Forecasting with DSGE models: What frictions are important?∗

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1. Introduction

Economic forecasts are essential for decision-makers, both at individual level and for the government policies. They are especially relevant for central banks, since monetary policy transmission lags require forward-looking decisions. Traditionally, both judgmental and model-based forecasts represent point predictions—the most likely future outcomes for certain variables. However, in recent years density predictions became an active area of research and represent the current standard approach for inflation-targeting central banks to communicate their forecasts. A density forecast is defined in Tay and Wallis (2000) as the estimated probability distribution of future values. The point forecast is just a moment of the density forecast, usually the mean. Hence, as opposed to point predictions, density forecasts provide a complete quantitative description of the uncertainty, which is usually visualized in form of a fan chart, each band showing possible future paths of the variables with an associated probability. Important central banks, like the Bank of England or the Sveriges Riksbank, are experienced users of fan charts in their monetary policy process.

Practical importance of density forecasts for economic decision-makers are surveyed in Tay and Wallis (2000). Given the inflation targeting strategy pursued by many central banks worldwide, predictive densities and fan charts are useful and efficient communication tools. First, they represent the (subjective) assessment of the macro-economic risks’ balance by the central bank. For example, in the context of the National Bank of Romania’s current inflation target of 2.5% with a target band of ±1 percentage point, a fan chart for consumer prices’ annual inflation rate can provide answers to questions like what is the probability of inflation being outside the targeted interval, quantifying in this way the risk for the central bank to miss its objective. Second, it is generally acknowledged that agents have asymmetric loss functions and non-linear preferences, so that point forecasts are only partially relevant for them. In general, consumers are risk averse, implying that equal (in absolute value) losses and gains are perceived differently, while certain producers may be more concerned with unexpected future price increases than price decreases. Communicating the entire distribution of the forecasts—which is relevant for all users, regardless of their individual loss functions—has the potential of anchoring all agents’ expectations. Third, practical applications of density forecasts are represented by economic surveys, such as the ECB Survey of Professional Forecasters, or value at risk methods to quantify the level of financial risk.

In order to formalize their actions, policy-makers generally rely on model-based predictions. In this context, Dynamic Stochastic General Equilibrium (DSGE) models with New Keynesian ingredients have gained extreme popularity during the last decades. These are widely applied in academia and also by economic policy-makers to guide decision-making process and, more recently, to produce formal forecasts. Modern DSGE models embed a rich collection of frictions, incorporated to achieve an increased data fit and to match certain

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business cycle facts. For example, Smets and Wouters (2003) and Christiano et al. (2005) introduce habit behavior in consumption preferences and variable capital utilization rate to obtain hump-shaped responses of consumption and investment to monetary policy shocks, in line with evidences based on Vector Autoregressions (VAR). However, there are no a priori reasons to consider that these additional features are consistent with the business cycle dynamics of emerging economies and also whether they improve out-of-sample forecasting accuracy. To test this hypothesis, in this paper we compare the relative performance of a total of eight DSGE model specifications, with certain frictions turned off, and evaluate what mechanisms are consistent with the Romanian macroeconomic variables’ data generating process. Our general results are consistent with Wolters (2015), who reached the conclusion that “different frictions in different models seem to be useful for forecasting specific variables in certain periods only, while other frictions are more important for other periods” (p. 88).

Despite the advantage of generating predictions with economically meaningful interpretations, the record of DSGE-based forecasting is relatively limited compared to reduced-form time series methods. In this paper we apply the medium-size DSGE model developed in Smets and Wouters (2003) for the Euro area and in Smets and Wouters (2007) for the US (hereafter SW model). It is similar in terms of considered mechanisms with Christiano et al. (2005) and also with the subsequent generations of DSGE models: households’ utility is characterized by habit in consumption preferences; prices are sticky, following Calvo (1983) time-dependent staggered adjustment; stickiness in real wages is introduced along the lines of Erceg et al. (2000); non-optimizing firms and households are allowed to index their prices and wages, respectively; capital utilization rate is allowed to vary with the business cycle conditions, etc. Our contribution consists of determining the marginal importance of each of those ingredients at producing both point and density predictions for post-Great Recession Romanian data.

The SW model has become very popular in DSGE literature. Del Negro and Schorfheide (2013) provide a textbook exposition of DSGE model-based forecasting procedures, together with an empirical application featuring small- and medium-scale models, including SW. The specification which embeds financial frictions on top of the SW model is shown to improve predictive accuracy during the Great Recession. Herbst and Schorfheide (2012) analyze the SW model and a small textbook New Keynesian DSGE model in terms of point and density forecasting accuracy. Wolters (2015) compares several seminal DSGE models, including SW, to the Fed’s Greenbook projections and concludes that the former overestimate uncertainty, i.e. fan charts are too wide when compared to actual data frequencies.

Small open economy extensions of the SW model are due to Adolfson et al. (2007) and Christoffel et al. (2010). Both of which provide an extensive forecast evaluation for the Euro area data. Berg (2016) finds that DSGE models (including SW) are relatively more successful at multivariate density predictions as opposed to point predictions. Using Norwegian data, Bache et al. (2011) and Bjornland et al. (2011) perform density combination exercises for DSGE and non-structural models. The record of DSGE-based forecasts for emerging economies is extremely scarce. One notable exception is Balciar et al. (2015), who estimate a closed-economy non-linear New Keynesian model for South Africa (as Romania, also a small open economy). The general conclusion of the above mentioned papers is that DSGE models compare well in terms of predictive accuracy with time series methods (like Bayesian VARs) or professional forecasting services.

Our empirical application of the eight SW model variants allows us to reach several interesting conclusions. First, we find that the baseline model is always dominated by some of its competitors, suggesting that there is no need for the full set of typical DSGE frictions to optimally forecast Romanian macroeconomic variables. This happens in part because the uncertainty implied by the full model generates too wide predictive densities as compared to the statistical proprieties of actual data generating process. Second, for both point and density out-of-sample forecasts, different frictions have practical and statistically significant relevance at predicting specific variables. In particular, the model with constant capital utilization rate is preferred for GDP growth forecasts, while the specification with reduced consumption habit performs well in case of investment and consumption forecasts. Sticky prices and sticky wages are important features for obtaining satisfactory forecasts for nominal variables. For some series, like labor input and interest rate, univariate autoregressive models can not be defeated by any of the DSGE specifications. The simple univariate model is in general quite robust for one-quarter ahead predictions.

Third, we document some tension between the rankings of the models based on the two dimensions of forecasting, in the sense that the models preferred in case of point predictions do not always coincide with the ones favored based on density forecasting accuracy. Hence, policy-makers and users focusing only on one of the two dimensions risk being misguided and take uninformed decisions. Fourth, we find that in terms of multivariate density forecasts the overall preferred specification is the constant capital utilization rate model, owing to its outstanding GDP growth forecasts’ relative precision. Lastly, we implement the model confidence set (MCS) procedure of Hansen et al. (2011) to estimate the collection of strictly preferred models. The results show that only for GDP and consumption growth rates there exist a single “best” model, while for other variables the MCSs are not as decisive. Overall, the results we obtain imply that in order to take fully-informed decisions, policy-makers require an extensive collection of models, as not a single specification constantly dominates its competitors.

The rest of this paper is organized as follows. Section 2 briefly summarizes the baseline SW model, with the complete description of the log-linearized equations relegated to the Appendix. The data and estimation procedure, including the eight model specifications, are presented in Section 3. The results of our comparative forecasting exercise are extensively analyzed in Section 4. Finally, Section 5 concludes the paper.

2. The model

The DSGE model we use builds heavily on works of Smets and Wouters (2003, 2007). It is a medium-sized structural model that includes a series of nominal and real frictions—monopolistic competition, sticky prices and wages, partial indexation for non-adjusting firms and households, variable capital utilization rate, habit in consumption preferences—as well as a rich shock structure. All these modelling devices were added to obtain a better data fit in case of developed economies. In this paper we assess their relative importance in terms of forecasting accuracy for a developing economy. The full log-linearized model is presented in Appendix, while the reader is referred to the above-mentioned papers for additional technical details. In order to accommodate the model to some specific features of the Romanian economy and also given the short data sample used for estimation, we resort to some adjustments as compared to the original specifications: we keep some of the parameters fixed throughout the estimation, as motivated in the next section; the central bank responds to expected inflation (instead of the contemporaneous one), which is more likely to characterize the inflation targeting regime in place; the monetary policy rule is shocked by an i.i.d. innovation instead of an AR(1) process as in Smets and Wouters (2007).

The main concern regarding the model we use is that it is designed for a closed economy, while Romania is a small open economy. However, there are several observations to alleviate this mismatch.

\[ \text{Given the small open economy feature of the Romanian economy, a similar model would be a more realistic framework to follow, an extension we leave for future research.} \]