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# Contents

**Abstract**

A common practice in policy making institutions using DSGE models for forecasting is to re-estimate them only occasionally rather than every forecasting round. In this paper we ask how such a practice affects the accuracy of DSGE model-based forecasts. To this end we use a canonical medium-sized New Keynesian model and compare how its quarterly real-time forecasts for the US economy vary with the interval between consecutive re-estimations. We find that updating the model parameters only once a year usually does not lead to any significant deterioration in the accuracy of point forecasts. On the other hand, there are some gains from increasing the frequency of re-estimation if one is interested in the quality of density forecasts.

*Keywords*: forecasting; DSGE models; parameter updating
*JEL Classification*: C53; E37

# 1 Introduction

Dynamic stochastic general equilibrium (DSGE) models are currently the workhorse framework in macroeconomic analyses and forecasting. Their use is widespread in policy making institutions, and central banks in particular. One of the reasons for the popularity of DSGE models is that their forecasting performance has been found to be relatively good in comparison to standard time series models as well as expert judgment (see e.g. Smets and Wouters, 2003; Adolfson, Lindé, and Villani, 2007; Rubaszek and Skrzypczynski, 2008; Edge, Kiley, and Laforte, 2010; Kolasa, Rubaszek, and Skrzypczynski, 2012; Wieland and Wolters, 2012; Del Negro and Schorfheide, 2012).

A common practice in institutions using DSGE models for forecasting is to re-estimate them only occasionally rather than every time a new forecast is produced. The main reason, applying also to other econometric models, is that re-estimation complicates communication between the modelers and policy makers as the difference between consecutive forecasts is affected both by new data release and changes in parameter estimates. Infrequent re-estimation decreases the number of forecasting rounds during which this second source of the difference has to be taken into account. Also, the policy makers can get used to certain model properties, the response of the economy to a monetary shock for instance, hence do not want to see them change every time a new forecast is produced. Another argument supporting this practice, though its relevance is certainly diminishing due to increasing computing power of multi-core processors, is that the estimation process of large DSGE models can be very time consuming. Needless to say, if every change in model properties needs to be documented and communicated to the policy makers, frequent re-estimations eat up even more time and prevent modelers from getting involved in potentially more productive projects. The final argument is that, to our best knowledge, there are no clear guidelines in the literature on how frequently models should be re-estimated so that the accuracy of forecasts they generate is unaffected.

In contrast to real-life applications, most of the literature investigating performance of DSGE model-based forecasts is based on out-of-sample exercises where model parameters are updated quarterly. Only few studies re-estimate the model parameters at longer intervals, e.g. every four quarters (Adolfson, Lindé, and Villani, 2007; Smets and Wouters, 2007; Christoffel, Coenen, and Warne, 2010) or even only once, at the beginning of the evaluation sample (Giannone, Monti, and Reichlin, 2010). None of the above papers discuss how infrequent model re-estimation affects forecast accuracy. While it is possible that using most recent data does not necessarily improve forecasts obtained with econometric models (see e.g. Swamy and Schinasi, 1986), one can also be concerned that obsolete parameter estimates may have non-negligible costs in terms of the quality of predictions generated for some macroaggregates influencing the policy decisions.

To provide some guidelines for practitioners, in this study we ask the following question: how often should we update DSGE model parameters to obtain efficient predictions about the main macrovariables? To answer it, we take a canonical medium-sized New Keynesian model and compare how its quarterly real-time forecasts for the US economy vary with the interval between consecutive re-estimations. Our main results, based on three key macroeconomic variables (output, inflation and the interest rate), can be summarized as follows. We find that updating the model parameters only once a year does not lead to any significant deterioration in the accuracy of point forecasts. Even though there are some gains from increasing the frequency of re-estimation if one is interested in the quality of density forecasts, these gains are rather small. These general conclusions are robust to using looser priors in our benchmark model or augmenting it with financial frictions. Finally, much of the decrease in forecast precision that is observed when re-estimations become less frequent is because of shorter sample rather than due to data revisions.

The rest of this paper is organized as follows. Section two presents the benchmark model that we use in our investigation. Section three describes the settings of the forecasting contest. The main results and robustness checks are discussed in section four. The last section concludes.

# 2 Model

Our investigation is based on the canonical medium-sized New Keynesian framework of Smets and Wouters (2007). It features utility maximizing households, profit maximizing firms, a fiscal authority financing exogenous spending with lump sum taxes, and a central bank setting short term interest rates according to a Taylor-like rule. The model incorporates a number of real and nominal rigidities, including habits in consumption, investment adjustment costs, time-varying capacity utilization, as well as wage and price stickiness with indexation.

The exact specification we use differs from Smets and Wouters (2007) only in that we additionally allow for trend investment-specific technological progress. This modification is aimed to account for the deviation between the average growth rate of real investment and that of other GDP components.[1] A full list of log-linearized model equations can be found in the Appendix.

All estimations are done using Bayesian methods and seven standard quarterly macroeconomic variables for the US: output, consumption, investment, wages, hours worked, inflation and the interest rate. Full definitions and sources of the real-time data used are given in the Appendix. The prior assumptions are identical to those in Smets and Wouters (2007) and also listed in the Appendix. The posterior distributions are approximated using the Metropolis-Hastings algorithm with 250,000 replications, out of which we drop the first 50,000.

[1] Smets and Wouters (2007) deal with this discrepancy in long-run trends by defining real investment as nominal investment deflated with the GDP deflator. We cannot follow this path since there is no nominal investment series in our real-time database.

# 3 Forecasting contest

We compare the accuracy of forecasts generated by the DSGE model, the parameters of which are re-estimated according to the following five schemes:[2]

**update 1Q:** the model is re-estimated each quarter (baseline variant),

**update 2Q:** estimation is repeated when the data for the 2nd or 4th quarter are available,

**update 1Y:** the model is re-estimated when full-year data are available,

**update 2Y:** the model is re-estimated only in even years,

**fixed:** the parameters are estimated once, at the beginning of the forecast evaluation sample.

Our investigation proceeds in three steps. First, we collect quarterly real time data (RTD) describing the US economy in the period between 1966:1 and 2011:4. The data are taken from the Philadelphia Fed "Real-Time Data Set for Macroeconomists", which is described in more detail by Croushore and Stark (2001). The use of RTD enables us to control for both reasons that support frequent re-estimation, which we call *sample* and *vintage* effects. To be more precise, let $\theta_T^v$ be the vector of parameter estimates based on the sample $1:T$ from vintage date $v$. The difference between the current estimates and those done $q$ quarters ago using the data vintage available at that time can be decomposed into:

$$\theta_T^v - \theta_{T-q}^{v-q} = \underbrace{\left(\theta_T^v - \theta_{T-q}^{v}\right)}_{\text{sample effect}} + \underbrace{\left(\theta_{T-q}^v - \theta_{T-q}^{v-q}\right)}_{\text{vintage effect}}. \tag{1}$$

Hence, our main forecasting contest that uses RTD captures both sample and vintage effects. In the case in which we use the latest available data (LAD), the differences in

[2]In practice, some of re-estimations might be carried out in response to changes in model structure or data definitions rather than according to fixed schedule. Our alternative schemes do not account for such a possibility.

forecast accuracy between the five schemes is only due to the *sample effect*.

In the second step, for each moment of forecast formulation $t$ from the period 1989:4 - 2011:3, horizon $h$ and forecasting scheme $j$ we compute point forecasts - $y^f_{t+h}|t, j$ - as well as the predictive scores $p(y_{t+h}|t, j)$. More precisely, out of 200,000 posterior draws for parameter vector $\theta$ obtained with the Metropolis-Hastings algorithm, we select $N = 5,000$ equally spaced subdraws $\theta^{(n)}$ for $n = 1, 2, \ldots, N$. For each $\theta^{(n)}$ we calculate the first two moments of the predictive density $p(Y_{t+h}|t, j, \theta^{(n)})$, which has Gaussian distribution.[3] Subsequently, following Geweke and Amisano (2014), the point forecast is computed as the mean of the first moments:

$$y^f_{t+h}|t, j = \frac{1}{N} \sum_{n=1}^{N} E(Y_{t+h}|t, j, \theta_i^{(n)}), \tag{2}$$

whereas the predictive score is obtained as the average of the predictive densities evaluated at the realization $y_{t+h}$ of $Y_{t+h}$:

$$p(y_{t+h}|t, j) = \frac{1}{N} \sum_{n=1}^{N} p(y_{t+h}|t, j, \theta_i^{(n)}). \tag{3}$$

The forecasting scheme is recursive,[4] the evaluation sample spans from 1990:1 to 2011:4 and the maximum forecast horizon is twelve quarters. Thus, the first set of forecasts is generated for the period 1990:1-1992:4 with the model estimated on the sample spanning 1966:1-1989:4. The second set of forecasts is for the period 1990:2-1993:1 with the model estimated on the sample 1966:1-1990:1 (baseline scheme) or 1966:1-1989:4 (remaining schemes). The third set of forecasts is for the period 1990:3-1993:2 with the model estimated on the sample 1966:1-1990:2 (baseline and update 2Q) or 1966:1-1989:4 (re-

[3]For each parameter draw, the Kalman filter is used to obtain smooth estimates of unobservable model states given the data available at the time the forecast is formulated (RTD variant) or the latest available data (LAD variant).

[4]The results for the rolling forecasting scheme, which are available upon request, lead to broadly the same conclusions as those presented in Section 4.

maining schemes), etc. Since our dataset ends in 2011:4, the number of forecasts that we can use in evaluation ranges from 77 (for 12-quarter ahead forecasts) to 88 (for 1-quarter ahead forecasts).

In the third stage, we assess the quality of forecasts for the key three US macroeconomic time series: output, inflation and the interest rate. Given that the maximum forecast horizon is relatively long, the comparisons are for output and price levels rather than growth rates. The realizations, which we call *actuals*, are taken from the latest available vintage, i.e. the data released in 2012:1.

# 4 Results

In this section we report the relative accuracy of point and density forecasts, which is evaluated with the root mean squared forecast error (RMSFE) and the average log predictive scores (LPS), respectively.

## 4.1 Point forecasts

We begin our comparison by analyzing point forecasts. Table 1 reports the values for the RMSFEs, both using real-time and latest available data. As discussed above, the former case allows us to capture both *sample* and *vintage* effects, while the latter distills the *sample* effect. The numbers for the *update 1Q* scheme (our baseline) represent the values of the RMSFEs, while the remaining numbers are expressed as ratios so that values above (below) unity indicate that a given scheme underperforms (overperforms) the baseline. Moreover, to provide a rough gauge of whether the RMSFE ratios are significantly different from unity, we report the results of the Diebold-Mariano test.

The RTD results show that the accuracy of *update 2Q* and *update 1Y* schemes are not significantly different from the baseline. For the *update 2Y* variant the ratios for output, inflation and the interest rate tend to be above unity, and in many cases significantly so. This brings us to the first conclusion: the parameters of the canonical medium-sized DSGE model can be re-estimated once a year without a significant loss of point forecasts accuracy for the main macrovariables. However, less frequent re-estimation leads to a significant deterioration in the quality of predictions for these variables.

As regards the *fixed* scheme, the loss in forecast precision is very large. For instance, the RMSFEs for the interest rate go up by as much as 30% compared to the baseline. The ratios are even larger for output and the price level, exceeding 1.5 and 1.8 for the 3-year horizon. Hence, our second conclusion is that evaluating the forecasting performance of DSGE models without updating their parameters can give a distorted picture.

The comparison of the RTD and LAD results for the baseline scheme indicates that the use of RTD generates the RMSFEs for output and inflation that are about 10% higher than in the LAD case. For the remaining updating schemes, except for the *fixed* one, the RMSFE ratios are very similar. Since there is no *vintage* effect for LAD, our third finding is: conclusion one (re-estimate the model at least once a year) is driven mainly by the *sample* effect.

## 4.2 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. The quality of the density forecast is assessed with the average log predictive score statistic, which for $h$-step ahead forecasts from the $j$-th scheme is equal to the mean value of *log* of $p(y_{t+h}|t, j)$ computed with formula (3).

In Tables 2 and 3 we report the values of average LPS for each of the three key macroeconomic variables separately, and for their joint distribution, respectively. As before, we present the results for models estimated with RTD as well as with LAD. The numbers for the baseline represent the levels, whereas the remaining numbers are expressed as differences so that values below zero indicate that a given scheme underperforms the baseline. 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.

The RTD results for individual variables show that decreasing the frequency of model re-estimation leads to a deterioration in the quality of density forecasts. However, the decrease in the fit, although in some cases statistically significant, is not large for the *update 2Q* and *update 1Y* schemes: the average value of the predictive likelihood is up to 1.3% lower than for the baseline, depending on the variable and horizon. For the multivariate forecasts, which take into account the covariances, the differences in the average LPSs for the *upadete 1Y* scheme are somewhat higher, amounting up to 2.6%, and statistically significant. For the *update 2Y* and *fixed* schemes, the LPS differences are significantly negative for most variables and horizons. Moreover, their values indicate a sizeable decline in the average predictive likelihood, amounting in the *update 2Y* scheme to around 7% for the joint density of all three macrovariables. The loss under the *fixed* scheme is even larger, reaching 80% in the multivariate case. We interpret these results as confirming our conclusions formulated for point forecasts, i.e. that DSGE models should be re-estimated at least once a year. Moreover, they also show that there are some gains from re-estimating the model more frequently than once a year, especially if one is interested in the quality of multivariate density forecasts.

The comparison of the RTD and LAD results for the baseline scheme shows that the use of RTD decreases the accuracy of density forecasts for output and inflation, with the fall in the average LPSs ranging from 5 to 15%. The decline is most sizable for the short-term inflation forecasts. The comparison of the LPS differences for the remaining schemes indicates that they are broadly the same for the RTD and LAD cases. This confirms our earlier finding that the *sample* effect dominates the *vintage* effect.

## 4.3 Robustness checks

The results presented above suggest that the parameter estimates of our benchmark model are quite stable. At least to some extent, this may be due to the prior assumptions borrowed from the original Smets and Wouters (2007) model, which are sometimes considered to be rather tight. To check if this is the case, we repeat our calculations with looser priors. More specifically, we increase the standard deviations of prior distributions for all structural parameters by 50%, except for the degree of indexation and capacity utilization cost curvature, for which the standard deviations are raised by 33%.[5]

The results of this robustness check are presented in Table 4. They show that loosening the priors usually slightly improves the quality of short-term forecasts and quite sizeably decreases it for longer horizons. Looking at a comparison across alternative updating schemes, this variant suggests that re-estimations can be carried out every two years without significantly affecting the quality of point forecasts for output and inflation. As regards the density forecasts, the main conclusions are broadly the same as those formulated using our baseline results.

Our next check is motivated by the absence of a financial sector in the benchmark Smets and Wouters (2007) model, even though one might argue that risk premium shocks can capture, at least to some extent, disruptions in financial intermediation. This simplified description of financial markets may significantly affect the forecasting performance, especially during times of financial stress. We address this concern by augmenting the benchmark model with the financial accelerator mechanism in the spirit of Bernanke, Gertler, and Gilchrist (1999). The exact implementation of this extension follows Del Negro, Giannoni, and Schorfheide (2014) and uses corporate bond spreads as an additional observable variable. The details can be found in the Appendix.

Table 5 summarizes the results of this robustness check. In the short-run, the quality

[5]For these parameters, increasing the standard deviations of the prior (beta) distributions by 50% would result in bimodality.

of point forecasts for output and the interest rate improve. However, if we focus on longer horizons, the picture is reversed and the accuracy of predictions for prices clearly deteriorates across the board. Similar patterns emerge for density forecasts. These findings are in line with Del Negro and Schorfheide (2012) and Kolasa and Rubaszek (2015), who show that including financial frictions in the corporate sector usually generates less accurate forecasts, even though their quality improves during the Great Recession. As regards the frequency of re-estimation in this alternative specification, the results suggest to do it twice rather than once a year if the main focus is on point forecasts for output and prices. Otherwise, and especially if the quality of density forecasts is the main target, the results are consistent with our baseline conclusions.

Finally, one might be concerned that our recommended interval between consecutive model re-estimations might be driven by choosing the first quarter of the year in the 1Y and 2Y schemes as the time of parameter update, or by some special events occurring just before re-estimation in the 1Y schedule (and hence one year before that done according to the 2Y scheme). The additional checks (not reported but available upon request) prove that this is not the case and that our main conclusions are based on the intrinsic features of the alternative updating schemes.

# 5 Conclusions

The results of this study show that the common practice used by the policy making institutions to re-estimate DSGE models only occasionally is justified and does not lead to any sizable loss in forecast accuracy for the main macrovariables as long as the interval between consecutive re-estimations does not exceed one year. Such a frequency of updating the model parameters facilitates the communication between the modelers and policy makers and allows to save on model maintenance costs, without coming at the expense of forecast quality. The main source of deterioration in forecast precision when re-estimations become less frequent is related to new data arrival (*sample* effect) rather than data revisions (*vintage* effect). Finally, according to our results, while assessing the forecasting performance of DSGE models it might matter whether real-time or latest available data are used.

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# Tables

Table 1: Root Mean Squared Forecast Errors (RMSFE)

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ |
|---|---|---|---|---|---|---|
| | **Real time data results** | | | | | |
| | *Output* | | | | | |
| update 1Q | 0.66 | 1.17 | 2.02 | 2.61 | 3.08 | 4.14 |
| update 2Q | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.01* |
| update 1Y | 1.01 | 1.01 | 1.01 | 1.01 | 1.02 | 1.01 |
| update 2Y | 1.03 | 1.02 | 1.03* | 1.04** | 1.04*** | 1.04** |
| fixed | 1.01 | 0.99 | 1.14 | 1.35 | 1.51** | 1.55** |
| | *Prices* | | | | | |
| update 1Q | 0.26 | 0.47 | 0.87 | 1.30 | 1.77 | 2.77 |
| update 2Q | 1.00 | 0.99 | 0.99 | 0.99 | 1.00 | 1.01 |
| update 1Y | 1.00 | 0.99 | 0.99 | 1.00 | 1.00 | 1.02 |
| update 2Y | 1.00 | 1.00 | 1.01 | 1.02 | 1.04 | 1.07** |
| fixed | 1.01 | 1.10 | 1.38** | 1.61*** | 1.73*** | 1.81*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.12 | 0.22 | 0.38 | 0.46 | 0.52 | 0.57 |
| update 2Q | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.00* | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 |
| update 2Y | 1.02** | 1.03** | 1.02* | 1.01 | 1.01 | 0.98 |
| fixed | 1.27*** | 1.29*** | 1.30*** | 1.27*** | 1.22*** | 1.16*** |
| | **Latest available data results** | | | | | |
| | *Output* | | | | | |
| update 1Q | 0.61 | 1.07 | 1.92 | 2.50 | 2.88 | 3.65 |
| update 2Q | 1.01 | 1.01 | 1.01 | 1.00 | 1.01 | 1.01 |
| update 1Y | 1.01 | 1.02 | 1.01 | 1.01 | 1.02* | 1.01 |
| update 2Y | 1.03 | 1.03 | 1.03 | 1.03 | 1.04 | 1.03 |
| fixed | 1.13* | 1.11* | 1.02 | 0.97 | 0.94 | 0.92 |
| | *Prices* | | | | | |
| update 1Q | 0.21 | 0.39 | 0.77 | 1.20 | 1.72 | 2.85 |
| update 2Q | 1.01 | 1.01 | 1.01 | 1.00 | 0.99 | 0.99 |
| update 1Y | 1.02 | 1.03 | 1.02 | 1.02 | 1.02 | 1.03 |
| update 2Y | 1.03 | 1.05 | 1.05 | 1.04 | 1.04 | 1.05 |
| fixed | 1.06 | 1.10 | 1.20** | 1.31*** | 1.39*** | 1.48*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.12 | 0.23 | 0.39 | 0.48 | 0.54 | 0.59 |
| update 2Q | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.02* | 1.02 | 1.01 | 1.00 | 1.00 | 1.00 |
| update 2Y | 1.01 | 1.02 | 1.02 | 1.02 | 1.01 | 0.99 |
| fixed | 1.22** | 1.23** | 1.24*** | 1.26*** | 1.29*** | 1.35*** |

Notes: For the baseline (update 1Q) the RMSFEs are reported in levels, whereas for the remaining schemes they appear as the ratios so that the values above unity indicate that a given scheme has a higher RMSFE than the baseline. Asterisks ***, **and *denote the 1%, 5% and 10% significance levels of the Diebold-Mariano test, where the long-run variance is calculated with the Newey-West method.

Table 2: Average univariate Log Predictive Scores (LPS)

| | $H = 1$ | $H = 2$ | $H = 4$ | $H = 6$ | $H = 8$ | $H = 12$ |
|---|---|---|---|---|---|---|
| | **Real time data** | | | | | |
| | *Output* | | | | | |
| update 1Q | -1.121 | -1.660 | -2.197 | -2.461 | -2.628 | -2.895 |
| update 2Q | -0.004 | -0.002 | -0.003 | -0.003 | -0.004 | -0.008* |
| update 1Y | -0.010*** | -0.009 | -0.012* | -0.013* | -0.012 | -0.010 |
| update 2Y | -0.022*** | -0.023** | -0.032*** | -0.032*** | -0.030** | -0.026* |
| fixed | -0.123** | -0.099 | -0.132 | -0.231 | -0.323* | -0.422** |
| | *Prices* | | | | | |
| update 1Q | -0.144 | -0.797 | -1.506 | -1.933 | -2.232 | -2.635 |
| update 2Q | 0.000 | 0.002 | 0.002 | 0.001 | 0.000 | -0.004* |
| update 1Y | -0.002 | 0.000 | -0.001 | -0.001 | -0.003 | -0.008 |
| update 2Y | -0.008* | -0.005 | -0.008 | -0.012* | -0.016** | -0.029*** |
| fixed | -0.134*** | -0.204*** | -0.297*** | -0.355*** | -0.392*** | -0.439*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.324 | -0.128 | -0.549 | -0.738 | -0.841 | -0.941 |
| update 2Q | -0.004** | -0.004** | -0.003 | -0.003 | -0.002 | 0.001 |
| update 1Y | -0.008*** | -0.009*** | -0.009*** | -0.006 | -0.003 | 0.003 |
| update 2Y | -0.019*** | -0.023*** | -0.024*** | -0.021** | -0.018 | 0.006 |
| fixed | -0.175*** | -0.202*** | -0.211*** | -0.194*** | -0.162*** | -0.108*** |
| | **Latest available data** | | | | | |
| | *Output* | | | | | |
| update 1Q | -1.082 | -1.599 | -2.148 | -2.420 | -2.574 | -2.799 |
| update 2Q | -0.005 | -0.007 | -0.006 | -0.003 | -0.004 | -0.004 |
| update 1Y | -0.010* | -0.013 | -0.012 | -0.012* | -0.015** | -0.011* |
| update 2Y | -0.020* | -0.024 | -0.028* | -0.030** | -0.035** | -0.028** |
| fixed | -0.139*** | -0.124*** | -0.076 | -0.055 | -0.057 | -0.042 |
| | *Prices* | | | | | |
| update 1Q | 0.013 | -0.673 | -1.431 | -1.883 | -2.202 | -2.633 |
| update 2Q | -0.004 | -0.004 | -0.002 | -0.001 | 0.000 | 0.000 |
| update 1Y | -0.009 | -0.010 | -0.010 | -0.009 | -0.010 | -0.014 |
| update 2Y | -0.016 | -0.020* | -0.023** | -0.023** | -0.023** | -0.028** |
| fixed | -0.093*** | -0.141*** | -0.194*** | -0.233*** | -0.263*** | -0.318*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.334 | -0.122 | -0.551 | -0.742 | -0.843 | -0.933 |
| update 2Q | -0.004* | -0.004 | -0.003 | -0.001 | 0.000 | 0.002 |
| update 1Y | -0.012*** | -0.014** | -0.009 | -0.003 | -0.001 | 0.001 |
| update 2Y | -0.015*** | -0.019*** | -0.021** | -0.020 | -0.018 | 0.004 |
| fixed | -0.162*** | -0.172*** | -0.183*** | -0.204*** | -0.229*** | -0.268*** |

Notes: For the baseline (update 1Q) LPSs are reported in levels, whereas for the remaining schemes they appear as the differences so that the values below zero indicate that a given scheme has a lower LPS than the baseline. Asterisks ***, **and *denote the 1%, 5% and 10% significance levels for the Amisano and Giacomini (2007) test, where the long-run variance is calculated with the Newey-West method.

Table 3: Average multivariate Log Predictive Scores (LPS) for output, prices and iterest rate

| | $H = 1$ | $H = 2$ | $H = 4$ | $H = 6$ | $H = 8$ | $H = 12$ |
|---|---|---|---|---|---|---|
| | **Real time data** | | | | | |
| update 1Q | -0.889 | -2.503 | -4.108 | -4.960 | -5.507 | -6.246 |
| update 2Q | -0.007* | -0.004 | -0.006 | -0.007 | -0.010* | -0.014** |
| update 1Y | -0.020*** | -0.018** | -0.025*** | -0.026** | -0.025** | -0.015 |
| update 2Y | -0.050*** | -0.052*** | -0.070*** | -0.073*** | -0.068*** | -0.044* |
| fixed | -0.393*** | -0.432*** | -0.531*** | -0.642*** | -0.726*** | -0.800*** |
| | **Latest available data** | | | | | |
| update 1Q | -0.679 | -2.300 | -3.962 | -4.847 | -5.404 | -6.122 |
| update 2Q | -0.012* | -0.014* | -0.011 | -0.007 | -0.007 | -0.006 |
| update 1Y | -0.027** | -0.031** | -0.027** | -0.024* | -0.027** | -0.022 |
| update 2Y | -0.047*** | -0.057*** | -0.064*** | -0.068** | -0.071** | -0.045* |
| fixed | -0.370*** | -0.390*** | -0.366*** | -0.353*** | -0.362*** | -0.392*** |

Notes: See notes to Table 2.

Table 4: Relative forecast accuracy of model with loose priors

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ |
|---|---|---|---|---|---|---|
| | **Root Mean Squared Forecast Errors** | | | | | |
| | *Output* | | | | | |
| update 1Q | 0.64 | 1.12 | 1.95 | 2.59 | 3.21 | 4.65 |
| update 2Q | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.01 | 1.00 | 1.01 | 1.01 | 1.00 | 1.00 |
| update 2Y | 1.01 | 1.00 | 1.01 | 1.02* | 1.02 | 1.02 |
| fixed | 1.06 | 1.04 | 1.15 | 1.31 | 1.39* | 1.34** |
| | *Prices* | | | | | |
| update 1Q | 0.25 | 0.46 | 0.91 | 1.45 | 2.07 | 3.43 |
| update 2Q | 1.00 | 1.00* | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.00 | 1.00 | 1.00 | 0.99 | 0.99 | 0.99 |
| update 2Y | 1.00 | 1.00 | 1.00 | 1.01 | 1.01 | 1.02 |
| fixed | 1.09 | 1.26** | 1.56*** | 1.71*** | 1.74*** | 1.71*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.11 | 0.21 | 0.36 | 0.46 | 0.52 | 0.60 |
| update 2Q | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.01** | 1.01* | 1.01* | 1.01* | 1.01 | 1.00 |
| update 2Y | 1.02* | 1.02** | 1.02** | 1.02* | 1.01 | 1.00 |
| fixed | 1.41*** | 1.45*** | 1.43*** | 1.37*** | 1.30*** | 1.21*** |
| | **Average Log Predictive Scores** | | | | | |
| | *Output* | | | | | |
| update 1Q | -1.098 | -1.636 | -2.172 | -2.454 | -2.652 | -2.979 |
| update 2Q | -0.003 | -0.001 | -0.002 | -0.003 | -0.003 | -0.005 |
| update 1Y | -0.008*** | -0.007** | -0.007 | -0.006 | -0.005 | -0.002 |
| update 2Y | -0.013*** | -0.013** | -0.018*** | -0.023** | -0.023* | -0.024* |
| fixed | -0.139*** | -0.120 | -0.147 | -0.218 | -0.267** | -0.287** |
| | *Prices* | | | | | |
| update 1Q | -0.112 | -0.755 | -1.474 | -1.930 | -2.265 | -2.731 |
| update 2Q | 0.000 | 0.002 | 0.001 | 0.002 | 0.002 | 0.001 |
| update 1Y | -0.003 | 0.000 | 0.000 | 0.001 | 0.003 | 0.004 |
| update 2Y | -0.007 | -0.002 | -0.003 | -0.004 | -0.003 | -0.006 |
| fixed | -0.184*** | -0.279*** | -0.391*** | -0.447*** | -0.471*** | -0.493*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.345 | -0.107 | -0.529 | -0.724 | -0.840 | -0.972 |
| update 2Q | -0.004** | -0.005** | -0.004 | -0.003 | -0.002 | 0.002 |
| update 1Y | -0.011*** | -0.012*** | -0.012*** | -0.011*** | -0.008* | 0.001 |
| update 2Y | -0.018*** | -0.018*** | -0.018*** | -0.018*** | -0.016** | -0.003 |
| fixed | -0.216*** | -0.254*** | -0.270*** | -0.251*** | -0.211*** | -0.136*** |
| | *3 variables* | | | | | |
| update 1Q | -0.810 | -2.404 | -3.990 | -4.854 | -5.435 | -6.256 |
| update 2Q | -0.008* | -0.004 | -0.003 | -0.004 | -0.006 | -0.005 |
| update 1Y | -0.020*** | -0.014** | -0.012* | -0.012 | -0.010 | -0.004 |
| update 2Y | -0.035*** | -0.027*** | -0.027** | -0.031** | -0.032* | -0.035* |
| fixed | -0.483*** | -0.559*** | -0.680*** | -0.767*** | -0.805*** | -0.787*** |

Notes: See notes to Tables 1 and 2.

Table 5: Relative forecast accuracy of model with financial frictions

| | $H=1$ | $H=2$ | $H=4$ | $H=6$ | $H=8$ | $H=12$ |
|---|---|---|---|---|---|---|
| | **Root Mean Squared Forecast Errors** | | | | | |
| | *Output* | | | | | |
| update 1Q | 0.61 | 1.07 | 1.97 | 2.76 | 3.51 | 4.93 |
| update 2Q | 1.01 | 1.00 | 1.01 | 1.01 | 1.01 | 1.01* |
| update 1Y | 1.02** | 1.01** | 1.02*** | 1.03*** | 1.02** | 1.02** |
| update 2Y | 1.02** | 1.02** | 1.03*** | 1.03*** | 1.03** | 1.03** |
| fixed | 1.22* | 1.36* | 1.47** | 1.54** | 1.57** | 1.57*** |
| | *Prices* | | | | | |
| update 1Q | 0.26 | 0.52 | 1.20 | 2.12 | 3.25 | 5.86 |
| update 2Q | 1.00 | 1.00 | 1.01 | 1.01 | 1.01 | 1.02 |
| update 1Y | 1.01* | 1.02* | 1.03* | 1.04* | 1.05** | 1.05** |
| update 2Y | 1.04*** | 1.06*** | 1.10*** | 1.11*** | 1.11*** | 1.10*** |
| fixed | 1.21** | 1.48*** | 1.91*** | 2.15*** | 2.28*** | 2.43*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.11 | 0.20 | 0.37 | 0.52 | 0.65 | 0.83 |
| update 2Q | 1.00** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| update 1Y | 1.00 | 1.00 | 1.01 | 1.02* | 1.02* | 1.02* |
| update 2Y | 1.01 | 1.02 | 1.02 | 1.02 | 1.02 | 1.03** |
| fixed | 1.32*** | 1.42*** | 1.58*** | 1.71*** | 1.81*** | 1.96*** |
| | **Log Predictive Scores** | | | | | |
| | *Output* | | | | | |
| update 1Q | -1.071 | -1.587 | -2.139 | -2.457 | -2.682 | -3.022 |
| update 2Q | -0.004 | -0.001 | -0.006* | -0.006 | -0.006 | -0.012* |
| update 1Y | -0.009*** | -0.010*** | -0.020*** | -0.021*** | -0.018** | -0.021* |
| update 2Y | -0.015*** | -0.015*** | -0.025*** | -0.022** | -0.016 | -0.023 |
| fixed | -0.138** | -0.203** | -0.308* | -0.425** | -0.557** | -0.877*** |
| | *Prices* | | | | | |
| update 1Q | -0.157 | -0.891 | -1.699 | -2.210 | -2.591 | -3.133 |
| update 2Q | -0.004 | -0.003 | -0.005 | -0.006 | -0.006 | -0.007 |
| update 1Y | -0.022* | -0.025* | -0.030** | -0.032** | -0.031** | -0.031** |
| update 2Y | -0.079** | -0.100** | -0.108** | -0.096*** | -0.090*** | -0.076*** |
| fixed | -0.335*** | -0.446*** | -0.613*** | -0.723*** | -0.801*** | -0.921*** |
| | *Interest rate* | | | | | |
| update 1Q | 0.316 | -0.127 | -0.586 | -0.852 | -1.037 | -1.271 |
| update 2Q | -0.002*** | -0.002*** | -0.002* | -0.002 | -0.001 | -0.002 |
| update 1Y | -0.006*** | -0.007*** | -0.010** | -0.009 | -0.008 | -0.009 |
| update 2Y | -0.018*** | -0.021*** | -0.021** | -0.017** | -0.016** | -0.024* |
| fixed | -0.240*** | -0.296*** | -0.380*** | -0.452*** | -0.518*** | -0.627*** |
| | *3 variables* | | | | | |
| update 1Q | -0.902 | -2.633 | -4.388 | -5.346 | -5.989 | -6.897 |
| update 2Q | -0.009 | -0.005 | -0.017 | -0.019* | -0.019* | -0.026* |
| update 1Y | -0.033** | -0.030* | -0.046* | -0.054** | -0.056** | -0.059** |
| update 2Y | -0.095*** | -0.090* | -0.117* | -0.115** | -0.114** | -0.126*** |
| fixed | -0.548*** | -0.634*** | -0.835*** | -1.062*** | -1.313*** | -1.899*** |

Notes: See notes to Tables 1 and 2.

# Appendix

## A List of model equations

This section lays out the full system of log-linearized equations that make up the DSGE model analyzed in the main text. The specification is the same as used by Smets and Wouters (2007). The only difference concerns trend investment specific technological progress, which we include to account for a secular trend in the real investment to output ratio observed in the data.

This modification means that for the model to have a well defined steady state, the trending real variables need to be normalized both with neutral ($\gamma$) and investment specific ($\gamma_i$) technological progress (see e.g. Greenwood, Herzowitz and Krussel, 1997). In particular, if we define $\gamma_y = \gamma\gamma_i^{\frac{\alpha}{1-\alpha}}$, the stationarization is as follows: $y_t = Y_t/\gamma_y^t$, $y_t^p = Y_t^p/\gamma_y^t$, $c_t = C_t/\gamma_y^t$, $i_t = I_t/(\gamma_y\gamma_i)^t$, $k_t = K_t/(\gamma_y\gamma_i)^t$, $k_t^s = K_t^s/(\gamma_y\gamma_i)^t$, $w_t = W_t/(P_t\gamma_y^t)$, $r_t^k = R_t^k\gamma_i^t/P_t$ and $q_t = Q_t\gamma_i^t$, where $Y_t$ is output, $Y_t^p$ is potential output, $C_t$ is consumption, $I_t$ is investment, $K_t$ is capital, $K_t^s$ is capital services, $W_t$ is nominal wage, $R_t^k$ is the nominal rental rate on capital, $Q_t$ is the real price of capital and $P_t$ is the price level. As regards the remaining endogenous variables showing up in the equations below, $l_t$ stands for labor, $r_t$ is the nominal interest rate, $\pi_t$ is inflation, $\mu_t^p$ is price markup, $\mu_t^w$ is wage markup and $z_t$ is capital utilization.

The model is driven by seven stochastic disturbances: total factor productivity $\varepsilon_t^a$, investment specific technology $\varepsilon_t^i$, risk premium $\varepsilon_t^b$, exogenous spending $\varepsilon_t^g$, price markup $\varepsilon_t^p$, wage markup $\varepsilon_t^w$, and monetary policy $\varepsilon_t^r$. The two markup shocks are assumed to follow ARMA(1,1) processes. All remaining disturbances are modeled as first-order autoregressions, except that the government spending shock additionally depends on the current innovation to total factor productivity. All variables presented in the equations below are expressed as log deviations from the non-stochastic steady state. The parameters are defined in section D. Stars in subscripts indicate the steady state values, which are functions of deep model parameters.

Aggregate resource constraint

$$y_t = (1 - (\gamma_y\gamma_i - 1 + \delta)k_*y_*^{-1} - g_y)c_t + (\gamma_y\gamma_i - 1 + \delta)k_y i_t + r_*^k k_* y_*^{-1} z_t + g_y\varepsilon_t^g \tag{A.1}$$

Consumption Euler equation

$$c_t = \frac{\lambda}{\lambda+\gamma_y}c_{t-1} + \frac{\gamma_y}{\lambda+\gamma_y}E_t c_{t+1} + \frac{\gamma_y(\sigma_c-1)\frac{w_* l_*}{c_*}}{\sigma_c(\gamma_y+\lambda)(1+\lambda_w)}(l_t - E_t l_{t+1})$$
$$- \frac{\gamma_y-\lambda}{\sigma_c(\gamma_y+\lambda)}(r_t - E_t\pi_{t+1}) + \varepsilon_t^b \tag{A.2}$$

Investment Euler equation

$$i_t = \frac{1}{1+\beta\gamma_y^{1-\sigma_c}}i_{t-1} + \frac{\beta\gamma_y^{1-\sigma_c}}{1+\beta\gamma_y^{1-\sigma_c}}E_t i_{t+1} + \frac{1}{(1+\beta\gamma_y^{1-\sigma_c})\gamma_y^2\gamma_i^2\varphi}q_t + \varepsilon_t^i \tag{A.3}$$

Value of capital

$$q_t = \frac{\beta(1-\delta)}{\gamma_y^{\sigma_c}\gamma_i}E_t q_{t+1} + \frac{\gamma_y^{\sigma_c}\gamma_i - \beta(1-\delta)}{\gamma_y^{\sigma_c}\gamma_i}E_t r_{t+1}^k - (r_t - E_t\pi_{t+1}) + \frac{\sigma_c(\gamma_y+\lambda)}{\gamma_y-\lambda}\varepsilon_t^b \tag{A.4}$$

Aggregate production function

$$y_t = \phi_p(\alpha k_t^s + (1-\alpha)l_t + \varepsilon_t^a) \tag{A.5}$$

Capital services

$$k_t^s = k_{t-1} + z_t \tag{A.6}$$

Optimal capacity utilization

$$z_t = \frac{1-\psi}{\psi}r_t^k \tag{A.7}$$

Capital accumulation

$$k_t = \frac{1-\delta}{\gamma_y\gamma_i}k_{t-1} + \frac{\gamma_y\gamma_i - 1 + \delta}{\gamma_y\gamma_i}i_t + (\gamma_y\gamma_i - 1 + \delta)(1+\beta\gamma_y^{1-\sigma_c})\gamma_y\gamma_i\varphi\varepsilon_t^i \tag{A.8}$$

Price markup

$$\mu_t^p = \alpha(k_t^s - l_t) + \varepsilon_t^a - w_t \tag{A.9}$$

Phillips curve

$$\pi_t = \frac{\iota_p}{1+\beta\gamma_y^{1-\sigma_c}\iota_p}\pi_{t-1} + \frac{\beta\gamma_y^{1-\sigma_c}}{1+\beta\gamma_y^{1-\sigma_c}\iota_p}E_t\pi_{t+1}$$
$$- \frac{(1-\beta\gamma_y^{1-\sigma_c}\xi_p)(1-\xi_p)}{(1+\beta\gamma_y^{1-\sigma_c}\iota_p)\xi_p((\phi_p-1)\varepsilon_p+1)}\mu_t^p + \varepsilon_t^p \tag{A.10}$$

Input cost minimization

$$r_t^k = -(k_t - l_t) + w_t \tag{A.11}$$

Wage markup

$$\mu_t^w = w_t - (\sigma_l l_t + \frac{1}{\gamma_y - \lambda}(\gamma_y c_t - \lambda c_{t-1})) \tag{A.12}$$

Real wage dynamics

$$\begin{aligned} w_t = & \frac{1}{1+\beta\gamma_y^{1-\sigma_c}} w_{t-1} + \frac{\beta\gamma_y^{1-\sigma_c}}{1+\beta\gamma_y^{1-\sigma_c}}(E_t w_{t+1} - E_t \pi_{t+1}) - \frac{1+\beta\gamma_y^{1-\sigma_c}\iota_w}{1+\beta\gamma_y^{1-\sigma_c}}\pi_t \\ & + \frac{\iota_w}{1+\beta\gamma_y^{1-\sigma_c}}\pi_{t-1} - \frac{(1-\beta\gamma_y^{1-\sigma_c}\xi_w)(1-\xi_w)}{(1+\beta\gamma_y^{1-\sigma_c})\xi_w((\phi_w - 1)\varepsilon_w + 1)}\mu_t^w + \varepsilon_t^w \end{aligned} \tag{A.13}$$

Taylor rule

$$r_t = \rho r_{t-1} + (1-\rho)[r_\pi \pi_t + r_y(y_t - y_t^p)] + r_{\Delta y}(\Delta y_t - \Delta y_t^p) + \varepsilon_t^r \tag{A.14}$$

# B Data

The source of all data used to estimate the model is the "Real-Time Data Set for Macroeconomists" (RTDSM) database maintained by the Federal Reserve Bank of Philadelphia. The only exception is the short-term interes rate, which is not subject to revisions and taken from the Federal Reserve Board statistics. The exact definitions follow below (RTDSM codes in parentheses).

**Ouptut:** Real gross domestic product (ROUTPUT) divided by civilian noninstitutional population (POP).

**Consumption:** Real personal consumption expenditures (RCON) divided by civilian noninstitutional population (POP).

**Investment:** Real gross private domestic nonresidential investment (RINVBF) divided by civilian noninstitutional population (POP).

**Hours:** Aggregate weekly hours (H) divided by civilian noninstitutional population (POP), normalized to average one over the estimation sample.

**Wages:** Nominal wage and salary disbursements (WSD) divided by civilian noninstitutional population (POP) and deflated by the price index for gross domestic product (P).

**Price level:** Price index for gross domestic product (P).

**Interest rate:** Federal funds rate.

# C Measurement equations

The following equations relate the model variables to their empirical conterparts defined in section B:

$$\Delta \log Output_t = \gamma_y - 1 + y_t - y_{t-1} \tag{C.1}$$

$$\Delta \log Consumption_t = \gamma_y - 1 + c_t - c_{t-1} \tag{C.2}$$

$$\Delta \log Investment_t = \gamma_y \gamma_i - 1 + i_t - i_{t-1} \tag{C.3}$$

$$\log Hours_t = \bar{l} + l_t \tag{C.4}$$

$$\Delta \log Wages_t = \gamma_y - 1 + w_t - w_{t-1} \tag{C.5}$$

$$\Delta \log PriceLevel_t = \bar{\pi} + \pi_t \tag{C.6}$$

$$InterestRrate_t = \beta^{-1} \gamma_y^{\sigma_c} (1 + \bar{\pi}) - 1 + r_t \tag{C.7}$$

# D Calibration and prior assumptions

The calibrated parameters are reported in Table D.1, while Tables D.2 and D.3 describe the prior assumptions used in Bayesian estimation.

Table D.1: Calibrated parameters

| Parameter | Value | Description |
|---|---|---|
| $\delta$ | 0.025 | Depreciation rate |
| $g_y$ | 0.18 | Exogenous spending share in output |
| $\lambda_w$ | 1.5 | Steady-state wage markup |
| $\varepsilon_p$ | 10 | Kimball aggregator curvature in the goods market |
| $\varepsilon_w$ | 10 | Kimball aggregator curvature in the labor market |

Table D.2: Prior assumptions - structural parameters

| Parameter | Type | Mean | Std. | Description |
|---|---|---|---|---|
| $\varphi$ | normal | 4 | 1.5 | Investment adjustment cost curvature |
| $\sigma_c$ | normal | 1.5 | 0.37 | Inv. elasticity of intertemporal substitution |
| $h$ | beta | 0.7 | 0.1 | Habit persistance |
| $\xi_w$ | beta | 0.5 | 0.1 | Calvo probability for wages |
| $\sigma_l$ | normal | 2 | 0.75 | Inv. Frisch elasticity of labor supply |
| $\xi_p$ | beta | 0.5 | 0.1 | Calvo probability for prices |
| $\iota_w$ | beta | 0.5 | 0.15 | Wage indexation |
| $\iota_p$ | beta | 0.5 | 0.15 | Price indexation |
| $\psi$ | beta | 0.5 | 0.15 | Capacity utilization cost curvature |
| $\phi$ | normal | 1.25 | 0.12 | Steady-state price markup |
| $r_\pi$ | normal | 1.5 | 0.25 | Weight on inflation in Taylor rule |
| $\rho$ | beta | 0.75 | 0.1 | Interest rate smoothing |
| $r_y$ | normal | 0.12 | 0.05 | Weight on output gap in Taylor rule |
| $r_{\Delta y}$ | normal | 0.12 | 0.05 | Weight on output gap change in Taylor rule |
| $\bar{\pi}$ | gamma | 0.62 | 0.1 | Steady-state inflation rate |
| $100(\beta^{-1} - 1)$ | gamma | 0.25 | 0.1 | Rate of time preference |
| $\bar{l}$ | normal | 0 | 2 | Steady-state hours worked |
| $100(\gamma_y - 1)$ | normal | 0.4 | 0.1 | Trend growth of output |
| $100(\gamma_i - 1)$ | normal | 0.3 | 0.1 | Trend growth of relative price of investment |
| $\alpha$ | normal | 0.3 | 0.05 | Capital share |

Table D.3: Prior assumptions - shocks

| Parameter | Type | Mean | Std. | Description |
|---|---|---|---|---|
| $\sigma_a$ | inv. gamma | 0.1 | 2 | Volatility of productivity shock |
| $\sigma_b$ | inv. gamma | 0.1 | 2 | Volatility of risk premium shock |
| $\sigma_g$ | inv. gamma | 0.1 | 2 | Volatility of exogenous spending shock |
| $\sigma_i$ | inv. gamma | 0.1 | 2 | Volatility of investment specific shock |
| $\sigma_r$ | inv. gamma | 0.1 | 2 | Volatility of monetary policy shock |
| $\sigma_p$ | inv. gamma | 0.1 | 2 | Volatility of price markup shock |
| $\sigma_w$ | inv. gamma | 0.1 | 2 | Volatility of wage markup shock |
| $\rho_a$ | beta | 0.5 | 0.2 | Persistence of productivity shock |
| $\rho_b$ | beta | 0.5 | 0.2 | Persistence of risk premium shock |
| $\rho_g$ | beta | 0.5 | 0.2 | Persistence of exogenous spending shock |
| $\rho_i$ | beta | 0.5 | 0.2 | Persistence of investment specific shock |
| $\rho_r$ | beta | 0.5 | 0.2 | Persistence of monetary policy shock |
| $\rho_p$ | beta | 0.5 | 0.2 | Persistence of price markup shock |
| $\rho_w$ | beta | 0.5 | 0.2 | Persistence of wage markup shock |
| $\mu_p$ | beta | 0.5 | 0.2 | Moving average term in price markup |
| $\mu_w$ | beta | 0.5 | 0.2 | Moving average term in wage markup |
| $\rho_{ga}$ | beta | 0.5 | 0.2 | Impact of productivity on exogenous spending |

# E Introducing financial frictions

As one of the robustness checks considered in the paper, we augment the benchmark Smets and Wouters (2007) model with financial frictions as in Bernanke, Gertler, and Gilchrist (1999). They introduce an additional type of agents, called entrepreneurs, who manage capital, finance their operations by borrowing from banks owned by households, and are subject to idiosyncratic risk that can be observed by lenders only at a cost. This contracting friction results in an endogenous and time-varying wedge between the rate of return on capital and the risk-free rate.

Our exact specification follows Del Negro, Giannoni, and Schorfheide (2014) and is implemented by replacing the value of capital equation (A.4) with

$$E_t\left\{r^e_{t+1} - r_t\right\} = \zeta_{pr,b}(q_t + k_t - n_t) - \frac{\sigma_c(\gamma_y + \lambda)}{\gamma_y - \lambda}\varepsilon^b_t + \varepsilon_{\sigma,t} \tag{E.1}$$

where $\varepsilon_{\sigma,t}$ is a shock to the standard deviation of idiosyncratic risk faced by entrepreneurs, $r^e_t$ is the rate of return on capital defined as

$$r^e_t = \frac{r^k_*}{r^k_* + 1 - \delta} r^k_t + \frac{1-\delta}{r^k_* + 1 - \delta} q_t - q_{t-1} + \pi_t \tag{E.2}$$

and the law of motion for entrepreneurs' net worth $n_t$ can be written as

$$n_t = \zeta_{n,r^e}(r^e_t - \pi_t) - \zeta_{n,r}(r_{t-1} - \pi_t) + \zeta_{n,qk}(q_{t-1} + k_{t-1}) + \zeta_{n,n} n_{t-1} - \frac{\zeta_{n,\sigma_\omega}}{\zeta_{pr,\sigma_\omega}} \varepsilon_{\sigma,t-1} \quad \text{(E.3)}$$

The family of parameters $\zeta$ showing up in the new equations depend on the deep parameters of the augmented model, including the following four describing the financial frictions block: the survival rate of entrepreneurs $\nu$, steady-state standard deviation of idiosyncratic productivity, monitoring costs and transfers from households to entrepreneurs. Conditional on other model parameters, the last three of the four new parameters can be uniquely pinned down by the debt elasticity of the external finance premium $\zeta_{pr,b}$ and two steady-state proportions, i.e. the quarterly bankruptcy rate $F_*$ and the premium $r^e_* - r_*$.[6] As in Del Negro, Giannoni, and Schorfheide (2014), we fix $F_*$ at 0.008, $\nu$ at 0.99, and estimate $\zeta_{pr,b}$, $r^e_* - r_*$, as well as the standard deviation and autocorrelation of $\varepsilon_{\sigma,t}$. Our prior assumptions are summarized in Table E.4. They are taken from Del Negro, Giannoni, and Schorfheide (2014), except for the risk shock characteristics which we parametrize identically to other AR(1) shocks in the benchmark model.

Table E.4: Prior assumptions - financial frictions block

| Parameter | Type | Mean | Std. | Description |
|---|---|---|---|---|
| $r^e_* - r_*$ | gamma | 0.5 | 0.025 | Steady-state external finance premium |
| $\zeta_{pr,b}$ | beta | 0.05 | 0.005 | Premium elasticity wrt. debt |
| $\sigma_\sigma$ | inv. gamma | 0.1 | 2 | Volatility of risk shock |
| $\rho_\sigma$ | beta | 0.5 | 0.2 | Persistence of risk shock |

Finally, while estimating the augmented model we additionally use the time series on credit spreads, defined as the difference between the Moody's seasoned Baa corporate bond yields and the 10-year treasury note yields (source: Federal Reserve Board statistics), and linked to the model concept of the external finance premium via the following measurement equation

$$Spread_t = r^e_* - r_* + E_t\left\{r^e_{t+1} - r_t\right\} \quad \text{(E.4)}$$

[6] See technical appendix to Del Negro and Schorfheide (2012) for derivations.

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