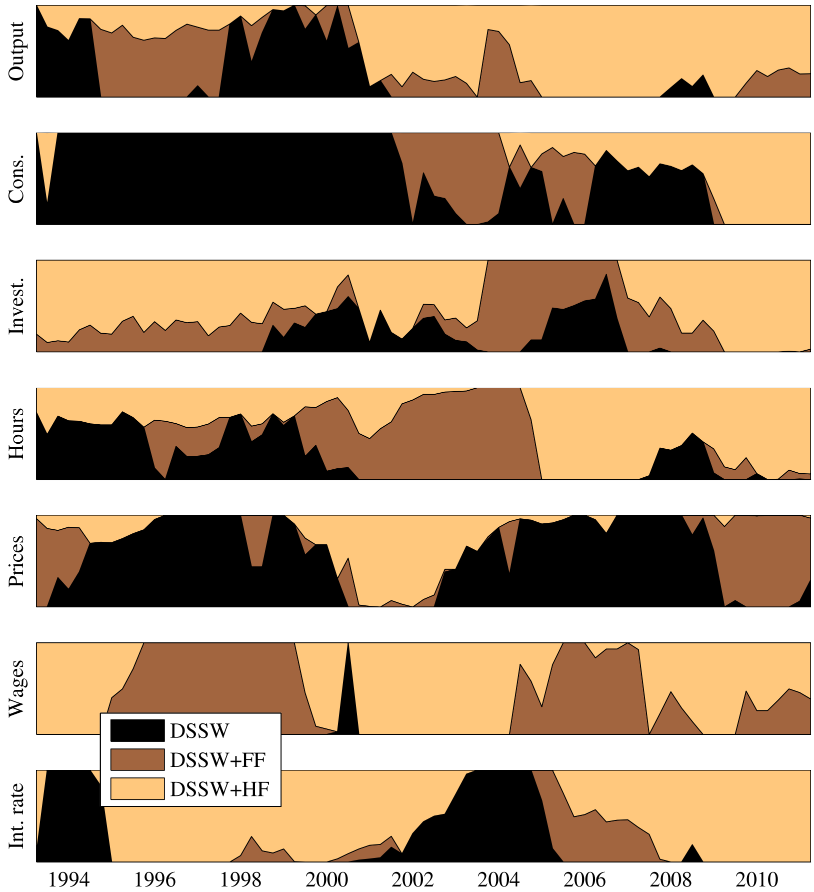

Fig. 2. Rolling weights minimizing the 1-step-ahead RMSFE. Notes: The weights are calculated for three-year windows.

Figs. 2 and 3, respectively, present the evolution of the weights that optimize the RMSFEs and LPSs. Several interesting conclusions can be ventured. First of all, the "optimal" weights exhibit a substantial degree of time variation, especially for point forecasts. Another interesting finding is that the RMSFE and LPS optimizing weights may 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 the LPS, and almost 100% for most periods if one is focusing on the quality of point forecasts. Moreover, it can be seen that models with financial frictions 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 for 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 times of 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 which include the housing sector should provide better guidance during turbulent times. However, our results also indicate that maintaining all three model variants may be warranted. This recommendation is supported by the relatively good performance of pooled forecasts and a substantial degree of time variation in the weights that optimize the forecast errors or predictive densities.

weights for the Smets and Wouters (2007) model and its Bernanke et al. (1999, chap. 21) extension. Their main finding is that the weight attributed to the model incorporating financial frictions is much higher during times of financial turmoil than in normal times.

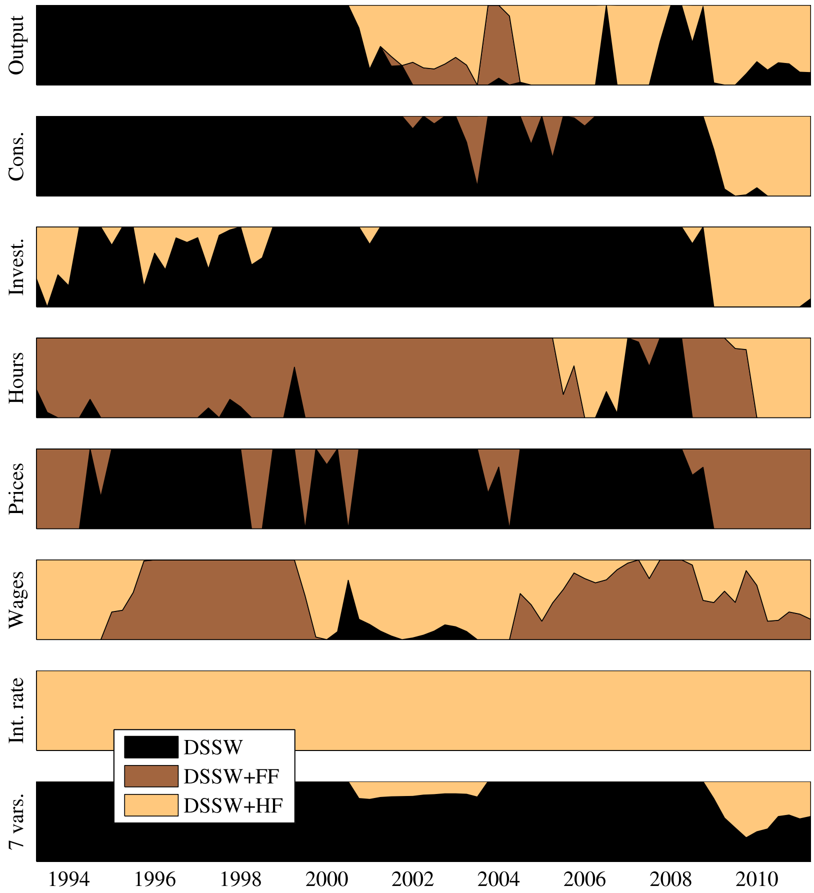

Fig. 3. Rolling weights maximizing the 1-step-ahead LPS. Notes: The weights are calculated for three-year windows.

Acknowledgments

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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

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

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

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

Rate of return on capital

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

Optimal capital holdings

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

Optimal capacity utilization

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

Marginal cost

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

Price set by reoptimizing firms

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

Output of reoptimizing firms

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

Aggregate price level

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

Taylor rule

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

Aggregate resource constraint

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

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

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

In the equations above, the notation is as per 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 wages, 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. Tildes 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 Appendix 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, the disutility of labor ϕ_t, price markup $\lambda_{f,t}$, government purchases g_t, and monetary policy $\epsilon_{R,t}$. Except for the monetary policy shock, which is assumed to be white noise, all shocks follow independent first-order autoregressive processes. The following model variables are treated as observable in the 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

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

Optimal contract

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

Auxiliary functions

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

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

Rate of interest paid by non-defaulting entrepreneurs

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

Net worth

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

Aggregate resource constraint

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

Eqs. (A.23) and (A.28) in the DSSW+FF model replace Eqs. (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 ω is denoted by $F(\omega)$. All new parameters are described in Appendix 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 $R^d_t-R_t$.

A.3. DSSW+HF model

Housing demand by patient households

$$\frac{a_t}{O^p_t}+\beta^p(1-\delta_o)E_t\left\{\Lambda^p_{t+1}Q^o_{t+1}\right\}=Q^o_t\Lambda^p_t. \tag{A.29}$$

Impatient households' budget constraint

$$P_tC^i_t+R^i_{t-1}D^i_{t-1}+T^i_t+P_tQ^o_t(O^i_t-(1-\delta_o)O^i_{t-1})$$
$$=W^i_tL^i_t+D^i_t. \tag{A.30}$$

Euler equation for impatient households

$$\beta^iE_t\left\{\frac{\Lambda^i_{t+1}}{\pi_{t+1}}R^i_t\right\}+\Theta_tR^i_t=\Lambda^i_t. \tag{A.31}$$

Housing demand by impatient households

$$\frac{a_t}{O^i_t}+\beta(1-\delta_o)E^i_t\left\{Q^o_{t+1}\Lambda^i_{t+1}\right\}$$
$$+\Theta_tm_t(1-\delta_o)E_t\left\{\pi_{t+1}Q^o_{t+1}\right\}=Q^o_t\Lambda^i_t. \tag{A.32}$$

Collateral constraint

$$R^i_tD^i_t=m_t(1-\delta_o)E_t\left\{P_{t+1}Q^o_{t+1}O^i_t\right\}. \tag{A.33}$$

Housing accumulation

$$O_t=(1-\delta_o)O_{t-1}+\mu^o_t\left(1-S_o\left(\frac{I^o_t}{I^o_{t-1}}\right)\right)I^o_t. \tag{A.34}$$

Residential investment demand

$$1=\mu^o_t\left(1-S_o\left(\frac{I^o_t}{I^o_{t-1}}\right)-I^o_tS'_o\left(\frac{I^o_t}{I^o_{t-1}}\right)\right)Q^o_t$$
$$+\beta E_t\left\{\frac{\Lambda^p_{t+1}}{\Lambda^p_t}\mu^o_{t+1}\frac{I^{o2}_{t+1}}{I^o_t}S'_o\left(\frac{I^o_{t+1}}{I^o_t}\right)Q^o_{t+1}\right\}. \tag{A.35}$$

Lending rate

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

Demand for patient households' labor

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

Demand for impatient households' labor

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

Total labor supply

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

Housing market clearing

$$O_t=n_pO^p_t+(1-n_p)O^i_t. \tag{A.40}$$

Aggregate resource constraint

$$\frac{1}{g_t}Y_t=n_pC^p_t+(1-n_p)C^i_t+I_t+I^o_t+a(u_t)\bar{K}_{t-1}. \tag{A.41}$$

Relative to the DSSW model, Eq. (A.41) replaces Eq. (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.5). The new variables showing up in the DSSW+HF model are: housing stock O_t, real house prices Q^o_t, residential investment I^o_t, loans to impatient households D^i_t, the interest rate

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

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 Appendix C.1.

There are four new stochastic disturbances, all of which are 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 $R_t^i - R_t$.

Appendix 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 by 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 mortgage 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.

When 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 by D_{adj} and $Q_{o,\mathrm{adj}}$ respectively, are estimated with relatively loose priors (see Appendix C.1).

Appendix C. Estimation

C.1. Prior assumptions

Our calibrations and prior assumptions, together with a short description of each parameter, are reported in Tables C.1–C.3. For the DSSW model, they are identical to those used by 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.

C.2. Posterior estimates

All estimations are done with Dynare, version 4.2.4. The posterior distributions are obtained using 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.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	0.215	0.01	Steady-state weight of housing in utility
β^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
λ_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
$Q_{o,\text{adj}}$	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

Appendix 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 5000 draws from the posterior distribution. For each of them, we draw seven shock trajectories in order to generate the predictions for the seven macrovariables of interest. The 35,000 trajectories thus obtained are draws from the predictive density, and hence can be used to evaluate the

Table C.4
Posterior estimates: selected structural parameters.

Parameter	DSSW			DSSW+FF			DSSW+HF		
	Mean	5%	95%	Mean	5%	95%	Mean	5%	95%
ζ_p	0.85	0.75	0.93	0.93	0.91	0.95	0.72	0.66	0.77
ι_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
ν_l	2.07	1.15	2.98	0.48	0.25	0.70	0.50	0.23	0.77
ζ_w	0.36	0.20	0.52	0.40	0.31	0.49	0.67	0.59	0.74
ι_w	0.15	0.05	0.25	0.18	0.09	0.28	0.24	0.12	0.36

density forecasts. The point forecasts are calculated as means of these draws.

References

Adolfson, M., Lindé, J., & Villani, M. (2007). Forecasting performance of an open economy DSGE model. *Econometric Reviews*, *26*(2–4), 289–328.

Amisano, G., & Giacomini, R. (2007). Comparing density forecasts via weighted likelihood ratio tests. *Journal of Business and Economic Statistics*, *25*, 177–190.

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In J. B. Taylor & M. Woodford (Eds.), *Handbook of macroeconomics*: *Vol. 1* (pp. 1341–1393). Elsevier.

Brzoza-Brzezina, M., Kolasa, M., & Makarski, K. (2013). The anatomy of standard DSGE models with financial frictions. *Journal of Economic Dynamics and Control*, *37*(1), 32–51.

Canova, F. (2012). *Bridging DSGE models and the raw data.* Working paper 635. Barcelona Graduate School of Economics.

Canzoneri, M. B., Cumby, R. E., & Diba, B. T. (2007). Euler equations and money market interest rates: a challenge for monetary policy models. *Journal of Monetary Economics*, *54*(7), 1863–1881.

Cayen, J.-P., Gosselin, M.-A., & Kozicki, S. (2009). *Estimating DSGE-model-consistent trends for use in forecasting*. Working papers 09-35. Bank of Canada.

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, *113*(1), 1–45.

Christiano, L. J., Motto, R., & Rostagno, M. (2003). The great depression and the Friedman–Schwartz hypothesis. *Journal of Money, Credit and Banking*, *35*(6), 1119–1197.

Christiano, L., Rostagno, M., & Motto, R. (2010). *Financial factors in economic fluctuations.* Working paper series 1192. European Central Bank.

Christiano, L. J., Trabandt, M., & Walentin, K. (2011). Introducing financial frictions and unemployment into a small open economy model. *Journal of Economic Dynamics and Control*, *35*(12), 1999–2041.

Del Negro, M., Giannoni, M. P., & Schorfheide, F. (2013). *Inflation in the Great Recession and New Keynesian models*. Staff reports 618. Federal Reserve Bank of New York.

Del Negro, M., Hasegawa, R. B., & Schorfheide, F. (2013). *Dynamic prediction pools: an investigation of financial frictions and forecasting performance.* Working paper. Federal Reserve Bank of New York.

Del Negro, M., & Schorfheide, F. (2004). Priors from general equilibrium models for VARs. *International Economic Review*, *45*(2), 643–673.

Del Negro, M., & Schorfheide, F. (2013). DSGE model-based forecasting. In G. Elliott & A. Timmermann (Eds.), *Handbook of economic forecasting*: *Vol. 2* (pp. 57–140). Elsevier.

Del Negro, M., Schorfheide, F., Smets, F., & Wouters, R. (2007). On the fit of new Keynesian models. *Journal of Business and Economic Statistics*, *25*, 123–143.

Diebold, F. X., Gunther, T. A., & Tay, A. S. (1998). Evaluating density forecasts with applications to financial risk management. *International Economic Review*, *39*(4), 863–883.

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, *13*(3), 253–263.

Edge, R. M., & Gurkaynak, R. S. (2010). How useful are estimated DSGE model forecasts for central bankers? *Brookings Papers on Economic Activity*, *41*(2), 209–259.

Edge, R. M., Kiley, M. T., & Laforte, J.-P. (2010). A comparison of forecast performance between Federal Reserve staff forecasts, simple reduced-form models, and a DSGE model. *Journal of Applied Econometrics*, *25*(4), 720–754.

Gerali, A., Neri, S., Sessa, L., & Signoretti, F. M. (2010). Credit and banking in a DSGE model of the euro area. *Journal of Money, Credit and Banking*, *42*(s1), 107–141.

Gerke, R., Jonsson, M., Kliem, M., Kolasa, M., Lafourcade, P., Locarno, A., Makarski, K., & McAdam, P. (2013). Assessing macro-financial linkages: a model comparison exercise. *Economic Modelling*, *31*(1), 253–264.

Geweke, J., & Amisano, G. (2011). Optimal prediction pools. *Journal of Econometrics*, *164*(1), 130–141.

Geweke, J., & Amisano, G. (2014). Analysis of variance for Bayesian inference. *Econometric Reviews*, *33*(1–4), 270–288.

Herbst, E., & Schorfheide, F. (2012). Evaluating DSGE model forecasts of comovements. *Journal of Econometrics*, *171*(2), 152–166.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, *95*(3), 739–764.

Ireland, P. N. (2004). Technology shocks in the New Keynesian model. *The Review of Economics and Statistics*, *86*(4), 923–936.

Justiniano, A., Primiceri, G., & Tambalotti, A. (2011). Investment shocks and the relative price of investment. *Review of Economic Dynamics*, *14*(1), 101–121.

Kiyotaki, N., & Moore, J. (1997). Credit cycles. *Journal of Political Economy*, *105*(2), 211–248.

Kolasa, M., Rubaszek, M., & Skrzypczynski, P. (2012). Putting the New Keynesian DSGE model to the real-time forecasting test. *Journal of Money, Credit and Banking*, *44*(7), 1301–1324.

Rubaszek, M., & Skrzypczynski, P. (2008). On the forecasting performance of a small-scale DSGE model. *International Journal of Forecasting*, *24*(3), 498–512.

Smets, F., & Wouters, R. (2003). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European Economic Association*, *1*(5), 1123–1175.

Smets, F., & Wouters, R. (2007). Shocks and frictions in US business cycles: a Bayesian DSGE approach. *American Economic Review*, *97*(3), 586–606.

Timmermann, A. (2006). Forecast combinations. In G. Elliott, C. Granger & A. Timmermann (Eds.), *Handbook of economic forecasting*: *Vol. 1* (pp. 135–196). Elsevier.

Wieland, V., & Wolters, M. H. (2013). Forecasting and policy making. In G. Elliott & A. Timmermann (Eds.), *Handbook of economic forecasting*: *Vol. 2* (pp. 239–325). Elsevier.

Wolters, M. H. (2014). Evaluating point and density forecasts of DSGE models. *Journal of Applied Econometrics*, in press.

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