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The Forecasting Performance of an Estimated Medium Run Model

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Tobias Kitlinski and Torsten Schmidt[1]

The Forecasting Performance of an Estimated Medium Run Model

Abstract

In recent times DSGE models came more and more into the focus of forecasters and showed promising forecast performances for the short term. We contribute to the existing literature by analyzing the forecast power of a DSGE model including endogenous growth for the medium run. Instead of only calibrating the model we apply a mixture of calibrating and estimating using Bayesian estimation methods. As forecasting benchmarks we take the Smets-Wouters model (2007) and a VAR model. The evaluation of the forecast errors shows that the Medium-Term model outperforms the Smets-Wouters model with respect to some key macroeconomic variables in the medium run. Compared to the VAR model the Medium-Term model forecast performance is competitive. These results show that the forecast ability of DSGE models is also valid for the medium term.

JEL Classification: C32, C52, E32, E37

Keywords: Bayesian analysis; DSGE model; medium run; forecasting

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1 All RWI. – We thank Christoph M. Schmidt and participants of the Scottish Economic Society's Annual Conference 2011 for valuable comments. – All correspondence to Tobias Kitlinski, RWI, Hohenzollernstr. 1–3, 45128 Essen, Germany. E-mail: tobias.kitlinski@rwi-essen.de.

1. Introduction

Dynamic stochastic general equilibrium (DSGE) models have run through a continuous development process and different research interests. But using DSGE models as a tool for forecasting was not an issue in academic research for a long time, because the models were viewed as too minimalistic and the missing link to data seemed to be a major obstacle. This gap started to close with the work of Smets and Wouters (2004), who demonstrated the good forecast ability of DSGE models. Yet, our knowledge about the prediction power of DSGE models beyond a forecast horizon of eight quarters is still limited. In a highly respected paper Smets and Wouters (2007) found that the forecasting performance of their model – which is often seen as the benchmark New Keynesian DSGE model – is able to outperform that of a vector autoregressive (VAR) model using data for the US with respect to all variables they used for estimation. Rubaszek and Skrzypczynsi (2008), using real-time data, confirm these results with respect to GDP but find larger forecast errors for inflation and the short term interest rate compared to other methods. The favorable forecasting performance of DSGE models is also documented for other countries and the Euro Area. Lees et al. (2010) compares DSGE model forecasts with other methods for New Zealand. Their results also show that the DSGE model forecasts are not significantly different from the published forecasts of the Reserve Bank of New Zealand. Both are inferior to a Bayesian VAR model, though. Dib et al. (2006) use a DSGE model to forecast Canadian time series. Adolfson et al. (2007) document a favorable forecasting performance of a DSGE model for the Euro Area. However, none of the mentioned studies analyzed a forecast horizon longer than eight quarters.

Therefore, we want to extend the existing literature of short-term forecast models by analyzing the forecasting performance of a DSGE model explicitly built for the medium-term. Medium-term economic forecasting has become common practice in government agencies as well as international organizations. For example, economists' forecasts seem to be consistent with medium-term projections of the growth rate of money supply and the inflation rate as described in Pierdzioch et al. (2011). In contrast, only scant attention is spent by academics to this topic compared with the remarkable number of methods for business cycle forecasting. One possible reason is that on the basis of the usual distinction between business cycles and economic growth it is straight forward to see the medium-term as a part of the business cycle. It is therefore not surprising that medium-term forecasts are in most cases an extension of the short-term projections performed with the same methods. For example, a common approach is to predict the evolution of potential output and assume that the output gap is closed at the end of the medium-term. The concrete transition path from the actual level of GDP to its potential level is then predicted using a structural econometric business cycle model.

In economic theory the medium-term is the transition phase from business cycle fluctuation to economic growth. In an empirical framework such a medium-term cycle can be identified as follows. First, we remove a long term trend from the data to construct a series for medium-term business cycles based on frequencies between 2 and 200 quarters. Next, we split the medium-term cycle into two frequencies: one component including frequencies between 2 and 32 quarters (high frequency component) and one component, consisting of the frequencies between 32 and 200 quarters (medium-term component). Figure 1 presents a medium-term cycle in this sense.[1] It is therefore likely that factors which are important for economic growth affect medium-term developments. Some empirical results point in this direction. Batista and Zalduendo (2004) compared forecasts based on growth equations including variables like openness and fertility rates with the official medium-term projections of the IMF. They find that forecasts based on growth equations have, on average, a 20 percent lower RMSE than the official IMF projections. In addition, Lindh (2004) found evidence that information about the population age structure contains valuable information for medium-term inflation and GDP growth forecasts. In contrast, Jaimovich and Siu (2009) find an age structure effect on the short run but not on the medium run cyclical volatility.

[1] Both frequencies are isolated by using a band pass filter. We use data from 1947:1 to 2009:1.

However, in practice it is an open question how to combine business cycle and growth models for the medium-term (Blanchard 1997, Solow 2000). The literature offers several approaches. Fujiwara and Teranishi (2008) extend the benchmark New Keynesian model by incorporating two types of households: workers and retirees. Using the specification of Gertler (1999) workers face a probability of retiring in the next period. A retiree faces a probability of dying. These extensions are sufficient to show that the demographic structure of an economy exert an effect on economy's business cycle properties. A second approach is to include human capital formation into a business cycle model (Stadler 1990). Learning by doing as well as investing in human capital enhances the empirical fit of an otherwise standard real business cycle model (Ozlu 1996; Collard 1999). A third approach incorporates research and development through creative destruction (Phillips and Wrase 2006), enhancing product variety (Comin and Gertler 2006) or technology diffusion (Braun et al. 2008). Again, these models are able to improve the empirical fit with respect to some important macroeconomic variables. However, most of these models are primarily used to analyze business cycle properties. One exception is the Medium-Term (MT) model of Comin and Gertler (2006). These authors extract medium-term frequencies from 2 to 200 quarters of important macroeconomic time series and evaluate the empirical fit of their model with respect to this medium-term cycle. In a subsequent paper Comin, Gertler and Santacreu (2009) estimate a slightly modified model with Bayesian methods and confirm the sound empirical fit of this model. It is our objective to provide the first analysis of the forecast power of such a DSGE model for the medium-run.

For this reason we introduce real rigidities in form of adjustment costs in investment into the MT model of Comin and Gertler (2006) to capture the empirical persistence of U.S. macroeconomic data to assess forecasting performance of this prototype medium-run model. While the usual forecasting horizon for medium-term projections is between 4 and 40 quarters we extend this range up to 60 quarters to explore the stability of our results. We compare the forecasting performance of the MT model with that of the Smets-Wouters (SM) model (2007), i.e. another prominent DSGE model, and a simple

VAR model. Most importantly, these alternatives do not incorporate aspects of economic growth in their model structure. The promising result is that the MT model outperforms the SM model with respect to forecasting the growth of GDP and consumption at medium-term horizons. For the variables investment and wage the results are mixed. However, compared to the VAR model the MT model performance is only competitive with regard to GDP and consumption and worse with respect to the other variables.

The outline of the paper is as follows: In section 2 we describe the building blocks of the Comin and Gertler model. Section 3 reports the data and the parameter estimation. In section 4 we present the results of the out-of-sample forecast performance analysis and we conclude in section 5.

2. The models

In this section we describe the models used in this paper to forecast different key macroeconomic variables of the U.S. economy. We start with an extensive description of the structure of the MT model and then we provide a brief outline to the two benchmark models.

2.1 The Medium-Term model

To understand how the MT model generates medium-term cyclical fluctuations we sketch the main features of the model.[2] The medium-term business cycle propagation mechanism which is at heart of the model is introduced by the interaction of endogenous productivity, countercyclical markups and endogenous factor utilization whereby non-technology shocks can generate the kind of medium-term movements we observe in the data.

[2] A detailed derivation of the model can be found in Comin/Gertler (2006).

Households

Using a discount factor β, each household h maximizes its present discounted utility with respect to consumption $\left(C_t\right)$ and a specific type of labor $\left(L_t^h\right)$

$$E_t \sum_{i=0}^{\infty} \beta^i \left[ln\, C_{t+i} - \frac{\left(L_{t+i}^h\right)^{1-\zeta}}{1+\zeta} \right] \tag{1}$$

subject to the following budget constraint:

$$C_t = W_t^h L_t^h + \Pi_t + \left[D_t + P_t^k\right] K_t - P_t^k K_{t+1} + R_t B_t - B_{t+1} - T_t \ , \tag{2}$$

where W_t^h is the wage of household *h*. Π_t are the profits in the adoption sectors, the term $\left[D_t + P_t^k\right] K_t$ describes the return of capital of the final goods producers, $R_t B_t - B_{t+1}$ is the payoff on loans less future bonds and T_t are lump-sum taxes.

Firms

In the production sector firms produce two types of final goods: a capital good $\left(Y_{k,t}\right)$ and a consumption $\left(Y_{c,t}\right)$ good. The final output composite $Y_{x,t}$ in each of the two sectors $x = k, c$ is a CES aggregate of $N_{x,t}$ final goods firms, respectively, where each firm produces a differentiated product $Y_{x,t}^j$:

$$Y_{x,t} = \left(\int_0^{N_{x,t}} \left(Y_{x,t}^j\right)^{\frac{1}{\mu_{x,t}}} dj \right)^{\mu_{x,t}} \tag{3}$$

Where $\mu_{x,t}$ is a measure for the price markup in these sectors. Every final good producer combines several inputs for $Y_{x,t}^j$ in the following Cobb-Douglas production function: capital services $U_{x,t}^j K_{x,t}^j$, with $U_{x,t}^j$ as the capital utilization rate, labour $L_{x,t}^j$, and a set of intermediate goods $M_{x,t}^{j}$:

$$Y_{x,t}^{j} = \left[\left(U_{x,t}^{j} K_{x,t}^{j} \right)^{\alpha} \left(L_{x,t}^{j} \right)^{1-\alpha} \right]^{1-\gamma} \left[M_{x,t}^{j} \right]^{\gamma} \tag{4}$$

The intermediate good composite $\left(M_{x,t}^{j} \right)$ itself is again a CES aggregate, where $A_{x,t}$ is the number of specialized goods used by firm j for each sector x:

$$M_{x,t}^{j} = \left(\int_{0}^{A_{x,t}} \left(M_{x,t}^{j,k} \right)^{1/\vartheta} dk \right)^{\vartheta}, \tag{5}$$

with $\vartheta > 1$. In each sector producer k is a monopolistic competitor. This allows for increasing gains from expanding variety. Hence, creation and adoption of new intermediate goods is the main source of productivity growth.

In a standard real business cycle model we would assume fixed values for $A_{x,t}$ and $N_{x,t}$. Endogenizing the number of intermediate goods $A_{x,t}$ introduces endogenous productivity growth into the model. Another important feature is that the number of firms in each sector $N_{x,t}$ is endogenous. Competition in each sector leads to entry and exit of firms while the number of firms is inversely related to the price markup in each sector. This leads to countercyclical markups.

Innovators and adopters

New intermediate goods $\left(M_{x,t}^{j,k} \right)$ are created and adopted by specialized firms (Romer 1990). In this model these two steps are carried out by two different sectors. This allows to endogenize the adoption rate. In this modified setup, each innovator p in sector x develops the blueprint of a new product, using the final consumption good $\left(Y_{c,t} \right)$ as an input. The total stock of innovations for each innovator $\left(Z_{x,t}^{p} \right)$ evolves according to

$$Z_{x,t+1}^{p} = \varphi_{x,t} S_{x,t}^{p} + \phi Z_{x,t}^{p}, \tag{6}$$

where ϕ describes the product survival rate. Let $S_{x,t}^{p}$ be the total amount of R&D and $\varphi_{x,t}$ a productivity parameter that the innovator p takes as given. In this case $1/\varphi_{x,t}$ $1/\varphi_{x,t}$ are the marginal costs of research. In equilibrium they have to equal the discounted marginal benefit because it takes some time to develop a new blueprint. Denoting the price at which an innovator can sell the new technology to an adopter with $J_{x,t}$ the following arbitrage condition must hold:

$$1/\varphi_{x,t} = \phi E_t \left\{ \Lambda_{t+1} J_{x,t+1} \right\}, \tag{7}$$

where Λ_{t+1} is a stochastic discount factor. According to equation (7), the expected value of an "unadopted" good $\left(E_t J_{x,t+1} \right)$ increases during a boom because the profit flow from intermediate goods rises and the gain of creating these goods is lifted.

Adoption of the new technologies is characterized the following way. First, adopters buy the rights of the new technologies. In a second step they form the new technology in usable form which is a costly and time consuming process. Adaptors obtain loans from the household to finance the adoption expenses. Finally, the adaptor sells the new product to final good producers who use it in the production function (4) as a new intermediate good. The pace of adoption and the diffusion of the new products depend positively on the adoption expenditures $\left(H_{x,t} \right)$.

For an adopter the price he is willing to spend for a blueprint $(J_{x,t})$ depends negatively on the adoption expenditures and positively on the value of a successfully adopted good $\left(V_{x,t+1} \right)$ and the future price of the blueprint:

$$J_{x,t} = \max_{H_{x,t}} \left\{ -H_{x,t} + \phi E_t \left(\Lambda_{t+1} \left[\lambda_{x,t} V_{x,t+1} + \left(1 - \lambda_{x,t} \right) J_{x,t+1} \right] \right) \right\} \tag{8}$$

The adjustment equation for adoptions is given by:

$$A_{x,t+1}^{q} = \lambda_{x,t}\phi\left[Z_{x,t}^{q} - A_{x,t}^{q}\right] + \phi A_{x,t}^{q} \tag{9}$$

The number of adoptions depends on the probability of adopting a blueprint successfully $(\lambda_{x,t})$, the survival rate of a blueprint (ϕ), and the stock of blueprints the adopter has not yet converted $(Z_{x,t}^{q} - A_{x,t}^{q})$. It can be shown in this framework that R&D activity is positively influenced by the business cycle because R&D intensity and adoption expenditures vary procyclically.

To close the model, resource constraints for aggregate net value added output (Y_t) are added:

$$Y_t = \sum_{x=c,k}\left[P_{x,t}Y_{x,t} - \left(A_{x,t}\right)^{1-\vartheta} M_{x,t} - \psi_{x,t}\right] \tag{10}$$

It equals gross output in each final good sector net expenditures on intermediate goods and operation costs ($\psi_{x,t}$). From a demand perspective net value added output equals consumption, investment and total costs of R&D and adoption.

$$Y_t = C_t + P_{k,t}Y_{k,t} + \sum_{x=c,k}\left[S_{x,t} + \left(Z_{x,t-j} - A_{x,t}\right)H_{x,t}\right] \tag{11}$$

In contrast to the MT model we introduce adjustment costs as in Comin et al. (2009) into the capital accumulation equation as follows:

$$K_{t+1} = \left(1-\delta\right)K_t + Y_{k,t}\left(1-\gamma\left(\frac{Y_{k,t}}{\left(1+g_k\right)Y_{k,t-1}} - 1\right)^2\right) \tag{12}$$

In contrast to the standard RBC model, this model is driven by non-technological shocks. Here, exogenous shocks to the markup generate the medium-term fluctuations. This kind of shock can be interpreted as reflecting preference shifts or other factors that influence the degree of labour market efficiency like shifts in the wage markup brought about by varying union pressures. Hall (1997) showed that these kinds of shocks are the most important source of cyclical variation. Due to endogenous technological change and countercyclical price markups this model generates medium-term cycles. To solve the model the equations are linearized around the steady state.

2.2 The Benchmark models

We compare the forecasting performance of the MT model with two different benchmark models: The Smets-Wouters model and a VAR-model. The SM model is currently the prototype New Keynesian business cycle model (see Wickens 2008). In contrast to the MT model a single final good is produced monopolistically and no R&D sector is included. Another difference to the MT model is that inflation and the interest rate are endogenous. The SM model is taken as given here. We do not change any equation or parameter but have taken the longer time series for estimating into account. We have chosen the SM model because of its promising forecasting performance.

The VAR model is a purely data-driven approach and a widely used benchmark for analyzing the forecasting power of DSGE models (Smets and Wouters (2007), Rubaszek and Skrzypczynsi (2008) and Christoffel et al. (2010)). We follow this literature and also use a VAR-modelwith the four variables: real GDP, consumption, investment and real wage. For the vector of these variables, X_t, the VAR is given by:

$$X_t = \Gamma_0 + \Gamma_1 X_{t-1} + \ldots + \Gamma_p X_{t-p} + \mu_t \, , \tag{13}$$

where Γ_i, $i = 0, 1, \ldots, p$, are matrices of coefficients, p is the lag order and u_t is a vector of residuals.

3. Estimation of the Medium-Term model and the benchmark models

This section presents the data used, the estimation method and the results of estimating the different models. We start with a description of the data and then provide a brief outline of the Bayesian estimation techniques and its subsequent implementation. Finally, we report some estimation results of the benchmark models.[3]

3.1 Data

For all three models we use the same data set as Smets-Wouters (2007), including seven key macroeconomic time series for the U.S. economy: the log differences of real GDP, real consumption, real investment and the real wage, log hours worked, the log difference of the GDP deflator, and the federal funds rate. These variables represent the models growth rates of output, consumption, investment, wage and inflation, while the hours worked and the interest rate are in log levels. We extend the original sample period, from 1947:1 to 2004:4, up to 2009:1. Following Fernández-Villaverde (2010) that Bayesian estimation techniques require the number of series to be less than or equal to the number of shocks in the model, we estimate the MT model on four time series since the model contains four shocks. Specifically, we take the variables into account that we intend to forecast, namely GDP, consumption, investment and the real wage. Since we want to keep close to the research of Smets and Wouters (2007) and to make our results comparable to them we take the whole data set for the SM model. The VAR model is estimated using again the four variables that are forecasted.

The forecast performance of the different models is assessed by using an expanding window procedure. We analyze four different forecast horizons (*h*): 4 quarters, 20 quarters, 40 quarters and 60 quarters. In a first step all models are estimated from 1947:3 to 1988:3. In a second step, we execute the forecasts for the four different forecast horizons, beginning with 1988:4 to 1989:3 and ending with 1988:4 to 2003:3.

[3] For the DSGE models we used the Dynare package in Matlab. The VAR model was estimated and forecasted with EViews 7.

Then, we expand the estimation period for one quarter from 1947:3 to 1988:4 and proceed once again through our two steps, estimating the models again, and forecasting the U.S. economy for the period 1989:1 to 1989:4 and so forth. This procedure is repeated until the last forecast regarding a horizon of 60 quarters reaches 2009:1. Overall, we derive 26 forecasts for each forecast horizon, model and variable.

3.2 Estimation of the Medium-Term and the benchmark models

While the VAR model is estimated using OLS and a simple lag structure of one lag[4], the DSGE models used in this paper are estimated utilizing Bayesian techniques. Bayesian estimation techniques have become quite popular for DSGE models in recent times. The Bayesian statistics have several theoretical advantages that have been enumerated frequently, for example in Robert (2001). Most prominently, estimating a model allows a closer empirical approach since some of the parameters are not calibrated anymore but estimated directly using time series. In addition, it is more difficult to maximize a complex function like the likelihood of a DSGE model than to integrate it with Bayesian techniques as described in Fernández-Villaverde (2010).

Bayesian estimation consists of four parts (Fernández-Villaverde, 2010). First, we have the data set $y^T \equiv \{y_t\}_{t=1}^{T} \in \mathbb{R}^{N\times T}$. Second, we have a model i and a set of parameters $\Theta_i \in \mathbb{R}^{k_i}$ for the model. It defines all the values of the parameters that go into the functions of the model. Third, a likelihood function $p(y^T \left| \theta, i) : \mathbb{R}^{N\times T} \times \Theta_i \to \mathbb{R}^+\right.$ is specified capturing the probability which the model allocates to each observation, given the parameters. Next, a prior distribution $\pi\left(\theta \middle| i\right) : \Theta_i \to \mathbb{R}^+$ is needed. It reflects the pre-sample beliefs about the value of the parameters. Combining these four parts, the Bayesian theorem provides the posterior distribution of the parameters:

[4] Nevertheless, we analysed a VAR model with four lags but the results were more or less the same. Therefore we keep the model with one lag for having a higher degree of freedom.

$$\pi\left(\theta \middle| y^T, i\right) = \frac{p\left(y^T \middle| \theta, i\right)\pi\left(\theta \middle| i\right)}{\int p\left(y^T \middle| \theta, i\right)\pi\left(\theta \middle| i\right)d\theta} \tag{14}$$

Bayes' theorem states that combination of the the prior beliefs, $\pi\left(\theta \middle| i\right)$, with the sample information of the likelihood, $f\left(y^T \middle| \theta, i\right)$ yields a new set of beliefs, $\pi\left(\theta \middle| y^T, i\right)$. This combination of the Maximum-Likelihood (ML) approach and priors promises to lead to more sensible estimated values of the parameters than the ML estimation without any additional information.

We follow the empirical approach exposed in Smets and Wouters (2004) for the MT model. Therefore, we fix some of the parameters of the model, since the chosen time-series do not contain information for all of the parameters. The values for the calibrated parameters are taken from a quarterly version described in Comin et al. (2009). Before estimation we log-linearize the model around its steady state.[5] The evaluation of the posterior density function is done by using the standard tool of Markov Chain Monte Carlo (MCMC). Here, we use a particular version of the MCMC algorithm, the Metropolis & Metropolis-Hasting version. Figure 2 depicts the prior and posterior distributions of the estimated parameters for the MT model using the full sample. For the SM model we use exactly the same priors as well as the same data series as in the original paper Smets and Wouters (2007), taking the extended sample period up to the end of the year 2009 into account.

4. Forecast Performance

In this section we want to report the out-of-sample forecast performance of the three models for GDP, investment, real wage and consumption. We evaluate forecasts at horizons up to 60 quarters using an expanding window for all models. The evaluation is

[5] A log-linearized version of the model is available upon request.

done by comparing the Mean Error (ME), the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) of the different forecast horizons. Furthermore, we test in separate exercises whether the forecast accuracy of the MT model exceeds that of the candidate models, respectively.

According to the results which are reported in Table 1, we find strong evidence for the superiority of the VAR for the forecasts of four quarters ahead, i.e. the short-term forecasts. This result is not surprising since the forecasting power of time series models in the short run is already well known as in Ibrahim and Otsuki (1975) or Wallis (1989). Even the SM model as a model designed for the short-term has higher MAEs and RMSEs than the competitive models. However, it should be emphasized, that the SM model has the lowest ME for GDP for all forecast horizons except 20 quarters ahead. The described results do not change much for the forecasts of 20 quarters ahead. Still, the VAR dominates the other models. Again, for all variables the VAR has the lowest MAEs and RMSEs.

For the forecast horizons of 40 and 60 quarters ahead the results change and the superiority of the VAR does not apply anymore. At least one forecast for each variable has a lower MAE and RMSE for the MT model than the benchmark models. Therefore, two main results can be found. First, the MT model outperforms the SM model for forecast horizons of 40 and 60 quarters for all variables. Second, the MT model and the VAR are approximately equivalent concerning the forecast power in the longer run. Overall, the results indicate that a model explicitly built for the medium term could improve forecasts for longer forecast horizons for some of the key macroeconomic variables. And they show that the VAR is not only a high benchmark for the short term but also for the longer run.

Since simple descriptive statistics and their reproduction do not indicate whether one model is statistically better than another, we apply the Harvey-Leyborne-Newbold (1997) modification of the Diebold-Mariano (1995) test for the null hypothesis of equal forecast accuracy from two different models. The results are reported in Table 2 and confirm the descriptive results. First, we test the MT against the SM model. For almost all variables, the sign of the test-statistics indicates a lower RMSE of the MT model than the SM model. Furthermore, for the medium term we find that the MT model is significantly better than the SM model for some of the variables. For example, the forecasts of GDP (consumption) are significantly better for the forecast horizons of 20 and 40 (20, 40 and 60) quarters ahead. For the variables investment and wage we find no significant difference between the models.

Next, the MT model is tested against the VAR model. Not surprisingly, the latter is significantly better than the MT model for all variables for forecasts of 4 quarters. Even for the forecast horizon of 20 quarters it shows it good forecasting performance, since all signs are positive but not all of them are statistically significant. For the longer run, the results are mixed. For the forecast horizon of 40 quarters we find no significant difference between the models. While the MT model is significantly better for the forecast horizon of 60 quarters for GDP, consumption and investment, the VAR model is significantly better for the variable wage.

5. Conclusions

This paper analyzes the forecasting performance of a DSGE model for forecast horizons up to 60 quarters. Until now, most of the studies analyzed the forecasting power for the short term up to eight quarters. We believe that this is the first study that analyzes the forecast errors of a DSGE model explicitly built for the medium term.

The calculations show that an estimated DSGE model for the medium-term forecasts significantly better than the two benchmark models for key macro variables like GDP and consumption. Since the model is focus on medium-term forecast we are not surprised that the forecasting performance in the short term is quite poor. Furthermore, the forecasting power of all models is generally weak for the variables investment and real wage. All in all we find two main results. First, not surprisingly, the VAR is a good benchmark for short-term forecasts. Here it shows in comparison to both other models a similar or in some cases even better forecast performance. Second, we find evidence that the estimated MT model is able to forecast medium-term cycles for variables like GDP or consumption. This is the first evaluation of this kind of model. We expect even better forecasts if more shocks are added to the model to implement more time series for estimation. Besides the forecast evaluation different topics can be explored with this model, especially issues concerning the medium term like public finances.

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Appendix A Tables and Figures

Table 1 Out-of-sample forecast evaluation

	GDP			Consumption			Investment			Wage		
h	Medium-Term	Smets-Wouters	VAR	Medium-Term	Smets-Wouters	VAR	Medium-Term	Smets-Wouters	VAR	Medium-Term	Smets-Wouters	VAR
ME												
4	1,18	**0,05**	0,13	0,45	-0,25	**0,10**	-0,91	0,84	**0,13**	5,34	0,27	**0,20**
20	-0,25	-0,32	**-0,24**	-0,30	-0,31	**-0,26**	-0,99	-1,03	**-0,98**	**-0,01**	0,21	0,03
40	0,09	**-0,06**	0,09	-0,06	-0,11	**-0,03**	0,10	**0,03**	0,12	-0,11	**0,01**	-0,14
60	0,33	**0,17**	0,33	0,28	0,21	0,31	1,29	1,34	1,29	0,29	0,38	**0,23**
MAE												
4	1,18	0,45	**0,36**	0,53	0,46	**0,33**	3,05	1,71	**1,06**	5,43	0,62	**0,51**
20	0,36	0,46	**0,34**	0,38	0,44	**0,36**	1,16	1,21	**1,15**	0,75	0,62	**0,48**
40	**0,49**	0,75	0,50	**0,41**	0,61	0,41	**1,45**	1,78	1,46	0,67	0,83	**0,64**
60	**0,52**	0,72	0,53	0,47	0,72	0,48	**2,31**	2,65	2,33	0,62	0,74	**0,60**
RMSE												
4	1,32	0,58	**0,46**	0,67	0,64	**0,45**	3,63	2,26	**1,27**	7,89	0,71	**0,60**
20	0,47	0,61	**0,45**	0,49	0,54	**0,46**	1,39	1,52	**1,37**	0,88	0,86	**0,60**
40	**0,67**	1,09	0,67	0,49	1,00	**0,49**	1,64	2,47	**1,63**	**0,81**	1,29	0,84
60	**0,79**	1,12	0,80	**0,75**	1,12	0,77	**3,54**	3,98	3,55	0,81	1,21	**0,78**

Notes: The ME stands for the Mean Error, MAE for the Mean Absolute Error and RMSE for the Root Mean Squared Error Bold indicates the minimum absolute values for the MEs, MAEs and RMSEs.

Table 2 Tests for equal forecast accuracy

	GDP	Consumption	Investment	Wage
Forecast horizon h	Medium-Term vs. Smets-Wouters			
	HLN	HLN	HLN	HLN
4	3,07***	0,19	1,90**	2,52***
20	-2,44***	-1,36*	-1,04	0,09
40	-1,49*	-1,43*	-1,32*	-1,16
60	-1,17	-1,46*	-1,04	-0,96
	Medium-Term vs. VAR			
	HLN	HLN	HLN	HLN
4	3,93***	2,46***	3,00***	2,52***
20	1,05	2,85***	0,77	2,85***
40	-0,67	0,11	0,10	-0,82
60	-1,60*	-1,40*	-1,70**	1,84**

Notes: A positive value of the HLN statistic indicates that the RMSE of A is higher than that of B, i.e. that B is superior in forecasting to A.

Figure 1 Medium-Term Cycle

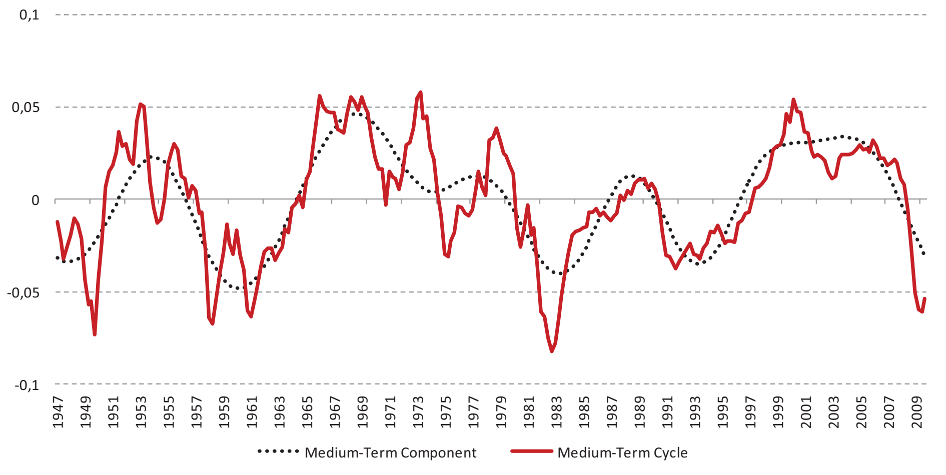

Figure 2 Prior and Posterior