Expectation Formation, Financial Frictions, and Forecasting Performance of Dynamic Stochastic General Equilibrium Models

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Oliver Holtemöller & Christoph Schult [*]

Abstract: »*Erwartungswertbildung, Finanzmarktfriktionen, und die Vorhersagegenauigkeit von dynamischen stochastischen Gleichgewichtsmodellen*«. In this paper, we document the forecasting performance of estimated basic dynamic stochastic general equilibrium (DSGE) models and compare this to extended versions which consider alternative expectation formation assumptions and financial frictions. We also show how standard model features, such as price and wage rigidities, contribute to forecasting performance. It turns out that neither alternative expectation formation behaviour nor financial frictions can systematically increase the forecasting performance of basic DSGE models. Financial frictions improve forecasts only during periods of financial crises. However, traditional price and wage rigidities systematically help to increase the forecasting performance.

Keywords: Business cycles, economic forecasting, expectation formation, financial frictions, macroeconomic modelling.

1. Introduction

Quantitative macroeconomic models are an important tool for economic policy analysis. Such models are employed to simulate the effects of policy actions on macroeconomic variables and to forecast future macroeconomic development. Since the worldwide financial crisis, state-of-the-art macroeconomic modelling has been heavily criticized.[1] A major reason for this critique is that state-of-the-

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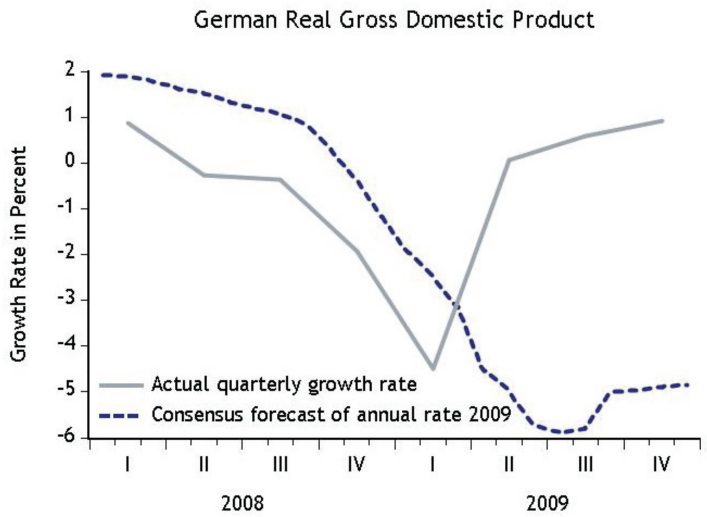
[1] The pre-crisis state-of-the-art features of macroeconomic models are described, for example, in Blanchard (2009). See Buch and Holtemöller (2014) for a discussion of shortcomings of pre-crisis macroeconomic models.

art macroeconomic models did not predict the financial crisis and, in some cases, also did not foretell the pace of recovery. Professional forecasters started to predict a downturn for the year 2009 when economic activity had already started to slow down during the year 2008. Figure 1 shows that the mean of forecasts for German GDP growth by professional forecasters considered in the consensus sample were positive until October 2008. Consensus forecasts reached their minimum in July 2009 while the actual second quarter growth rate of GDP was already becoming positive again. Overall, it seems that forecasts follow actual development rather than predicting it.

Figure 1: Monthly Consensus Forecasts of Annual German GDP Growth in 2009 and Actual Quarterly GDP Growth Rates



Sources: Consensus Economics, Federal Statistical Office of Germany, authors' illustration.

Why have economic forecasts not performed better? There are several possible answers to this question. Firstly, the technology employed by forecasters could be inadequate. Professional forecasts usually rely on some type of statistical or econometric forecasting model (wrong *type* of model). The underlying assumptions of these models could be fundamentally wrong; for example, the often-made assumption of normally distributed error terms or the assumption of rational behaviour of individuals. Secondly, forecasting models could be generally adequate, but not well specified due to data problems or incomplete information about economic relationships (wrong model *specification*). Thirdly, it could simply be that future economic developments are unpredictable.[2]

Here, we focus on the first two categories: the type and specification of macroeconomic forecasting models. At the centre of model criticism is the way individual economic behaviour, in particular expectation formation, is captured and the fact that the financial system and its frictions have been ignored in standard models for a long time. Standard models before the financial crisis usually relied on the rational expectations (RE) hypothesis (Muth 1961; Lucas 1976) and did not include money or credit aggregates.[3] In the aftermath of the financial crisis, various model extensions – both in the area of expectation formation and in the area of financial frictions – were developed. However, a new standard model has not been established yet.

Furthermore, from an empirical perspective, it is not clear what kinds of model features are important in order to improve the forecasting performance of standard models. In this paper, we document the forecasting performance of an estimated standard pre-crisis macroeconomic model and compare it to extended versions which consider alternative expectation formation assumptions and financial frictions. We also show how standard model features, such as price and wage rigidities, contribute to forecasting performance. Our results suggest that neither alternative expectation formation behaviour nor financial frictions can systematically increase the forecasting performance of simple estimated macroeconomic models. Only during periods of financial crises do financial frictions improve forecasts. Traditional price and wage rigidities, on the contrary, systematically help to increase forecasting performance.

The paper is structured as follows. In Section 2, we describe how the pre-crisis standard macroeconomic model has evolved from earlier approaches to macroeconomic modelling. In Section 3, we explain extensions to the simple standard model that became prominent after the financial crisis; specifically, financial frictions and adaptive learning. Then, we conduct pseudo out-of-sample forecasts and document forecast performance of the various models in Section 4. Finally, our concluding remarks are presented in Section 5.

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2 The unknowability of the future is stressed by Beckert (2016, 227): "Rather, the lesson forecasts teach us is that it is impossible to predict the future. … Society and the economy are endlessly complex, and the future is open: truly, hardly anything can be foreseen."

3 Of course, there were also models which included financial frictions before the crisis; for example, in the tradition of Bernanke, Gertler, and Gilchrist (1999). However, these models have only played a minor role in applied forecasting.

2. The Pre-Crisis Standard Macroeconomic Model

2.1 Short Review of Empirical Macroeconomic Modelling

The pre-crisis standard macroeconomic model was a small- or medium-sized dynamic stochastic general equilibrium (DSGE) model. The predecessors of DSGE models were traditional structural models, models which followed the London School of Economics (LSE) approach, and vector autoregressive (VAR) models.[4]

In the sixties and seventies of the 20th century, structural models were the dominant macroeconometric modelling technique. These traditional, structural models are sometimes designated as having a Cowles commission approach (Favero 2001, 103). A typical empirical analysis within this paradigm consists of three steps: (1) specification of the theoretical model, (2) estimation of parameters, and (3) simulation of the effects of policy actions. The economic model is formulated in terms of behavioural equations and definitional identities and is summarized in the following econometric model:

(1) $A_0 x_t = A_1^* x_{t-1} + Q^* z_t + e_t.$

In this equation, $x_t = (x_{1t}, x_{2t}, \dots, x_{pt})'$ is a $(p \times 1)$ vector of endogenous variables, z_t is a vector of exogenous variables (especially policy instruments), A_0 and A_1 are $(p \times p)$ coefficient matrices, the matrix Q stores the coefficients of the exogenous variables, and e_t is a $(p \times 1)$ vector of error terms that is normally distributed with mean zero and covariance matrix Σ_e, $e_t \sim N(0, \Sigma_e)$. Deterministic terms as well as further lags of endogenous and exogenous variables can be added, but are ignored in the following. This set of p equations describes the simultaneous relationships between the variables. The impact of exogenous and lagged endogenous variables on the actual endogenous variables is expressed by the reduced form:

(2) $x_t = \underbrace{A_0^{-1} A_1^*}_{A_1} x_{t-1} + \underbrace{A_0^{-1} Q^*}_{Q} z_t + \underbrace{A_0^{-1} e_t}_{u_t}.$

Equation (2) can also be used to forecast x_t (and also the future time path $\{x_{t+h}\}, h \geq 0$), conditional on lagged realizations and exogenous variables.

The Cowles commission approach has been criticized extensively for the following reasons: (1) the a priori exogeneity assumptions are controversial; (2) the aggregated behavioural equations in traditional structural models have usually been ad-hoc equations without microeconomic foundations; (3) the coefficient estimates of non-structural models might depend on policy rules and could change over time – therefore, those estimates are not useful for evaluating policy changes (Lucas-Critique); (4) the statistical performance of the esti-

[4] The modelling review is based on Holtemöller (2002).

mated model has not been considered seriously. Specifically, static regressions of non-stationary variables have led to spurious regressions.

A partial response to these criticisms has been the LSE approach which focuses specifically on the statistical properties of the estimated model, but does not question the paradigm of simulating policy effects on the basis of structural forms in principle.[5] The first step of the LSE procedure is the estimation of a general dynamic reduced form model that has to pass a sequence of diagnostic tests. Equations for variables that are confirmed to be statistically exogenous can be omitted. Non-stationary variables can also be modelled appropriately (error correction models). A reduction technique is applied to impose non-rejected restrictions on the parameters of the model. The resulting structural form is used for the simulation of policy effects.

While the LSE approach is mainly a response to the statistical problems of traditional structural models, the VAR approach, which achieved enormous popularity following the seminal works of Sims (1972, 1980), abandons the a priori exogeneity assumptions by including all relevant variables in the vector of endogenous variables and estimating the reduced form

(3) $x_t = \sum_{i=1}^{k} A_i x_{t-i} + u_t,$

where $u_t \sim N(0, \Sigma_u)$. Deterministic terms are again neglected. The lag length k is determined by statistical criteria. In this framework, whether a variable is exogenous or not can be tested. Different exogeneity concepts have been developed for this purpose; see, for example, Engle, Hendry, and Richard (1983) and Dufour and Renault (1998). One of these concepts is Granger causality (Granger 1969) which is based on the chronological asymmetry of cause and effect.[6] The main purpose of VAR models is not to simulate the effects of policy actions, but to analyse the impact of policy shocks on the variables of interest and to forecast economic variables. This empirical evidence is used to build theoretical models based on microeconomic foundations that are able to produce empirically observed responses. If a theoretical model is able to reproduce the observed response patterns, it can be used to derive policy implications.

The VAR approach has been extended over time. The observation that many macroeconomic time series exhibit stochastic trends (Nelson and Plosser 1982) has led to the development of cointegration models which were introduced by Engle and Granger (1987). The second main extension of the VAR model was the development of structural VAR (SVAR) models; one of the first contributions to the literature on SVAR models was Bernanke (1986). Following Amisano and Giannini (1997), SVAR models can be characterized by the so-called AB model:

[5] The econometric issues of this approach are discussed in Hendry (1995).
[6] The econometric analysis of VAR models is discussed in Hamilton (1994) and Lütkepohl (2005).

(4) $A_0 x_t = \sum_{i=1}^{k} \underbrace{A_0 A_i}_{A_i^*} x_{t-i} + A_0 u_t, \quad A_0 u_t = B e_t, \quad e_t \sim N(0, I_p),$

where I_p denotes a *p*-dimensional identity matrix. The notional AB model is based on the definition $A = A_0$, such that the matrices *A* and *B* characterize the contemporaneous relationships between endogenous variables and exogenous structural shocks e_t.[7]

While VAR models usually have a very good fit and can provide a reasonable characterization of statistical properties of macroeconomic data, they ignore theoretical restrictions that stem from general equilibrium considerations or forward-looking behaviour. Kydland and Prescott (1982) developed an empirical characterization of macroeconomic time series that is completely derived from the optimizing behaviour of economic agents and which takes general equilibrium restriction into account. This type of model is today known as dynamic stochastic general equilibrium (DSGE) model and can be represented as follows:[8]

(5) $\Gamma(E_t x_{t+1}, x_t, e_{t+1}) = 0,$

where E_t denotes the expectation operator. Expectations are rational in this framework in the sense that they are compatible with the mathematical structure of the model. Often, these models are log-linearized:

(6) $A x_{t+1} = B x_t + C e_t + D f_{t+1},$

where f_{t+1} denotes the difference between expectation and actual realization (expectational error). The solution of this model is a recursive law of motion:

(7) $x_{t+1} = F x_t + G e_t,$

which is again a VAR representation of the data, but with theory-based cross-equation restrictions imposed.

While early small-scale DSGE models have not performed as well as reduced-form VAR models in terms of statistical fit and forecast performance, models that are used today usually have a very good statistical fit and can even outperform reduced-form models without restrictions in terms of forecasting for certain forecasting horizons (Del Negro and Schorfheide 2006; Cai et al. 2018).

2.2 The New Keynesian Standard Model

The pre-crisis standard DSGE model was developed from the framework introduced by Kydland and Prescott (1982) by adding (New)Keynesian elements such as price and wage rigidities. Galí (1999) showed that a small-scale New Keynesian model can explain important dynamic correlations in macroeconomic data. Methods for estimating DSGE models were developed, and Smets and

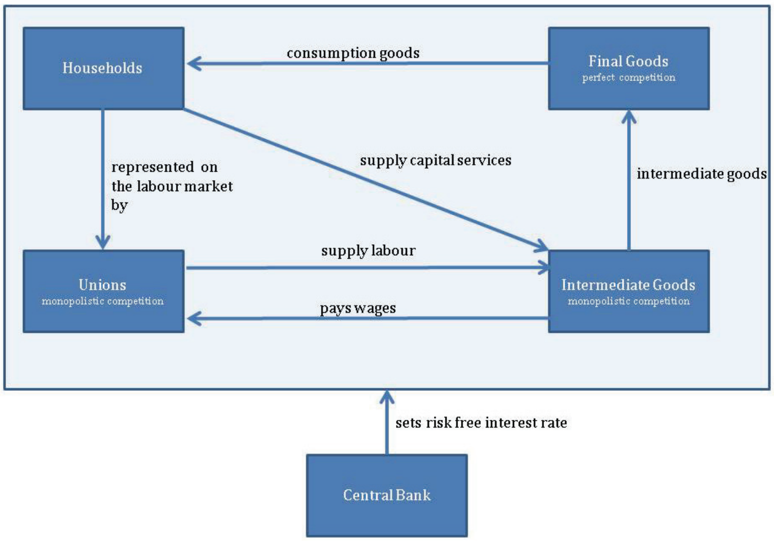
7 See Kilian and Lütkepohl (2017) for a detailed discussion of SVARs and the identification of structural shocks.

8 See DeJong and Dave (2011) for an introduction to DSGE models.

Wouters (2003, 2007) advanced an estimated New-Keynesian DSGE model that has been extensively used in applied work.[9]

The structure of the Smets and Wouters (SW) model is depicted in Figure 2. Five types of agents are considered: households, unions, final good producers, intermediate good producers, and a central bank. The model represents a closed economy without considering international trade or capital flows.

Figure 2: Main Structure of the Standard New-Keynesian Model



Source: authors' illustration.

There is a continuum of households modelled as one representative household. Potential implications of heterogeneous behaviour by households experiencing aggregate development are not considered.[10] The representative household maximizes inter-temporal discounted utility over time. The household has multiple income sources: labour, capital services, and interest-paying securities. Unions negotiate wages and households supply the amount of labour demanded at the negotiated wage. In order to introduce the empirically observed sluggishness of wages, only a fraction of unions is able to reset the wage in the current period. Therefore, today, re-optimizing unions take future develop-

9 An overview of DSGE models and their usage in policy institutions is given by Christiano, Eichenbaum, and Trabandt (2017).

10 Imposing homogenous behaviour on all agents is a further central critique against the standard model. However, the discussion of heterogeneity in DSGE models is beyond the scope of this paper. See Galí (2018) for an overview of extensions to account for heterogeneity.

ments into account. Consequently, future expected developments will affect wages today more than under flexible wages.

There are two types of firms: intermediate-good-producing firms and final-good-producing firms (retailers). Retailers have no market power and are price takers. However, intermediate good producers can set prices above marginal costs because retailers produce final goods from differentiated products. Intermediate good producers use labour and capital services from households to produce intermediate goods. They first choose the amount of labour and capital services as inputs according to their marginal products and costs. In a further step, they maximize inter-temporal profits by setting prices, given the retailer demand for their products. Only a fraction of intermediate good producers is able to set prices according to current marginal costs and desired mark-ups, similar to unions. Price-setting behaviour is forward-looking and future increases in marginal costs lead to higher inflation today than under flexible prices.

The central bank sets the short-term risk-free interest rate for securities. It follows a monetary policy reaction function and varies the interest rate in response to deviations of the inflation rate from target inflation and of the output from potential output.

To complete and solve the model, it is necessary to specify how agents form expectations about consumption, investment, labour, price of capital services, wages and inflation. In the Smets and Wouters model it is assumed, just as for most other pre-crisis macroeconomic general equilibrium models, that expectations are rational and fully model consistent. Rational expectations require that agents not only know their own behavioural equations, but also the complete structure of the economy. In addition, agents use all information at a specific time point to form their expectations. Systematic expectation errors are excluded.

3. Model Extensions

3.1 Financial Frictions

The pre-crisis standard New Keynesian model abstracts from financial markets and does not consider financial frictions as a potential source of business cycle fluctuations. In recent years, various extensions of the New Keynesian standard model have been developed that include financial frictions. Gertler and Kiyotaki (2010), for example, incorporate financial frictions based on earlier work by Bernanke, Gertler, and Gilchrist (1999) as a propagation mechanism into the model framework (financial accelerator). In this type of model, creditors must pay a risk premium in addition to the risk-free rate due to monitoring costs. Christiano, Motto, and Rostango (2014), Merola (2015), and Cai et al.

(2018) show that financial frictions can account for a significant proportion of business cycle fluctuations in a standard medium-scale DSGE model.

In our forecasting exercise, we use a log-linearized version of the model by Merola (2015). Only the external finance premium enters the standard Smets and Wouters model as an additional observable variable: financial frictions are shocks to the spread between the risk-free interest rate and the return to capital.[11] These shocks trigger a decrease in borrowing activities by firms and therefore reduce capital services. This, in turn, has a negative effect on output and consumption. Since agents know the structure of the economy (rational expectations), the amount of borrowing today is affected by expectations about future developments.

3.2 Adaptive Learning

Figure 1 indicates that even professional forecasters slowly adapt to new information. This poses serious doubts about the rational expectation hypothesis; models which rely on alternative expectation formation assumptions have evolved. In particular, models with adaptive learning (AL) have been developed; for example, Evans (2001), Bullard and Mitra (2002), Evans and Honkapohja (2003, 2006), Carceles-Poveda and Giannitsarou (2007), and Slobodyan and Wouters (2012).

Adaptive learning assumes that agents use forecasting models to form beliefs. They update the parameters of their forecasting model in real time. That is, the most recent information is utilized to form beliefs, chronologically. While the VAR law of motion implied by rational expectation DSGE models (7) exhibits time-invariant coefficient matrices F and G, models with adaptive learning imply time-varying coefficients. The source of the variation in the parameters originates from updating beliefs.

In our forecasting exercise, we use an adaptive learning model in which agents adjust their forecasting model and update the coefficients of the model each period.[12] Over time, agents learn from their expectation errors and adjust decision rules and beliefs. In contrast to rational expectation models, this approach allows for systematic expectation errors by agents, but requires that agents learn from their mistakes.

In rational expectation models, persistence is to a large extent captured by price and wage rigidities. Adaptive learning introduces an additional source of persistence. Consequently, estimated parameters in wage and price setting equations, for example, depend on the way in which expectation formation is specified.

[11] See Brzoza-Brzezina and Kolasa (2013) for a comparison of different approaches to incorporating financial frictions into DSGE models.

[12] This is based on a Kalman filter approach (Hamilton 1994).

Milani (2007) shows that a small-scale New Keynesian DSGE model estimated with adaptive learning has a better in-sample fit than the same model using rational expectations. Furthermore, Milani and Rajbhandari (2012) find that adaptive learning models have a better in-sample fit than models estimated with news shocks or nearly rational expectations. However, the in-sample fit measures only the performance of the model evaluated with data used for estimation. This measure alone is not appropriate to determine how useful models are as indicators for future developments. Slobodyan and Wouters (2012) and Milani and Rajbhandari (2012) show that adaptive learning performs better for short-run forecasts, but rational expectations are better in producing long-run forecasts. In our forecasting exercise we will evaluate the relative importance of various model features for forecast performance.

4. Forecast Performance

4.1 Estimation and Data

To investigate whether the extensions to the baseline model are useful for forecasting purposes, we estimate various models and compute pseudo out-of-sample forecasts. We start from the standard New Keynesian model characterized in Section 2.2, but without price and wage rigidities. We exclude price rigidities by allowing all firms to reset their prices and unions to negotiate wages in each period. The special case without price and wage rigidities collapses to a pure, real business cycle model.

The full set of models is as follows: baseline model without nominal rigidities (SW-NRI), without price rigidities (SW-NPR), without wage rigidities (SW-NWR), baseline model with price and wage rigidities (SW-RI) and the baseline model with financial accelerator (SW-FA). All models are estimated for rational expectations and adaptive learning. We further estimate a vector autoregressive (VAR) model with and without the external finance premium as an endogenous variable with lag order one as a restriction-free naive benchmark model.

The model is estimated for the United States of America (US), the United Kingdom (UK) and the Euro area. For the US, the full sample covers the period from 1954-Q3 to 2017-Q3 at a quarterly frequency. The samples for the UK and the Euro area cover the period between 1999-Q1 and 2017-Q3. So far, most studies estimating DSGE models with adaptive learning have only used US data. We use quarterly, seasonally adjusted national accounts data for gross domestic product (GDP), consumption, investment, wages and salaries, and total hours worked.[13] Inflation is measured with the GDP deflator and the short-term interest rate set by the central bank, which is the federal funds rate for the US and the money market rate in the UK and Euro area. For the financial accelerator version, an additional variable to measure the external finance premium is necessary. For the US, we use the spread between AAA and BAA rated corporate bond yields. For the Euro area and the UK,[14] we use the spreads implied by the inverse price index of AAA and BAA corporate bond yields in the Euro area.[15]

Bayesian techniques are used to estimate the structural parameters. The prior distribution or the starting distribution for all model specifications for each parameter are the same. The prior distributions are also identical across regions, except for trend parameters for inflation, output growth, and interest rate. For each region, those parameters are set to the mean of the current sample. The models are then estimated by drawing parameter values from the prior distribution and evaluating the likelihood of the model, given the vector of parameters. The posterior distribution of the parameters is the update of the prior distribution, given the observed data according to the theorem of Bayes; the posterior distribution is used in the next step to draw parameters. This procedure is repeated until the likelihood of the model does not improve any more or a predefined number of iterations is exceeded. A detailed description of this method is provided by Schorfheide (2000).

We estimate the model initially using data up to 2006-Q3 and expand the estimation window step-by-step by one year, respectively, to re-estimate the model. We use the same procedure for the VAR model estimated by standard ordinary least squares. Forecast errors for horizons one, four, and eight quarters at the posterior mode of the estimated parameters are computed. In total, we obtained 44 forecast errors for horizon one, 41 for horizon four and 37 for horizon eight. Based on these forecast errors, root mean squared percentage errors (RMSPE) are calculated.

4.2 Results

Figure 3 shows one-quarter-ahead forecasts for the US from 2007-Q4 onwards, together with ex-post observed data. The model without nominal rigidities in most cases delivers poor forecasts, independent of the expectation formation specification.

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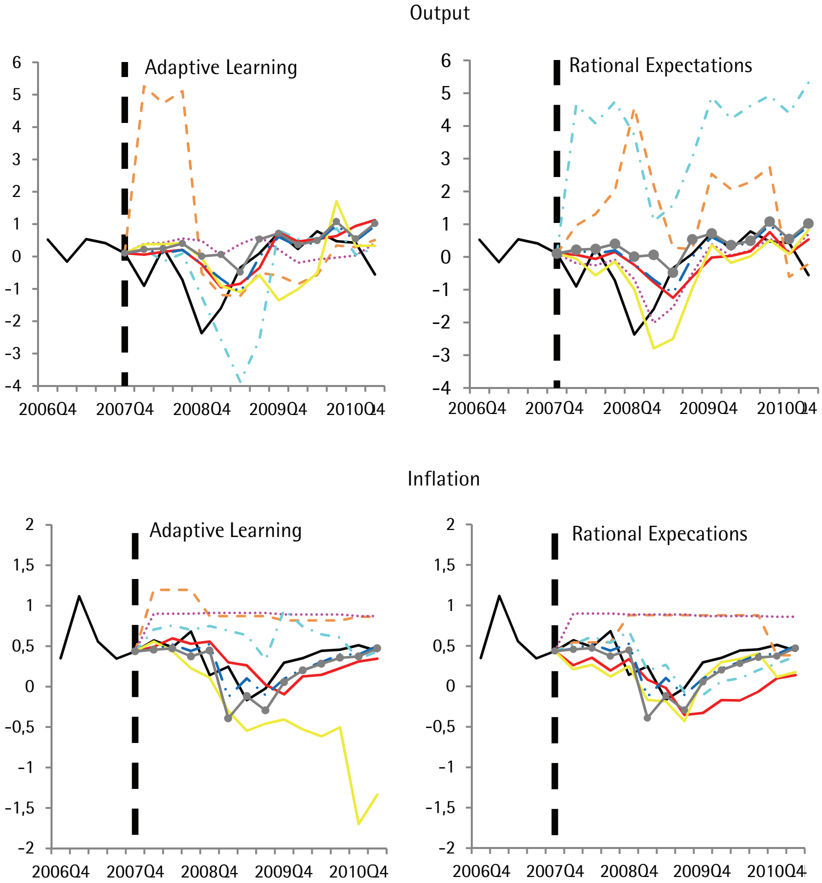
13 For the US, the data is provided by the Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org>). For the Euro area and UK, the data source is Eurostat (<http://ec.europa.eu/eurostat/de/data/database>).

14 Unfortunately, no comparable variables are available for the UK. Therefore, we follow the work by Hall (2001) and use Euro area spreads.

15 Corporate bond yields are published by IBOXX (<https://ihsmarkit.com/products/iboxx.html>).

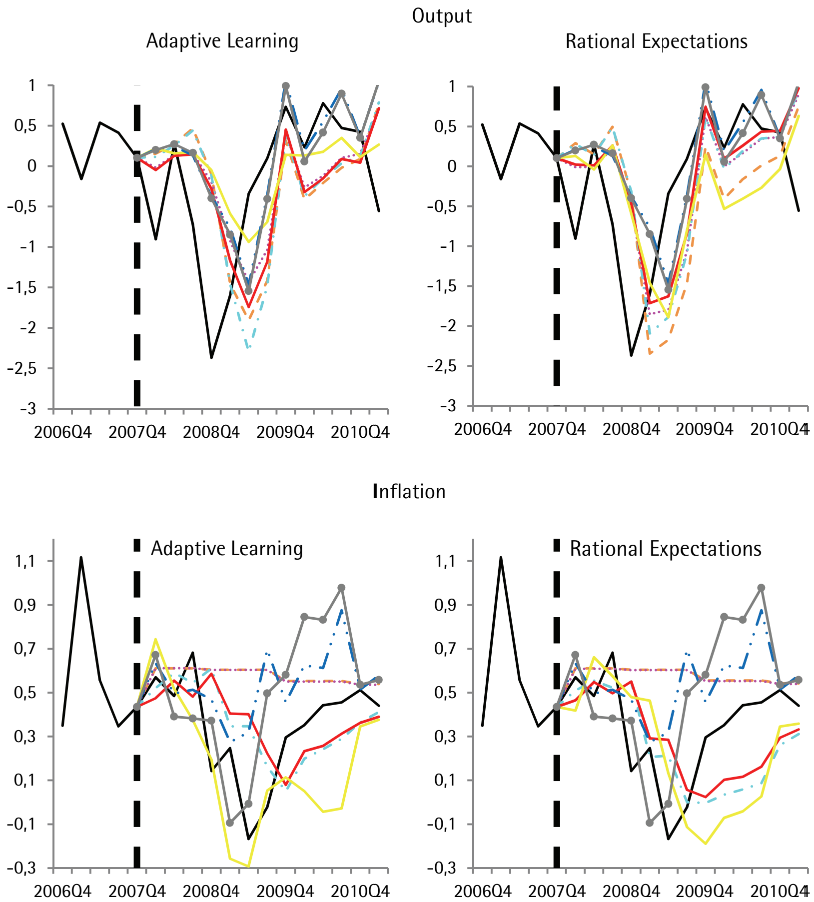
Figure 3: One-Quarter ahead Forecast Performance during the Crisis for the US (Full Sample)



Notes: The lines depict actual data (▬) and forecasts in percent: SW without nominal rigidities (- - -), SW without price rigidities (·······), SW without wage rigidities (– · –), SW with nominal rigidities (▬), SW with financial accelerator (▬) and VAR without external finance premium (– · ·) and with external finance premium (–●–).

However, the pre-crisis standard New Keynesian model (SW-RI) with rational expectations seems to produce reasonable forecasts. Adding features such as financial frictions (FA) or adaptive learning seem not to lead to substantial improvements on average; however, during the year 2009, financial frictions help to capture the deepness of the recession. This is compatible with the finding by Del Negro, Hasegawa, and Schorfheide (2016) that the predictive power of DSGE models with financial frictions for output growth and inflation is only better during periods of financial distress. For inflation, the SW-RI model and the financial accelerator model produce very similar forecasts. Under adaptive learning, the forecast for output growth of the SW-RI model and the model with a financial accelerator do not track the downturn as well as under rational expectations. Agents do not update their expectations given the current information as quickly under rational expectations. Figure 4 shows the same forecasts, but estimated on a shorter sample to make the results comparable to results for the UK and the Euro area, which rely on shorter samples due to data limitations.

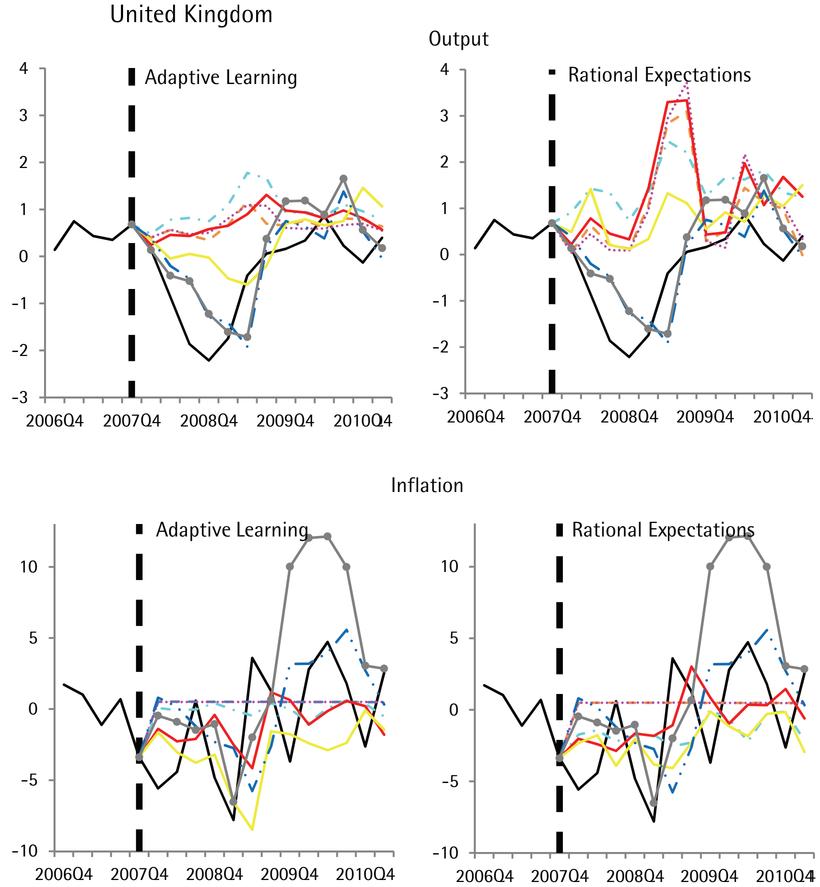
Figure 4: One-Quarter Ahead Forecast Performance during the Crisis for the US (Short Sample)



Notes: The lines depict actual data (——) and forecasts in percent: SW without nominal rigidities (- - -), SW without price rigidities (·······), SW without wage rigidities (–·–·), SW with nominal rigidities (——), SW with financial accelerator (——) and VAR without external finance premium (–··) and with external finance premium (—●—).

The one-quarter-ahead forecasts for the UK are depicted in Figure 5. Models with rational expectations predicted no downturn after 2007-Q4 for output growth. Under adaptive learning, only the financial accelerator model predicts a downturn, but with a severe lag. In contrast with the US, the GDP deflator in the UK is more volatile in the respective period. Therefore, all models have difficulties tracking this volatile behaviour. The financial accelerator model under adaptive learning does the best job in tracing this behaviour.

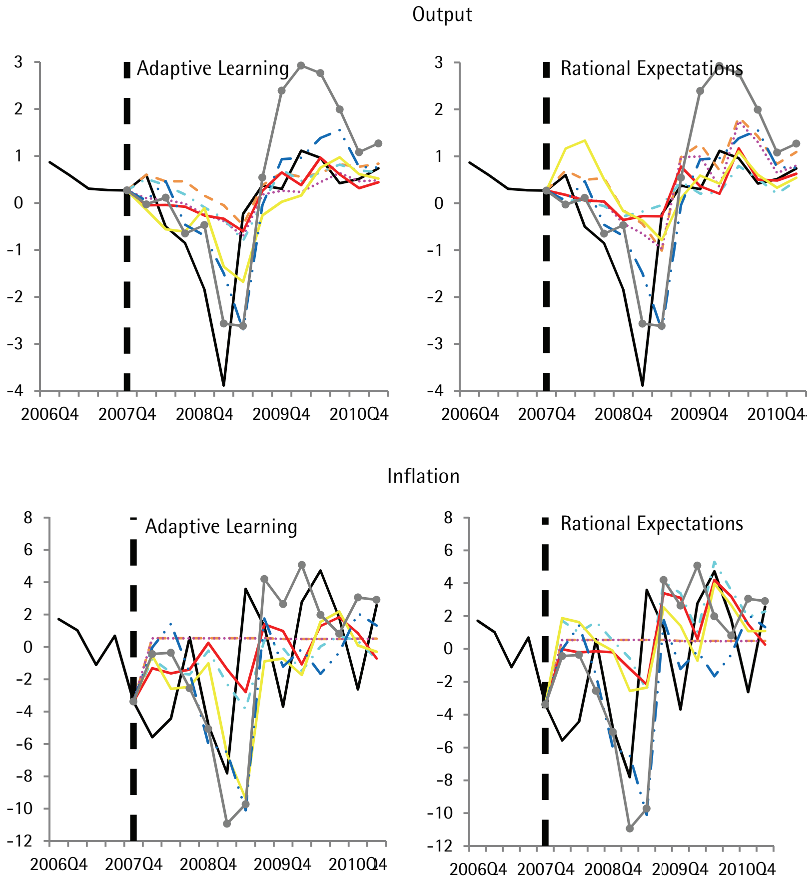
Figure 5: One-Quarter Ahead Forecast Performance during the Crisis for the United Kingdom



Notes: The lines depict actual data (▬) and forecasts in percent: SW without nominal rigidities (- - -), SW without price rigidities (·······), SW without wage rigidities (-·-·), SW with nominal rigidities (▬), SW with financial accelerator (▬) and VAR without external finance premium (-··) and with external finance premium (-●-).

Output growth in the Euro area during the crisis is also better predicted one quarter ahead under adaptive learning with a financial accelerator (see Figure 6). The same is true for the GDP deflator in the Euro area. All models can predict the downturn only with a lag.

Figure 6: One-Quarter ahead Forecast Performance during the Crisis for the Euro Area



Notes: The lines depict actual data (——) and forecasts in percent: SW without nominal rigidities (- - -), SW without price rigidities (……), SW without wage rigidities (– · – ·), SW with nominal rigidities (——), SW with financial accelerator (——) and VAR without external finance premium (— · ·) and with external finance premium (—●—).

In line with the literature, our estimation results show that adaptive learning improves the in-sample fit of the SW-RI model compared with the rational expectations variant. Table 1 reports the log-likelihood for the US, the UK, and the Euro area models. The SW-RI model with adaptive learning has for all countries a larger likelihood than the SW-FA model with financial accelerator. This is also true for rational expectations for the US and Euro area, but not for the UK. In general, the inclusion of wage and price rigidities increases the log-likelihood.

Table 1: Likelihoods

Model	Adaptive Learning	Rational Expectations
	US (full sample)	
SW-NRI	-3449.74	-8411.14
SW-NWR	-2201.14	-8215.23
SW-NPR	-2588.75	-1844.63
SW-RI	-1628.28	-1686.84
SW-FA	-1736.63	-1369.70
	UK	
SW-NRI	-793.89	-810.49
SW-NWR	-807.49	-819.72
SW-NPR	-783.48	-797.32
SW-RI	-747.64	-788.56
SW-FA	-982.40	-906.31
	Euro area	
SW-NRI	-643.11	-659.35
SW-NWR	-641.62	-664.30
SW-NPR	-667.35	-647.83
SW-RI	-575.83	-614.06
SW-FA	-904.96	-762.56
	US (short sample)	
SW-NRI	-450.81	-455.99
SW-NWR	-451.60	-466.44
SW-NPR	-374.68	-386.46
SW-RI	-375.58	-393.38
SW-FA	-822.81	-369.38

Notes: Likelihoods are the log of the marginal likelihood based on the Laplace approximation evaluated at the posterior mode. A higher likelihood reflects a better model fit for the data used to estimate the structural parameters of the model. Except for the financial accelerator model, the likelihoods for the respective currency unions are comparable.

Tables 2 to 5 report the RMSPE for the different regions. RMSPE for all structural models and the VAR with external finance premium are reported relative to the RMSPE of the VAR without external finance premium for the respective region and horizon.

Table 2: Root Mean Squared Percentage Errors – US (Full Sample)

Horizon	Output Growth	Inflation	Log-Det.	Output Growth	Inflation	Log-Det.
	Adaptive learning			Rational expectations		
Smets and Wouters without nominal rigidities (SW-NRI)						
1	2.19	3.34	2.21	4.67	4.12	2.42
4	1.04	2.05	1.24	1.11	3.41	1.28
8	1.30	2.19	1.26	1.27	1.21	1.05
Smets and Wouters without price rigidities (SW-NPR)						
1	0.66	4.21	1.06	0.65	4.14	1.07
4	0.20	2.19	0.91	0.14	2.17	0.83
8	0.10	1.92	0.76	0.14	1.88	0.89
Smets and Wouters without wage rigidities (SW-NWR)						
1	0.79	1.47	1.49	8.06	1.09	2.34
4	0.88	4.86	1.34	1.59	1.57	1.22
8	2.51	2.10	1.41	1.81	1.56	1.19
Smets and Wouters with nominal rigidities (SW-RI)						
1	1.54	0.98	0.92	0.75	1.05	0.95
4	1.07	0.95	0.95	0.46	0.32	0.78
8	0.70	0.92	1.04	0.38	0.54	0.78
Smets and Wouters with financial accelerator (SW-FA)						
1	0.44	2.11	0.95	0.79	1.21	0.65
4	1.61	0.80	0.97	0.37	0.73	0.76
8	2.64	1.20	1.17	0.44	0.67	0.64
Vector autoregressive model						
	without external finance premium			with external finance premium		
1	10.82	2.44	15.25	1.07	1.23	0.85
4	14.87	4.83	22.72	1.07	0.90	0.86
8	15.60	5.94	25.64	1.00	1.00	0.84

Notes: For the VAR without external finance premium the RMSPE for the out-of-sample forecast errors for the respective horizons are reported. RMSPE relative to the VAR model without an external finance premium are reported for the different models. Parameters are set to their posterior mode to compute the forecast errors. Posterior distributions of the parameters are estimated every year.

Tables 2 and 3 report the RMSPE for the full and short US sample, respectively. The RMSPE for output and the log-determinant[16] is smaller when using only more recent information to estimate the VAR. Including the external finance premium in the VAR as an endogenous variable does not improve the forecasts for output, but does for inflation. The SW-RI model and the SW-FA model are the best models to make one-quarter-ahead predictions, according to the log-determinant. They perform slightly better as the unrestricted VAR model. As expected, the forecast accuracy decreases almost monotonically with the horizon. Compared with a VAR with one lag, the forecast performance of

[16] The log-determinant of the forecast error covariance at a specific horizon measures the forecast accuracy for multiple variables at the same time. A higher log-determinant indicates higher forecast errors.

the structural models for output growth is pretty close, regardless of the underlying expectation formation process. The accuracy of inflation forecasts can be improved substantially by using restricted models compared with unrestricted models. Adaptive learning improves the forecast accuracy for output and inflation in the short sample, but not in the full sample. The exclusion of nominal rigidities deteriorates the forecast accuracy for output growth and inflation. For increasing forecast horizons, nominal rigidities become less important. Rigid wages help to improve forecasts for output growth and lead to worse forecasts for inflation. Rigid prices are helpful to forecast inflation, but not to forecast output growth. Including both rigidities leads to worse forecasts for inflation and output growth compared with the models with only one rigidity.

Table 3: Root Mean Squared Percentage Errors – US (Short Sample)

Horizon	Output Growth	Inflation	Log-Det.	Output Growth	Inflation	Log-Det.
	Adaptive learning			Rational expectations		
Smets and Wouters without nominal rigidities (SW-NRI)						
1	1.86	1.03	1.23	1.85	1.03	1.23
4	2.42	1.02	1.23	2.24	1.03	1.15
8	3.60	0.98	1.46	4.17	0.98	1.44
Smets and Wouters without price rigidities (SW-NPR)						
1	1.65	1.02	0.91	1.91	1.02	1.08
4	2.10	1.02	1.05	2.86	1.02	1.19
8	3.44	0.98	1.35	4.51	0.98	1.48
Smets and Wouters without wage rigidities (SW-NWR)						
1	1.90	0.53	1.13	2.17	0.51	1.25
4	2.69	0.96	1.22	3.19	0.84	1.24
8	4.15	0.95	1.49	4.82	0.88	1.51
Smets and Wouters with nominal rigidities (SW-RI)						
1	1.65	0.50	0.78	2.02	0.50	1.02
4	1.89	0.82	1.02	3.28	0.83	1.22
8	3.65	0.80	1.33	4.78	0.85	1.51
Smets and Wouters with financial accelerator (SW-FA)						
1	0.64	0.33	0.55	0.93	0.60	0.69
4	0.88	0.43	0.77	0.99	0.88	0.85
8	1.72	1.44	1.17	3.09	0.77	1.16
Vector autoregressive model						
	without external finance premium			with external finance premium		
1	8.53	6.35	13.53	0.99	0.91	0.71
4	7.29	6.62	19.00	1.09	0.93	0.92
8	4.59	7.37	16.77	1.19	0.98	0.83

Notes: For the VAR without external finance premium the RMSPE for the out-of-sample forecast errors for the respective horizons are reported. RMSPE relative to the VAR model without an external finance premium are reported for the different models. Parameters are set to their posterior mode to compute the forecast errors. Posterior distributions of the parameters are estimated every year.

Table 4: Root Mean Squared Percentage Errors – United Kingdom

Horizon	Output Growth	Inflation	Log-Det.	Output Growth	Inflation	Log-Det.
	Adaptive learning			Rational expectations		
Smets and Wouters without nominal rigidities (SW-NRI)						
1	1.10	0.33	1.06	2.72	0.33	1.12
4	0.77	0.45	0.88	1.10	0.43	0.92
8	1.29	0.31	0.91	1.29	0.30	1.02
Smets and Wouters without price rigidities (SW-NPR)						
1	1.20	0.34	0.90	3.24	0.32	1.09
4	0.53	0.45	0.78	1.14	0.44	1.09
8	1.10	0.32	0.78	1.40	0.30	1.09
Smets and Wouters without wage rigidities (SW-NWR)						
1	1.86	0.62	1.09	2.60	1.55	1.27
4	0.94	0.34	0.73	1.42	0.96	0.82
8	1.58	0.30	0.82	1.12	0.72	0.79
Smets and Wouters with nominal rigidities (SW-RI)						
1	1.47	1.04	0.96	3.19	0.71	1.28
4	0.70	0.91	0.86	1.37	2.91	1.02
8	1.09	0.43	0.92	1.11	1.01	0.98
Smets and Wouters with financial accelerator (SW-FA)						
1	2.00	0.72	1.07	1.36	1.16	1.30
4	0.72	1.20	0.94	1.50	0.84	1.12
8	0.90	0.92	1.14	0.97	0.30	1.06
Vector autoregressive model						
	without external finance premium			with external finance premium		
1	3.26	6.66	25.57	1.20	0.93	1.02
4	6.36	5.06	30.22	1.61	1.21	1.13
8	3.88	7.64	30.45	0.74	1.00	1.09

Notes: For the VAR without external finance premium the RMSPE for the out-of-sample forecast errors for the respective horizons are reported. RMSPE relative to the VAR model without external finance premium are reported for the different models. Parameters are set to their posterior mode to compute the forecast errors. Posterior distributions of the parameters are estimated every year.

Table 4 reports the results for the United Kingdom. Similar to the US, the inclusion of the external finance premium in the VAR does not lead to better forecasts. Including financial frictions in the structural model improves the forecasts up to one year for output growth compared to a VAR without an external finance premium and compared with the SW-RI model. Contrary to the US, the RMSPE do not improve by including nominal rigidities. Adaptive learning improves one-quarter-ahead output growth forecasts for the SW-RI, SW-NPR, and SW-NWR models compared with rational expectations. For one-year-ahead forecasts this statement remains valid and is also true for the SW-FA model. For two-year-ahead forecasts only the SW-NWR produces better forecasts with rational expectations compared with adaptive learning. The forecasts are not systematically better or worse than the VAR forecasts.

The log-determinant for the SW-RI model is smaller than for the unrestricted VAR model at all horizons.

The results for the Euro area are shown in Table 5. Wage rigidities improve the forecasts for output growth and price rigidities are not helpful for forecasting inflation. Therefore, it is important to account for rigid wages in the Euro area and not for rigid prices. Adaptive learning does not essentially improve the forecast accuracy of the models in the Euro area. Structural models forecast output growth and inflation better than unrestricted VAR models. It seems that the imposed structure on the implicit reduced-form VAR is helpful for improving inflation and output growth forecasts.

Table 5: Root Mean Squared Percentage Errors – Euro Area

Horizon	Output Growth	Inflation	Log-Det.	Output Growth	Inflation	Log-Det.
	Adaptive learning			Rational expectations		
Smets and Wouters without nominal rigidities (SW-NRI)						
1	0.92	0.24	0.72	0.89	0.22	0.72
4	0.49	0.42	0.62	0.80	0.40	0.89
8	1.27	0.49	0.76	2.73	0.46	1.09
Smets and Wouters without price rigidities (SW-NPR)						
1	0.58	0.24	0.51	0.64	0.22	0.54
4	0.44	0.43	0.63	0.77	0.39	0.87
8	1.17	0.48	0.78	2.89	0.45	1.09
Smets and Wouters without wage rigidities (SW-NWR)						
1	0.84	0.37	0.81	0.51	0.52	1.00
4	0.47	0.26	0.64	0.33	0.73	0.70
8	1.47	0.42	0.87	1.65	0.75	0.77
Smets and Wouters with nominal rigidities (SW-RI)						
1	0.42	0.50	0.46	0.73	0.75	0.91
4	0.34	0.19	0.47	0.47	0.75	0.80
8	1.56	0.21	0.60	1.43	1.13	0.89
Smets and Wouters with financial accelerator (SW-FA)						
1	0.50	0.57	0.81	0.48	0.76	0.71
4	0.68	0.53	0.86	0.34	0.54	0.86
8	1.55	0.79	1.16	1.17	1.16	1.36
Vector autoregressive model						
	without external finance premium			with external finance premium		
1	4.46	9.73	13.33	1.71	0.82	1.17
4	6.73	5.52	17.77	1.13	0.96	1.21
8	1.90	5.10	15.69	2.52	0.96	1.30

Notes: For the VAR without external finance premium the RMSPE for the out-of-sample forecast errors for the respective horizons are reported. RMSPE relative to the VAR model without an external finance premium are reported for the different models. Parameters are set to their posterior mode to compute the forecast errors. Posterior distributions of the parameters are estimated every year.

To compare the performance between adaptive learning and rational expectations more rigorously, we report the mean differentials between absolute forecast errors of models with AL and RE. We further test whether the mean is significantly different from zero with the help of a two samples t-test (Härdle et al. 2017, 160). The mean deviation in absolute forecast errors is used under the assumption that forecasters are generally only interested in how far away they are from the actual value. The implicit assumption here is that over- and under-prediction result in the same costs to the forecaster.

Table 6: Mean Deviations between AL and RE absolute Forecast Percentage Errors for the US

Horizon	Full sample			Short sample		
	Output	Inflation	All	Output	Inflation	All
Smets and Wouters without nominal rigidities (SW-NRI)						
1	-13.99	-0.52	-12.07	0.14	-0.01	0.06
	(0.07)	(0.77)	(0.01)	(0.97)	(1.00)	(0.93)
4	-0.98	-1.20	-1.40	0.49	-0.01	0.43
	(0.76)	(0.67)	(0.34)	(0.89)	(1.00)	(0.52)
8	0.32	1.52	0.17	-0.54	-0.01	0.59
	(0.94)	(0.50)	(0.94)	(0.89)	(1.00)	(0.48)
Smets and Wouters without price rigidities (SW-NPR)						
1	0.48	0.05	-0.06	-0.50	-0.00	-0.29
	(0.73)	(0.98)	(0.88)	(0.87)	(1.00)	(0.57)
4	0.42	0.04	0.21	-1.60	-0.00	-0.65
	(0.34)	(0.99)	(0.76)	(0.67)	(1.00)	(0.32)
8	-0.41	0.08	0.57	-1.67	-0.00	-0.87
	(0.17)	(0.97)	(0.62)	(0.68)	(1.00)	(0.29)
Smets and Wouters without wage rigidities (SW-NWR)						
1	-27.53	0.41	-17.31	-0.38	0.17	-0.12
	(0.03)	(0.50)	(0.00)	(0.91)	(0.79)	(0.88)
4	-1.01	3.61	0.71	-1.11	0.23	-0.19
	(0.80)	(0.33)	(0.52)	(0.80)	(0.85)	(0.82)
8	1.80	1.83	3.21	-1.12	0.25	-0.03
	(0.81)	(0.44)	(0.13)	(0.80)	(0.87)	(0.97)
Smets and Wouters with nominal rigidities (SW-RI)						
1	1.89	-0.08	0.15	-0.71	0.11	-0.35
	(0.48)	(0.86)	(0.75)	(0.82)	(0.87)	(0.48)
4	1.16	0.61	1.32	-2.91	-0.04	-1.02
	(0.65)	(0.36)	(0.04)	(0.47)	(0.98)	(0.13)
8	1.67	0.25	3.13	-2.08	-0.08	-1.23
	(0.37)	(0.79)	(0.00)	(0.63)	(0.95)	(0.13)
Smets and Wouters with financial accelerator (SW-FA)						
1	-0.47	1.39	0.51	-0.49	-0.21	0.01
	(0.72)	(0.09)	(0.12)	(0.71)	(0.72)	(0.96)
4	4.90	0.51	1.45	0.03	-0.57	-0.07
	(0.18)	(0.44)	(0.02)	(0.98)	(0.53)	(0.86)
8	6.15	2.21	3.67	-1.57	1.68	-0.35
	(0.36)	(0.04)	(0.00)	(0.54)	(0.36)	(0.60)

Notes: Values in parentheses denote p-values of two sample t-tests for zero mean of absolute forecast differentials.

For the US the results are tabulated in Table 6. Output growth is better predicted one quarter ahead by adaptive learning than rational expectations for the model without wage rigidities using the full sample.

The SW-RI with rational expectations predicts an initial increase in output growth after 2007-Q4 and under adaptive learning tracks the actual behaviour very well. Otherwise, the mean differential of absolute forecast errors is not significantly different from zero at the five percent level. For the baseline SW-RI model and the extension with financial frictions, it does not matter whether one uses AL or RE. Inflation is not better predicted under RE or AL for models excluding nominal rigidities. The two-year-ahead forecast by the baseline model with financial accelerator for inflation is significantly better under rational expectations than under adaptive learning. If we consider all variables, an RBC model performs better under adaptive learning for one-quarter-ahead forecasts. The baseline model and the extension with a financial accelerator perform better under rational expectations for one-year- and two-year-ahead forecasts. The results for the short sample reveal that neither adaptive learning nor rational expectations are significantly better for any horizon or variable.

The results for the UK and the Euro area are tabulated in Table 7. The mean absolute differentials for the UK and the Euro area are negative for the baseline model. This implies that absolute percentage errors are lower using adaptive learning. Nevertheless, the difference between adaptive learning and rational expectations is not statistically significant. Neither adaptive learning nor rational expectations are preferable in all models to improve forecasts for all variables in the UK and the Euro area. The one-quarter-ahead forecasts by the financial accelerator model, as depicted in Figures 5 and 6, with adaptive learning and rational expectations always follow the actual development of output growth in the UK and the Euro area with a lag. Therefore, it is not possible to reduce the bias significantly by using adaptive learning rather than rational expectations.

Table 7: Mean Deviations between AL and RE absolute Forecast Percentage Errors for the UK and the Euro Area

Horizon	United Kingdom			Euro area		
	Output	Inflation	All	Output	Inflation	All
Smets and Wouters without nominal rigidities (SW-NRI)						
1	−1.30 (0.32)	0.02 (0.97)	26.85 (0.86)	−0.38 (0.63)	0.05 (0.90)	-0.05 (0.86)
4	−0.90 (0.45)	0.02 (0.97)	2.67 (0.90)	-0.91 (0.30)	0.05 (0.91)	-0.69 (0.12)
8	-0.34 (0.74)	0.01 (0.98)	−16.54 (0.65)	-1.09 (0.19)	0.05 (0.92)	-0.87 (0.06)
Smets and Wouters without price rigidities (SW-NPR)						
1	−1.87 (0.24)	0.04 (0.93)	−32.40 (0.67)	−0.28 (0.57)	0.05 (0.89)	-0.04 (0.88)
4	−1.82 (0.10)	0.03 (0.94)	-28.06 (0.57)	−0.93 (0.27)	0.05 (0.89)	-0.63 (0.14)
8	−1.07 (0.28)	0.03 (0.95)	-50.76 (0.39)	-1.26 (0.14)	0.06 (0.90)	-0.86 (0.07)
Smets and Wouters without wage rigidities (SW-NWR)						
1	−1.25 (0.37)	−1.55 (0.33)	37.18 (0.80)	0.52 (0.37)	-0.61 (0.47)	-0.28 (0.49)
4	−1.07 (0.48)	−1.01 (0.15)	6.87 (0.63)	0.47 (0.36)	−0.76 (0.18)	0.13 (0.79)
8	0.41 (0.71)	-0.97 (0.27)	0.79 (0.97)	0.05 (0.93)	-0.54 (0.38)	0.09 (0.79)
Smets and Wouters with nominal rigidities (SW-RI)						
1	−1.95 (0.22)	0.28 (0.81)	-37.21 (0.56)	-0.21 (0.68)	-0.59 (0.63)	-0.42 (0.20)
4	-2.01 (0.14)	−1.65 (0.48)	5.73 (0.86)	-0.28 (0.59)	−0.83 (0.15)	-0.50 (0.15)
8	-0.22 (0.80)	−1.18 (0.35)	9.87 (0.56)	0.13 (0.82)	−1.20 (0.17)	-0.40 (0.21)
Smets and Wouters with financial accelerator (SW-FA)						
1	0.50 (0.64)	−0.67 (0.59)	−35.55 (0.39)	−0.07 (0.85)	−0.12 (0.93)	-0.02 (0.95)
4	−2.17 (0.14)	0.40 (0.70)	-4.68 (0.74)	0.60 (0.39)	0.29 (0.59)	0.08 (0.78)
8	0.17 (0.81)	1.80 (0.10)	-0.45 (0.97)	0.33 (0.51)	0.09 (0.93)	-0.21 (0.61)

Notes: Values in parentheses denote p-values of two sample t-tests for zero mean of absolute forecast differentials.

5. Conclusion

Standard macroeconomic models were heavily criticized after the financial crisis because they did not adequately predict the great recession of 2009. The main points of critique were the rational expectation hypothesis and the absence of financial variables. In recent years, model alternatives which include financial variables and which employ other expectation formation specifications than rational expectations have been developed. Empirical research has shown that these extensions can improve the in-sample fit of macroeconomic models. However, in general, they do not substantially improve forecasting performance.

The critique that standard macroeconomic models neglect the role of financial variables seems a plausible explanation for their poor performance during the last financial crisis. Including the financial accelerator in the Smets and Wouters model improves forecasts after the crisis for output growth. This improvement cannot simply be explained by the inclusion of the external finance premium. Its inclusion in an unrestricted vector autoregressive model does not improve the forecast performance of the model. However, the inclusion of the variable in a structural way improves the forecasting performance. Therefore, macroeconomists did not neglect an important variable, but rather the role of financial markets for the real economy. This paper only considers the external finance premium as an additional variable, as demonstrated by Merola (2015). Other papers, such as that by Christiano, Motto, and Rostango (2014), also use stock returns as measure for net worth to estimate the Smets and Wouters model with financial frictions. Nevertheless, as stated by Del Negro, Hasegawa, and Schorfheide (2016), financial frictions are very helpful for predicting output contraction after the financial crisis; however, in normal times these are not as important.

The use of rational expectations in DSGE models has also been heavily criticized. An alternative is expectations formed by adaptive learning such those as used by Slobodyan and Wouters (2012). This alternative framework has a slightly better in-sample fit, but is not able to significantly beat rational expectation models with regard to forecasting output and inflation.

The forecasting performance of all models is better when using a more recent, shorter sample than using the full sample for the US. This implies that more distant data might be less informative for predicting the present. A usual way to account for less informative data is using moving windows to estimate models or to assign data points further in the past a lower weight. Time-varying reduced form parameters per se, as introduced by adaptive learning models in the full sample for the US, do not necessarily improve the forecasting performance. The fundamental reason for the change in parameters is probably not alternating forecast models of economic agents. Macroeconomists should give more attention to how to select appropriate estimation windows for their models.

A major source of economic fluctuations is unpredictable structural shocks. These can be understood with the benefit of hindsight within macroeconomic models, and applied macroeconomic analysis should take the model extensions seriously. However, there is no best unique model to predict the future. Perhaps the most important lesson is that applied macroeconomists should not rely on one single model, but have several models in their toolkits.[17] Macroeconometric models are summaries of the empirical behaviour of important macroeconomic time series. What should be included in this summary depends on the question at hand (including the forecasting horizon) and the specific economic conditions in the period and region under investigation. The pre-crisis standard New Keynesian DSGE model is still an important tool in the toolkit and remains a good starting point for forecasts during normal times.

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[17] This conclusion can also be found in Wieland (2012), for example.

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