# Forecasting with DSGE models in the Presence of Data Revisions

Ana Beatriz Galvão*
School of Economics and Finance
Queen Mary University of London
a.ferreira@qmul.ac.uk

June 20, 2013

**Abstract**

Real-time forecasts of DSGE models are computed by estimating the DSGE model with bayesian methods using mainly heavily revised data, while forecasts are conditioned on lightly revised data. This paper shows how to solve this apples-oranges-mixing problem for DSGE models. The suggested approach rewrites the measurement equation used to estimate DSGE models to include both first-release and first-final estimates. I assume that economic agents are able to filter first-final estimates of macroeconomic variables based on observable current first releases and past first-final estimates. An advantage of this approach is providing a way of measuring the impact of structural shocks on unexpected data revisions. Estimates based on the proposed release-based approach suggest that 62% of initial output growth revisions are due to productivity shocks.

Key words: data revisions, medium-sized DSGE models, forecasting, variance decomposition.

JEL code: C53.

*Corresponding author: Dr. Ana Beatriz Galvao. Queen Mary University of London, School of Economics and Finance, Mile End Road, E1 4NS, London, UK. Phone: ++44-20-78828825. email: a.ferreira@qmul.ac.uk.

# 1 Introduction

Economists in central banks and international organizations would like to rely on structural models for macroeconomic forecasting. The advantages of structural models are their usefulness for policy analysis and the provision of economic scenario support for forecasts. Smets and Wouters (2007) paper was very influential in central banks because they were the first to show that we could turn to medium-scale Dynamic Stochastic General Equilibrium (DSGE) models to supply accurate long-horizon forecasts of macroeconomic variables. Del Negro and Schorftheide (2012) show that long-horizon output growth and inflation forecasts from medium-scale DSGE models are more accurate than Federal Reserve Greenbook forecasts and professional forecasters even if evaluated with real-time data.

An additional issue if evaluating real-time forecasts is the choice of forecast target. Del Negro and Schorftheide (2012) assess forecasts using the latest available vintage, which contain the best estimates available, including annual and benchmark revisions for many observations, and the "first final", which is the estimate published after the first round of monthly revisions, excluding annual and benchmark revisions. They claim both loss functions deliver similar ranks across models. However, from the point of view of a professional forecaster evaluating his/her forecast in real-time, the "first final" may be a more adequate target since forecasting errors can be computed three months after the end of the observational quarter (as in Edge and Gurkaynak (2011)), instead of three or even five years later. Another issue is that initial data revisions are mainly caused by adding new information to the original trend-based estimates (Landefeld, Seskin and Fraumeni, 2008). As a consequence, professional forecasters are able to anticipate these revisions based on information released after the publication of the previous release (Clements and Galvão, 2012a). The evidence on the predictability of annual and benchmark revisions is weaker (Faust, Rogers and Wright, 2005; Corradi, Fernandez and Swanson, 2009).

Suppose a forecaster that targets the first-final estimate of output growth and inflation and has the current vintage to compute forecasts using a DSGE model. The conventional approach to evaluate real-time forecasts, as employed by Edge and Gurkaynak (2011), Woulters (2012) and Del Negro and Schorftheide (2012), is to estimate the model with the vintage available at each point in time, and then compute forecasts that are condition on early estimates. This approach suffers the apples-oranges-mixing problem identified by Kishor and Koenig (2012) in the context of forecasting with VAR models in real time. The problem is that the forecasting model is estimated with heavily revised data, while forecasts are conditioned on lightly revised data.[1]

This paper shows how to use DSGE models, estimated with bayesian methods, for real-time forecasting while dealing with the apples-oranges-mixing problem. The suggested approach rewrites the measurement equation used to estimate DSGE models to include both first-release and first-final estimates. I assume that economic agents inside the model are able to filter first-final estimates of macroeconomic variables based on observable current first releases and past first-final estimates. My approach does not argue for changes on the model microfundations. I consider issues from data availability in real time as a measurement problem that needs to be solved by the econometrician/forecaster.

An advantage of this approach is that provides a way of measuring the impact of structural shocks on unexpected data revisions. In contrast with Casares and Vazquez (2012) I do not assume that data revisions may change economic decisions.[2] Instead my assumption is that initial revisions can be partially predicted while they also increase the variance of the first release. Economic decisions are then taken based on filtered values of the first release, incorporating expected future data revisions. Gilbert (2011) argues that equity markets react at the day of the first release of GDP not only to the surprise to the initial publication, but also to expected future data revisions. The evidence that professional forecasters are able to predict the first monthly revision of GDP also supports this claim (Clements and Galvão, 2012a). Because initial revisions are only partially predictable, unexpected data revisions may be related to structural shocks since revisions may be caused by adding new information due to unexpected structural shocks.[3] In this paper I show that innovations to initial revisions to GDP are strongly correlated to technological shocks, and innovations to revision inflation are weakly correlated to price-markup shocks.

This approach does not consider that data revisions may be a source of business cycles. The approach by Blanchard, L'Huillier and Lorenzoni (2012) to show how noisy productivity shocks can create business cycles does not rely on the existence of data revisions, but that consumers are not able to distinguish between permanent and temporary future changes in productivity. In this paper I am not interested in measuring the effect of using real-time data on measuring the implied policy rate as the seminal work of Orphanides (2001), applied to the case of DSGE policy estimation by

[1] This issue was addressed in the context of AR and ADL models by Koenig, Dolmas and Piger (2003) and Clements and Galvão (2013).

[2] The fact that earlier estimates may change the way agents behave was found by Rodriguez-Mora and Schulstad (2007), but Clements and Galvão (2010) argue that this finding could be caused by the data revision process.

[3] In context of VAR models, Kishor and Koenig (2012) assume that innovations to data revisions may be correlated with shocks to the true data if the statistical agency filters the available data in order compute initial releases as suggested by Sargent (1989).

Neri and Ropele (2011). My contribution is a modelling approach to accommodate data revisions to macroeconomic data when estimating DSGE models with data subject to revision.

The approach developed in this paper can be applied to any DSGE model that can be estimated based on a linear state-space representation. Section 2 describes the new approach in contrast with the conventional approach. In Section 3, I show how to apply the release-based approach to the medium-scale Smets and Wouters (2007) model. The model posterior densities are then compared with the ones obtained with the conventional approach, including an evaluation of the variance decomposition. I also contribute with a real-time forecast exercise, as in Herbst and Schorftheide (2012), for forecasting output growth, inflation, and the fed fund rates.

# 2 Forecasting with DSGE models in real time

This section describes what I call the conventional approach to use DSGE models for real-time forecasting, employed by Edge and Gurkaynak (2011), Woulters (2012), Herbst and Schorftheide (2012) and Del Negro and Schorftheide (2012). Then I show how to solve the apples-oranges-mixing problem using the release-based approach.

## 2.1 The Conventional Approach

Before estimation, endogenous variables of the DSGE model are detrended based on a common deterministic (Smets and Wouters, 2007) or stochastic (Del Negro and Schorftheide, 2012) trend, and then the model is log-linearised around the deterministic steady-state. Based on the log-linearized version, numerical methods are employed to solve the rational expectations model (see, e.g., Guerron-Quintana and Nason (2012) for description of usual techniques).

Define $x_t$ as a $n \times 1$ vector of the endogenous DSGE variables written as deviation of the steady-state. In practice $x_t$ may also include lagged variables depending on the specification of structural exogenous shocks and measurement equations. Define $\theta$ as the vector of structural parameters. The solution of the DSGE model for a given vector of parameters $\theta$ is written as:

$$x_t = F(\theta)x_{t-1} + G(\theta)v_t \tag{1}$$

where $v_t$ is $r \times 1$ vector of structural shocks, so the matrix $G(\theta)$ is $n \times r$. Note also that $v_t \sim iidN(0, Q)$. The equation (1) is the state equation of the state-space representation of the DSGE model.

Define $X_t$ as the $m \times 1$ vector of observable variables. Typically $m < n$ and $m \leq r$. Smets and Wouters (2007) medium-sized model has $m = r = 7$. The measurement equation is:

$$X_t = d(\theta) + H(\theta)x_t,$$

that is, the observable variables, such as inflation and output growth, are measured without error.

Edge and Gurkaynak (2011), Woulters (2012) and Del Negro and Schorftheide (2012) evaluate the accuracy of DSGE forecasts in real-time. This means that they use only data available at each forecast origin for estimating the vector of parameters $\theta$. Observables such as output, inflation, consumption and investment are National Accounts data. US and UK National Accounts data are initially published with one month delay with respect to the observational quarter. If the model is estimated at $T+1$, we have only data available up to $T$ for estimation. The measurement equation for real-time estimation is:

$$X_t^{T+1} = d(\theta) + H(\theta)x_t$$

for $t = 1, .., T$, where $T$ is the number of observations in the initial in-sample period. Suppose that the number of quarters in the out-of-sample period is $P$, a conventional real-time forecasting exercise re-estimates the model at each forecast origin from $T+1$ up to $T+P$, and forecasts are computed using data up to $T, ..., T+P-1$ at each origin.

The apples-oranges-mixing problem applies to the conventional real-time approach because the model is estimated mixing heavily revised data ($t = 1, ..., T-14$), data subject to annual revisions ($t = T-13, ..., T-1$), and data subject to the initial round of revisions and annual revisions ($t = T$)[4], while forecasts are computed conditioned on lightly revised data ($t = T$). Koenig et al. (2003) and Clements and Galvão (2013) show how to improve forecasts by dealing with this problem in the context of distributed lag regressions and autoregressive models, respectively. Clements and Galvão (2013) demonstrate that the conventional use of real-time data delivers estimates of autoregressive coefficients that do not converge to the values that would deliver optimal forecasts in real time. In this paper, I am not interested in understanding how different are the optimal forecasting parameters from the ones obtained using the conventional approach, but on the impact of disregarding the apples-oranges-mixing problem on the posterior distribution of the DSGE parameters and in the DSGE model real-time forecasting accuracy.

[4] This assumes three round of annual revisions published every July, as it is usually the case of US National Accounts Data published by the Bureau of Economic Analysis.

## 2.2 The Release-Based Approach

The approach I propose differs from Jacobs and van Norden (2011) and Casares and Vazquez (2012), but it is similar to Kishor and Koenig (2012). Casares and Vazquez (2012) assume that $q-1$ rounds of revisions are observable in order to estimate their model, and use $q = 6$ quarters. This implies that in order to estimate the model at $T+1$, only observations up to $T-5$ are available. While this is adequate for in-sample analysis, it implies that the most recent observations are not employed for real-time forecasting. My approach uses vintages from $t = 2, ..., T + 1$, and observations from $t = 1, ..., T$ of the first-release $X_t^{t+1}$and the first-final $X_{t-1}^{t+1}$ estimates.

As mentioned in the introduction, data revisions are incorporated by changing the measurement equations, with no changes in the structure of the DSGE model. This means that agents take decisions on filtered values of the endogenous variables, taking into account that the last observations are first estimates, subject to revisions that may be partially predictable.

Data revisions may add new information and/or reduce measurement error, following the definitions by Mankiw and Shapiro (1986) employed by Jacobs and van Norden (2011). I consider noise data revisions by allowing for serial correlation in the revisions as in Kishor and Koenig (2012), following the Howrey (1978) model, and news data revisions by allowing for non-zero contemporaneous correlation between innovations to revisions and structural shocks, following the Sargent (1989) model. As in Jacobs and van Norden (2011), data revisions may have news and noise components at the same time. The fact that I am able to link unexpected data revisions to structural shocks implies that we may empirically assess the contribution of structural shocks to news data revisions.

As argued in the introduction, it is reasonable to target the "first final" values, that is, $X_t^{t+2}$ in the case of evaluation of real-time forecasts. The model below requires the assumption that $X_t^{t+2}$ is an efficient estimate of $X_t$, as suggested by Kishor and Koenig (2012) and Garratt, Lee, Mise and Shields (2008) for US data. Based on this assumption, the release-based approach suggests to write the measurement equations using a vector of first-released values $\left\{X_t^{t+1}\right\}_{t=2}^{t=T}$, and vector of first-final values $\left\{X_{t-1}^{t+1}\right\}_{t=2}^{t=T}$. Recall that the conventional approaches uses only observations from the latest available vintage $\left\{X_t^{T+1}\right\}_{t=2}^{t=T}$. The release-based measurement equation is:

$$\begin{bmatrix} X_t^{t+1} \\ X_{t-1}^{t+1} \end{bmatrix} = \begin{bmatrix} d(\theta) + M \\ d(\theta) \end{bmatrix} + \begin{bmatrix} H(\theta) & 0_m & I_m \\ 0_m & H(\theta) & 0_m \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ rev_t \end{bmatrix},$$

where

$$rev_t = (X_t^{t+1} - X_t) - M.$$

The parameters in the $m \times 1$ vector $M$ allow for non-zero mean data revisions. Note that the first set of the equations imply that $X_t^{t+1} = d(\theta) + H(\theta)x_t + M + X_t^{t+1} - X_t - M$, that is, $X_t = d(\theta) + H(\theta)x_t$. This means that structural parameters are estimated with true values of the observables $X_t = X_t^{t+2}$ by employing filtered values $X_{T|T}$ of the last observations. In order to compute the filtered values, the following state equations are employed:

$$\begin{bmatrix} x_t \\ x_{t-1} \\ rev_t \end{bmatrix} = \begin{bmatrix} F(\theta) & 0_m & 0_m \\ I_m & 0_m & 0_m \\ 0_m & 0_m & K \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ rev_{t-1} \end{bmatrix} + \begin{bmatrix} G(\theta) & 0_m \\ 0_m & 0_m \\ 0_m & I_m \end{bmatrix} \begin{bmatrix} v_t \\ \eta_t \end{bmatrix},$$

where $\eta_t \sim iidN(0, Z)$ with $Z$ assumed to be diagonal, so revisions from different variables are not correlated.

The data revisions innovations $\eta_t$ may arise from two sources, as argued by Kishor and Koenig (2012), depending on the way the statistical agency employs the data available at the time of the release. The first source is a typical measurement error, that is, the statistical agency releases the estimate based on the data available that differs from the true values due to a measurement error. This is compatible with the Howrey (1978) model that also allows for serial correlation in the revisions, that is, elements of the $m \times m$ matrix $K$ are non zero. The second source is a filtering error. Sargent (1989) argues that it is optimal for the statistical agency to filter data before their initial release conditional on their available current and past data. This means that initial releases are efficient estimates of the true values, and unexpected data revisions $\eta_t$ may be correlated with the structural shocks $v_t$, since they are unpredictable conditional on past data. Kishor and Koenig (2012) explain that this correlation should be negative: if $v_t > 0$, the statistical agency may publish a $X_t^{t+1}$ that under-estimates $X_t$, so $\eta_t < 0$.

To allow for correlation between data revisions innovations and structural shocks, I define $u_t = \begin{bmatrix} v_t & \eta_t \end{bmatrix}'$, such that

$$var(u_t) = QN = \begin{bmatrix} Q & N' \\ N & Z \end{bmatrix}. \tag{2}$$

The assumption that data revisions are caused by statistical agency filtering mistakes implies that some of the covariances in $N$ maybe non-zero. To compute the variance decomposition of $x_t$

and/or $X_t^{t+1}$, a Cholesky decomposition of $QN$ is employed, that is, the data revisions may be related to innovations to structural shocks but not vice-versa. In the next section, I compute variance decompositions to assess the relative importance of the news and noise components in the data revision innovations $\eta_t$.

In practice, I assume that the matrix $K$ is diagonal in order to reduce the number of parameters to be estimated. Note also that some of the elements in $X_t^{t+1}$ may not be subject to revision. As a consequence the dimension of $X_{t-1}^{t+1}$ and $rev_t$ may be smaller than $m$.

Based on $d(\theta)$ and $H(\theta)$, we can compute forecasts of future true, or first-final, values of the observable variables using:

$$X_{T+h|T} = d(\theta) + H(\theta)x_{T+h|T},$$

where $x_{T+H|T}$ is obtained by iterating forward the state equation including errors drawn from the disturbances distribution.

# 3 The Release-Based Approach applied to the Smets and Wouters model

The equations of the log-linearised version of the Smets and Wouters (2007) model are described in Appendix A. The observation/measurement equations are:

$$X_t = \begin{bmatrix} \Delta\log(GDP_t) \\ \Delta\log(Cons_t) \\ \Delta\log(Inv_t) \\ \Delta\log(Wage_t) \\ \Delta\log(Hours_t) \\ \Delta\log(P_t) \\ FFR_t \end{bmatrix} = \begin{bmatrix} \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{\gamma} \\ \overline{l} \\ \overline{\pi} \\ \overline{r} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ l_t \\ \pi_t \\ r_t \end{bmatrix}. \tag{3}$$

All observable variables in $X_t$ are subject to revisions, except the fed fund rate $FFR_t$ and the total population above 16 used to compute $GDP_t$, $Cons_t$, $Inv_t$ and $Hours_t$. The GDP deflator is employed to compute $P_t$, and also to deflate the nominal observed values of $Cons_t$, $Inv_t$ and $Wage_t$. Table 1 provides details on how each one of these variables are computed using the available observable data, and their availability of quarterly vintages.

Initially I will attempt to model data revisions only to $GDP_t$ and $P_t$. This means that their updated measurement equations are:

$$\begin{aligned}
\Delta\log(GDP_t^{t+1}) &= \overline{\gamma} + (y_t - y_{t-1}) + M_y + rev_{yt} \\
\Delta\log(P_t^{t+1}) &= \overline{\pi} + \pi_t + M_\pi + rev_{\pi t} \\
\Delta\log(GDP_{t-1}^{t+1}) &= \overline{\gamma} + (y_{t-1} - y_{t-2}) \\
\Delta\log(P_{t-1}^{t+1}) &= \overline{\pi} + \pi_{t-1},
\end{aligned} \tag{4}$$

expanding the number of observable variables to nine. Note that I use data as in the conventional approach for the other observable variables subject to revision, that is, $Cons_t^{T+1}$, $Inv_t^{T+1}$, $Wage_t^{T+1}$ and $Hours_t^{T+1}$. However if they need to be deflated, I use, for example, the following:

$$\Delta\log(Cons_t^{T+1}) = 100[\log((PCE_t^{T+1}/P_t^{t+1})/POP_t) - \log((PCE_{t-1}^{T+1}/P_{t-1}^{t+1})/POP_{t-1})],$$

where $PCE$ is the nominal consumption measured by personal consumption expenditure and $POP$ is the population above 16, as detailed in Table 1. Because of the use of real values computed with the GDP deflator, the effect of data revisions on inflation may be pervasive.

The state vector is augmented with:

$$\begin{aligned}
rev_{yt} &= K_y rev_{yt-1} + \eta_{yt} \\
rev_{\pi t} &= K_\pi rev_{\pi t-1} + \eta_{\pi t},
\end{aligned} \tag{5}$$

where $var(\eta_{yt}) = Z_y^2$ and $var(\eta_{\pi t}) = Z_\pi^2$. In addition, I assume that $\eta_{yt}$ maybe correlated to $\eta_t^a$, which is the innovation to the technological shock that affects $y_t$ in the production function, as described in Appendix A. The innovations to inflation revisions $\eta_{\pi t}$ are assumed to be correlated to the price-markup innovation $\eta_t^p$. The price markup shock directly affects $\pi_t$ in the Phillips curve equation. The additional parameters estimated to measure the correlation follow $cov(\eta_{yt}, \eta_t^a) = \sigma_a Z_y P_{ya}$ and $cov(\eta_{\pi t}, \eta_t^p) = \sigma_p Z_\pi P_{\pi p}$, where $|P_{ya}|$ and $|P_{\pi p}|$ are $\leq 1$, and $\sigma_a$ and $\sigma_p$ are standard errors of productivity and price-markup innovations.

In summary, the modelling of data revisions on real output and inflation requires eight additional parameters $M_y$, $M_\pi$, $K_y$, $K_\pi$, $Z_y$, $Z_\pi$, $P_{ya}$ and $P_{\pi p}$, while the measurement equation has two additional equations and the equations of output growth and inflation are modified. The underlying assumption is that while unexpected variations on $y_t$ and $\pi_t$ are caused by structural shocks $v_t$, unexpected changes on the observed first release of GDP and Inflation, $GDP_t^{t+1}$ and $\Delta\log(P_t^{t+1})$ may be also caused by data revision innovations. An adequate response of the econometrician when estimating the DSGE model with real-time data is to filter initial estimates, so the additional variation caused by revisions does not affect forecasts.

### 3.1 Bayesian Estimation and Variance Decomposition

As Smets and Wouters (2007) and Herbst and Schorftheide (2012), I estimate the parameters of the medium-sized DSGE model by bayesian methods. The priors for the structural coefficients are as in Smets and Wouters (2007), and do not include the large set of calibrated coefficients suggested by Herbst and Schorftheide (2012). As in Herbst and Schorftheide (2012), I use observations since 1984, implying that the period of high inflation is not included in the estimation. In this subsection, I assume $T+1 = 2008Q4$.

The priors on the coefficients that describe the data revision processes allow for a wide range of values. I use a normal prior for the mean revisions and their autoregressive coefficients, allowing for negative values. I use inverse gamma priors for the standard error of data revisions innovations following the priors for the standard deviations of the structural shocks, but with a larger spread. The first parameter of the inflation innovation standard deviation is smaller than the output value due to scale. For the correlation between data revision innovations and structural shocks, I assume a uniform prior distribution between -1 and 1. The description of the complete set of priors is in Table 2.

Table 2 presents the mean of the posterior distributions, and 5% and 95% posterior quantiles for all parameters estimated.[5] The results with the conventional approach are based on data from the 2008Q4 vintage, while the release-based approach resorts to vintages from 1984Q1 up to 2008Q4 in order to build the time series for first releases and first finals of per capita output growth and inflation. The results in Table 2 indicate that the change in the data employed in the estimation has in general minor effects on the structural parameters posterior distributions. The parameters of the price-markup stochastic process are the exception. These parameters indicate that price-markup shocks are more persistent if estimated with release-based data.

The posterior distribution of the data revision processes parameters indicate that data revisions

[5] For the estimation and forecasting, I used my own GAUSS code based on the code provided by Herbst and Schorftheide (2012), available at http://economics.sas.upenn.edu/~schorf/.

tend to increase the unconditional mean of output growth and inflation. The uncertainty on the data revisions serial correlation coefficients is such that their posterior distributions have mean near to zero. In contrast, it is clear that the correlations between data revisions innovations and structural shocks are negative. The mean correlation between output growth data revisions innovations and productivity shocks is -0.44, implying that a productivity shock that unexpectedly raises output is correlated with a negative filtering error, that is, the statistical agency initial release of output growth underestimates the true value because of the productivity shock.

In order to understand the implications of these new estimates for the dynamics of the DSGE model, I plot the variance decompositions of output, inflation and federal fund rates computed at the posterior mean for horizons from 1 up to 20 quarters in Figure 1. Note that we use a Cholesky decomposition of eq. (2) to compute the variance decomposition at the impact as described in section 2. In each plot, I present the variance decomposition of the three structural shocks with the largest effects. In the case of output, I evaluate the effect of productivity ($a$), spending ($g$), and investment shocks ($i$). In the case of inflation, I evaluate productivity ($a$), price-markup ($p$), and wage-markup ($w$) shocks. For each one of these shocks, I plot the variance decomposition of $y_t$ and $\pi_t$ with the conventional ($\_cv$) and release-based estimation ($\_rb$). I also compute the variance decomposition of the observed first releases of output and inflation ($\_rb\_1$), which differ from the decompositions of $y_t$ and $\pi_t$ because they suffer data revision shocks. Finally, I also compute the variance decomposition of the fed fund rate for productivity, wage-markup and monetary policy ($r$) shocks.

The results in Figure 1 suggest that estimates of the variance decomposition using the release-based approach may be 5 p.p. above or below the conventional estimates. Large differences are detected if measuring the variation proportion due to productivity shocks, both for output and inflation. The shape of the decomposition over time also changes in particular if measuring the impact of productivity shocks. In summary, the impact of using release-based posterior means instead of the conventional approach values when computing variance decompositions is sizeable.

Figure 1 also shows that data revisions explain 2% of the unexplained variation of observed first-release output and 4.5% of the unexplained variation of observed first-release inflation at the first horizon. These proportions decrease over time. However small, they are larger than the variation explained by wage-markup shocks on output, and productivity shocks on inflation at the first horizon. In particularly in the case of inflation, data revisions innovations explain a proportion of inflation variance that is only smaller than price-markup and wage-markup shocks at short horizons.

The release-based approach also permits the computation of the impact of structural shocks on data revisions using the modified state equation. Based on the posterior means of Table 2, I find that 62% of the unexplained variation in output data revisions are explained by productivity shocks, while the remaining are explained by data revisions innovations at both short and long horizons. This implies that data revisions to output are mainly news and related to productivity shocks. This confirms the results of Clements and Galvão (2012a) that initial revisions are mainly anticipated based on new information.

In the case of inflation, only 16% of the unexplained variation is due to markup shocks, while the remaining are from own shocks. This suggests that data revisions to inflation are mainly noise since they reduce measurement errors. This confirms the results of Clements and Galvão (2012b) that earlier data revisions to inflation can be predicted by exploiting the serial correlation in the past real-time data.

In summary, data revisions to inflation are more sizeable than the ones to output, but the modelling of output revisions change our view on the relative importance of productivity to spending shocks. The measurement of productivity shocks using initial estimates of output under-estimates the relative size of productivity shocks since productivity shocks are strongly linked to data revisions to output.

## 3.2 Forecasting

In this subsection, I compare the relative real-time forecasting performance of the conventional and the release-based approach to estimate and forecast with DSGE models in real time. I apply the Smets and Wouters (2007) model to compute forecasts, which was also evaluated by Edge and Gurkaynak (2011), Herbst and Schorftheide (2012) and Del Negro and Schorftheide (2012). Instead of organizing real-time vintages to match the dates of computation of the Greenbook and/or Blue Chip forecasts, I organize the data by quarterly vintages dated at the middle of the quarter, as the Philadelphia Fed real-time dataset. Although this makes harder to compare my results with survey forecasts computed earlier in the quarter, it is easier to compare them with the literature on the impact of real-time in forecasting, surveyed by Croushore (2011). Details of the real-time datasets employed are in Table 1.

Following Del Negro and Schorftheide (2012) I evaluate forecasts using the 2012:Q2 vintage to compute forecast errors (the latest available vintage) and also first-final estimates as in Edge and Gurkaynak (2011). Because the modelling of data revisions embedded in the release-based approach assumes that the first final $X_t^{t+2}$ is already an efficient estimate of the true value, I expect that the qualitative forecasting evaluation will not change with the forecasting target.

I consider vintages at the forecasting origin from 1999Q1 up to 2008Q4 to predict horizons from 1 up to 8 quarters. At each forecast origin, the DSGE structural parameters and data revision processes parameters are re-estimated using bayesian methods and increasing number of observations. Forecasts are computed using 500 equally spaced draws from the posterior distribution of 200000 draws. For each posterior draw, I use 300 draws from the distribution of structural shocks and data revisions innovations to compute forecasts of $x_{T+h|T}$. The forecast for each horizon is the average across posterior draws for that horizon. As before and following Herbst and Schorftheide (2012), I use observations from 1984Q1.

A comparison of the relative forecasting performance in real time of the conventional and the release-based approaches applies to the Smets and Wouters (2007) model is presented in Figures 2 to 5. I computed RMSFEs over rolling windows of 20 observations, equivalent to five years of data. This accommodates changes in the relative forecast accuracy over time. Woulters (2012) shows that the best DSGE forecasting model changes over time using subperiods of five years. Edge and Gurkaynak (2011) suggest that the accuracy of DSGE forecasts deteriorates during the 2008/9 recession.

Figures 2 to 4 present the RMSFE for each window for $h = 1, 4, 8$ with both approaches. The dates are the last predicted observation in the window. It is clear for all the variables that the RMSFE increases for observations from 2008Q3 onwards. The increase in RMSFE is the largest if forecasting per capita output growth: the RMSFE jumps from .4 to 1 for one-step-ahead forecasts, if forecast errors are computed with the 2012Q2 vintage. Figure 4 suggests that the increase of RMFEs over forecasting horizons are steeper when predicting the fed fund rate, but RMSFEs during 2008-2010 are not higher than during 1999-2005.

Looking at the effect of changing the forecasting target, RMSFEs are generally smaller when predicting the 2012Q2 vintage of inflation than the inflation first-final values. In the case of output growth, predictions for the first-final values have smaller RMSFEs than for the last available vintage. Specifically to inflation forecasts in figure 3, the RMSFEs of one-step-ahead forecasts computed with the latest available vintage as the forecasting target suggest that inflation is getting gradually harder to forecast, while the values computed with the first-final release are roughly similar over time but they jump up at the end of 2008.

The relative forecast accuracy of release-based to the conventional approach is not very different if forecasting the fed fund rate, as indicated by the second panel in Figure 4. Figure 5 presents the ratio of the release-based RMSFEs to the conventional ones for $h = 1, 2, 4, 8$ if forecasting the 2012:Q2 vintage and first-final estimates. The most important suggestion from these plots is that the choice between either real-time forecasting approach may imply gains/losses in terms for RMSFE of around 15% for both output growth and inflation. In other words, the RMSFE differences are not small.

The evidence in favour of improvements in forecasting performance from using the release-based approach is stronger if predicting the latest-available inflation and the first-final output growth. Note that RMSFEs are generally smaller when the latter two targets are selected instead of the alternatives in Figure 5, suggesting that release-based forecast gains decrease with the variability of the forecasting target. Intuitively, the filtering provided by the release-based approach should decrease the variability of forecasts if the data revision model fits well the data. In general improvements with the release-based approach are more frequent at short-horizons when the impact of filtering first-release values may be more relevant. Finally, the release-based approach improves forecasts of inflation in all horizons during a large part of the out-of-sample period.

Even though the use of the release-based approach for forecasting may be advantageous, it is not clear if the DSGE model is a good forecasting model for these three macroeconomic variables. Del Negro and Schorftheide (2012) argue that medium-scale DSGE models are able to have better forecasting accuracy than AR(2) models when predicting output growth and inflation. Figure 6 presents the RMSFEs of the release-based approach to the AR(2) forecasting errors. The AR(2) is estimated using the conventional approach, that is, the time series available at each forecasting origin is employed to estimate the model and to compute forecasts. The results indicate that the DSGE is normally able to improve over the AR(2) to forecast output growth and inflation with gains up to 20%, except for one-year-ahead forecasts of output growth ($h = 4$). In contrast, the DSGE provides inaccurate forecasts of the fed fund rates, except at the $h = 8$ horizon. Del Negro and Schorftheide (2012) provide evidence that DSGE forecasts of interest rates are worse than the Blue Chip and Greenbook forecasts in all horizons. As a consequence, these results are not surprising if comparing with the previous literature, since they confirm that the release-based approach applied to the Smets and Wouters (2007) model deliver accurate real-time forecasts of output growth and inflation.

The contribution of this exercise is to show that we may be able to improve real-time forecasts of output growth and inflation, in particularly at short horizons, if using the release-based approach instead of the conventional one.

### 3.3 Inclusion of Data Revisions of Consumption and Investment

Output and inflation are not the only two variables generally employed to estimate medium-sized DSGE models that are part of National Account data and subject to an initial round revisions, and then a succession of annual revisions, following by less frequent benchmark revisions. Consumption and Investment are also subject to similar revision pattern. In this section, we consider to enlarge the measurement equation, originally eq. (3), but changed to include eqs. (4), with two additional equations by changing the measurement equations of consumption and investment. The updated and new measurement equations are:

$$\begin{aligned}
\Delta \log(Cons_t^{t+1}) &= \overline{\gamma} + (c_t - c_{t-1}) + M_c + rev_{ct} \\
\Delta \log(Inv_t^{t+1}) &= \overline{\gamma} + (i_t - i_{t-1}) + M_{iv} + rev_{ivt} \\
\Delta \log(Cons_{t-1}^{t+1}) &= \overline{\gamma} + (c_{t-1} - c_{t-2}) \\
\Delta \log(Inv_{t-1}^{t+1}) &= \overline{\gamma} + (i_{t-1} - i_{t-2}).
\end{aligned}$$

The state equations are enlarged to include:

$$\begin{aligned}
rev_{ct} &= K_c rev_{ct-1} + \eta_{ct} \qquad (6) \\
rev_{ivt} &= K_{iv} rev_{ivt-1} + \eta_{ivt},
\end{aligned}$$

where $var(\eta_{ct}) = Z_c^2$ and $var(\eta_{ivt}) = Z_{iv}^2$. The innovations to consumption revisions $\eta_{ct}$ may be be correlated to the innovations to the risk premium shock $\eta_t^b$, which is a shock to $c_t$ in the consumer Euler equation. The innovations to the investment revisions $\eta_{ivt}$ may be correlated to the innovations to the investment-specific technological shock $\eta_t^i$, which is a shock that affects the investment Euler equation and the dynamics of capital accumulation. The additional parameters estimated to measure the correlations are $cov(\eta_{ct}, \eta_t^b) = \sigma_b Z_c P_{cb}$ and $cov(\eta_{ivt}, \eta i) = \sigma_i Z_{iv} P_{ivi}$, where $|P_{cb}|$ and $|P_{ivi}|$ are $\leq 1$, and $\sigma_b$ and $\sigma_i$ are standard errors of risk-premium and investment-specific innovations. As before, we have to estimate additional eight parameters. In total, this specification of the release-based approach adds 16 parameters to the original 41 parameters of the Smets and Wouters (2007) model.

Following the estimation procedure described in section 3.1, Table A.1 presents the posterior mean and 5% and 95% quantiles. The use of the time series of first-release and first-final values of investment to estimate the model has a large effect on the parameters of the investment-specific shock equation. The variance of investment shocks increases, while the persistence increase. The mean correlation of innovations on investment revisions and the investment shock is -.27, indicating that an unexpected structural shock that raises investment could explain the fact that the initial release of investment underestimates the final value of investment.

Figure 7 presents the proportion of the variation of first-releases, that is, $\log(Cons_t^{t+1})$, $\log(Inv_t^{t+1})$, $\log(GDP_t^{t+1})$ and $\Delta\log(P_t^{t+1})$ explained by the variable-specific revision innovation. The variance decomposition was computed using a Cholesky decomposition of $QN$ in eq. 2, implying that structural innovations may have contemporaneous impact on revisions shocks, but unexpected revisions do not affect the structural equations. Data revisions to investment are relatively large explaining up to 17% of the variation in the first-released investment at the 20 quarter horizon; only investment-specific shocks are able to explain a larger variation (58%). In contrast, data revisions to consumption are relative unimportant to explain the variation of consumption. Data revisions to output are also sizeable since they explain 3% of variation of output at the 1 quarter horizon; larger than the proportion explained by price markup, wage markup and monetary policy shocks at the same horizon.

The variance decomposition of the revision processes suggests, as before, that 62% of the variation of the output revisions is explained by the productivity shock, while the remaining by the own shock. The proportion of the variation explained by structural shocks in the other variables is smaller: 25% of the inflation variation, 1% of the consumption variation, and 9% of the investment variation. Therefore these results suggest that data revisions are in general not caused by the effect of unexpected structural shocks in the statistical agency filtering process (as in Sargent (1989)), but by the data-revision-specific innovations, measurement errors, or noise as in Howrey (1978). An exception is the large impact productivity shocks on GDP revision innovations.

An interesting result from Table A.1 is that the parameter of the inflation in the Taylor rule ($r_\pi$) has a posterior mean of 1.7 in comparison with 1.4 if using the conventional approach. This has a large impact on the variance decomposition of shocks affecting interest rates, and it may affect the performance of the DSGE model in forecasting interest rates. Figure 8 presents the relative forecasting performance of the release-based to the conventional approach, employing the model with four revision processes (output, inflation, consumption and investment). The forecasting performance of output growth and inflation deteriorates in comparison with the model estimated jointly with data revision processes only for output and inflation. In contrast, the performance in forecasting the interest rates improves, in particularly for forecasting fed rates until 2007Q4 (before the crisis). Figure 8 suggests gains of RMSFE of up to 15% for all horizons. If compared with the AR(2) (not shown to save space), the DSGE is able to provide significantly more accurate forecasts at $h = 8$ for the period before the crisis.

In summary, while the modelling of additional revision processes is costly because it increases the parameter space of a reasonably large model, it provides additional information on the link between structural and data revision innovations.

# 4 Conclusions

Real-time forecasts of DSGE models are computed by estimating the DSGE model with bayesian methods using mainly heavily revised data, while forecasts are conditioned on lightly revised data. This apples-oranges-mixing problem is solved in this paper for the case of forecasting with DSGE models by augmenting the measurement equation to include both first-release and first-final values. Because data revisions may add new information, they may be correlated with structural shocks. The release-based approach proposed in this paper allow us to show that innovations to data revisions to US GDP are strongly correlated with productivity shocks. My estimates suggest that productivity shocks explain 62% of the unexplained variation of the GDP initial revisions, while the remaining variation is explained by own shocks. The relation between inflation data revisions and structural shocks is weaker, price markup shocks explain only 16-25% of the unexpected variation of inflation revisions. Data revisions to investment are reasonably large such that innovations to investment revision explain 17% of the unexpected variation of the first release of investment at a 20-quarter horizon, while the remaining variation is explained by the seven structural shocks.

The modelling of data revisions to output growth and inflation while estimating and computing forecasts with the Smets and Wouters (2007) model in real time improves forecast accuracy of output growth and inflation forecasts. The gains are generally larger before 2008Q3, and at short forecasting horizons ($h = 1, 2$) since these are the cases that filtering the initial release to remove the impact of measurement errors (Howrey, 1978) and statistically agency filtering errors (Sargent, 1989) may be more important. The additional inclusion of data revision processes for consumption and investment improves forecasts of the fed rate at all horizons but deteriorates forecasts of output growth and inflation.

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# A Smets and Wouters (2007) Model

In this appendix, I describe the log-linearized Smets and Wouters (2007) model. All endogenous variables are in the log-deviations from the steady-state.

The endogenous variables are: output $y_t$; consumption $c_t$; labour, hours worked $l_t$; nominal interest rate $r_t$; inflation $\pi_t$; real wage $w_t$; wage markup $\mu^w$; price markup $\mu^p$; investment $i_t$;value of capital stock $q_t$; capital installed $k_t$; capital services used in production $k_t^s$; rental rate of capital $r_t^k$; capital utilization costs $z_t$. The seven shocks are total factor productivity $\varepsilon_t^a$; investment-specific technology $\varepsilon_t^i$; risk premium $\varepsilon_t^b$; exogenous spending $\varepsilon_t^g$; price markup $\varepsilon_t^p$; wage markup $\varepsilon_t^w$; monetary policy$\varepsilon_t^r$.

1. Aggregate resource constraint: $y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g$
2. From consumption Euler equation: $c_t = c_1 c_{t-1} + (1 - c_1)E_t c_{t+1} + c_2(l_t - E_t l_{t+1}) - c_3(r_t - E_t\pi_{t+1} + \varepsilon_t^b)$
3. From investment Euler equation: $i_t = i_1 i_{t-1} + (1 - i_1)E_t i_{t+1} + i_2 q_t + \varepsilon_t^i$
4. Arbitrage equation for the value of capital: $q_t = q_1 E_t q_{t+1} + (1 - q_1)E_t r_{t+1}^k - (r_t - E_t\pi_{t+1} + \varepsilon_t^b)$
5. Production function $y_t = \phi_b(\alpha k_t^s + (1 - \alpha)l_t + \varepsilon_t^a)$
6. Capital used: $k_t^s = k_{t-1} + z_t$
7. Capital utilization costs: $z_t = z_1 r_t^k$
8. Dynamics of capital accumulation: $k_t = k_1 k_{t-1} + (1 - k_1)i_t + k_2\varepsilon_t^i$
9. Firms' markup: $\mu_t^p = \alpha(k_t^s - l_t) + \varepsilon_t^a - w_t$
10. Phillips Curve: $\pi_t = \pi_1\pi_{t-1} + \pi_2 E_t\pi_{t+1} - \pi_3\mu_t^p + \varepsilon_t^p$
11. Solution for rental-rate of capital: $r_t^k = -(k_t - l_t) + w_t$

12. Workers' markup: $\mu_t^w = w_t - \left[\sigma_l l_t + \frac{1}{1-\lambda/\gamma}(c_t - \lambda/\gamma c_{t-1})\right]$

13. Wage dynamics: $w_t = w_1 w_{t-1} + (1-w_1)(E_t w_{t+1} + E_t \pi_{t+1}) - w_2 \pi_t + w_3 \pi_{t-1} - w_4 \mu_t^w + \varepsilon_t^w$

14. Monetary Policy rule: $r_t = \rho r_{t-1} + (1-\rho)\{r_\pi \pi_t + r_Y (y_t - y_t^p)\} + r_{\Delta y}[(y_t - y_t^p) - (y_{t-1} - y_{t-1}^p)] + \varepsilon_t^r$

In order to link the parameters of the above equations with the structural parameters in Table 2, please see Smets and Wouters (2007).

And the equations for the shocks are:

1. exogenous spending: $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a$
2. risk premium: $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$
3. investment: $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \eta_t^i$
4. productivity: $\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \eta_t^a$
5. price markup: $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p$
6. wage markup: $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w - \mu_w \eta_{t-1}^w$
7. monetary policy: $\varepsilon_t^r = \rho_r \varepsilon_{t-1}^r + \eta_t^r$

Table 1: Data Availability.

| Name | Computed with | Data/Source |
|---|---|---|
| $GDP_t$ | Real GDP;<br>Population above 16. | vintages from 1965Q4, Philadelphia Fed;<br>CNP16OV, FRED/St Louis. |
| $Cons_t$ | Personal consumption expenditure;<br>GDP deflator;<br>Population above 16 | PCE, vintages from 1979Q4, ALFRED/St Louis;<br>vintages 1965Q4, Philadelphia Fed;<br>CNP16OV, FRED/St Louis. |
| $Inv_t$ | Fixed private investment;<br>GDP deflator.<br>Population above 16 | FPI, vintages from 1965Q4, ALFRED/St Louis;<br>vintages 1965Q4, Philadelphia Fed;<br>CNP16OV, FRED/St Louis. |
| $Wage_t$ | Hourly compensation;<br>GDP deflator. | COMPBNFB, vintages from 1997:Q1, ALFRED/St Louis.<br>vintages 1965Q4, Philadelphia Fed |
| $Hours_t$ | Civilian employment;<br>Average weekly hours;<br>Population above 16. | CE16OV, vintages from 1965Q4, ALFRED/St Louis;<br>AWHNONAG, vintages from 1970Q1, ALFRED;<br>CNP16OV, FRED/St Louis. |
| $P_t$ | GDP deflator. | vintages 1965Q4, Philadelphia Fed. |
| $FFR_t$ | Fed funds rate. | FEDFUNDS, FRED/St Louis. |

Note: Dated Vintages from ALFRED were converted to quarterly data vintages by using the vintage available at the middle of the quarter to match the organisation of the Philadelphia Fed real-time dataset. If source data is sampled monthly, data is converted to quarterly by averaging over quarter (before performing growth rates computation). Population and hours are converted to an index with base year 1995.

Table 2: Priors and Posteriors Distributions of the Conventional and the Released-Based Approaches.

| | Priors | | | Conventional | | | Release-Based | | |
|---|---|---|---|---|---|---|---|---|---|
| | density | Para(1) | Para(2) | mean | 0.05 | 0.95 | mean | 0.05 | 0.95 |
| $\varphi$ | normal | 4.00 | 1.5 | 6.36 | 4.55 | 8.60 | 6.71 | 5.11 | 8.75 |
| $\sigma_c$ | normal | 1.5 | 0.37 | 0.82 | 0.47 | 1.33 | 0.72 | 0.48 | 1.06 |
| h | beta | 0.70 | 0.10 | 0.68 | 0.56 | 0.79 | 0.72 | 0.63 | 0.80 |
| $\xi_w$ | beta | 0.50 | 0.10 | 0.80 | 0.72 | 0.87 | 0.78 | 0.68 | 0.86 |
| $\sigma_l$ | normal | 2.00 | 0.75 | 2.87 | 1.62 | 3.94 | 3.22 | 2.38 | 4.23 |
| $\xi_p$ | beta | 0.50 | 0.10 | 0.87 | 0.83 | 0.91 | 0.85 | 0.78 | 0.89 |
| $\iota_w$ | beta | 0.50 | 0.15 | 0.32 | 0.14 | 0.54 | 0.29 | 0.13 | 0.49 |
| $\iota_p$ | beta | 0.50 | 0.15 | 0.33 | 0.15 | 0.56 | 0.28 | 0.12 | 0.50 |
| $\psi$ | beta | 0.50 | 0.15 | 0.75 | 0.58 | 0.89 | 0.77 | 0.61 | 0.90 |
| $\Phi$ | normal | 1.25 | 0.12 | 1.61 | 1.43 | 1.78 | 1.52 | 1.36 | 1.68 |
| $r_\pi$ | normal | 1.50 | 0.25 | 1.43 | 1.08 | 1.80 | 1.41 | 1.05 | 1.79 |
| $\rho$ | beta | 0.75 | 0.10 | 0.86 | 0.81 | 0.90 | 0.87 | 0.83 | 0.90 |
| $r_y$ | normal | 0.12 | 0.05 | 0.19 | 0.12 | 0.27 | 0.20 | 0.12 | 0.26 |
| $r_{\Delta y}$ | normal | 0.12 | 0.05 | 0.13 | 0.07 | 0.18 | 0.11 | 0.06 | 0.16 |
| $\bar{\pi}$ | gamma | 0.62 | 0.10 | 0.63 | 0.54 | 0.72 | 0.63 | 0.53 | 0.72 |
| $100(\beta^{-1}-1)$ | gamma | 0.25 | 0.10 | 0.24 | 0.12 | 0.40 | 0.26 | 0.13 | 0.40 |
| $\bar{l}$ | normal | 0.00 | 2.00 | -0.35 | -1.49 | 0.66 | -0.12 | -1.80 | 1.37 |
| $\bar{\gamma}$ | normal | 0.40 | 0.10 | 0.38 | 0.29 | 0.46 | 0.41 | 0.35 | 0.45 |
| $\alpha$ | normal | 0.30 | 0.05 | 0.16 | 0.12 | 0.19 | 0.16 | 0.11 | 0.20 |
| $\rho_a$ | beta | 0.50 | 0.20 | 0.97 | 0.92 | 1.00 | 0.94 | 0.87 | 0.99 |
| $\rho_b$ | beta | 0.50 | 0.20 | 0.75 | 0.49 | 0.90 | 0.75 | 0.57 | 0.87 |
| $\rho_g$ | beta | 0.50 | 0.20 | 0.96 | 0.93 | 0.98 | 0.99 | 0.98 | 1.00 |
| $\rho_i$ | beta | 0.50 | 0.20 | 0.66 | 0.47 | 0.80 | 0.62 | 0.46 | 0.76 |
| $\rho_r$ | beta | 0.50 | 0.20 | 0.53 | 0.42 | 0.63 | 0.51 | 0.41 | 0.61 |
| $\rho_p$ | beta | 0.50 | 0.20 | 0.43 | 0.31 | 0.59 | 0.67 | 0.53 | 0.82 |
| $\rho_w$ | beta | 0.50 | 0.20 | 0.63 | 0.34 | 0.85 | 0.69 | 0.41 | 0.88 |
| $\mu_p$ | beta | 0.50 | 0.20 | 0.37 | 0.23 | 0.53 | 0.58 | 0.44 | 0.76 |
| $\mu_w$ | beta | 0.50 | 0.20 | 0.94 | 0.89 | 0.98 | 0.94 | 0.88 | 0.98 |
| $\rho_{ga}$ | beta | 0.50 | 0.20 | 0.29 | 0.15 | 0.42 | 0.36 | 0.21 | 0.50 |
| $\sigma_a$ | invgamma | 0.10 | 2.00 | 0.42 | 0.37 | 0.48 | 0.45 | 0.39 | 0.52 |
| $\sigma_b$ | invgamma | 0.10 | 2.00 | 0.10 | 0.07 | 0.14 | 0.10 | 0.07 | 0.14 |
| $\sigma_g$ | invgamma | 0.10 | 2.00 | 0.40 | 0.35 | 0.45 | 0.42 | 0.37 | 0.48 |
| $\sigma_i$ | invgamma | 0.10 | 2.00 | 0.36 | 0.26 | 0.48 | 0.38 | 0.28 | 0.49 |
| $\sigma_r$ | invgamma | 0.10 | 2.00 | 0.12 | 0.10 | 0.14 | 0.12 | 0.10 | 0.14 |
| $\sigma_p$ | invgamma | 0.10 | 2.00 | 0.15 | 0.13 | 0.18 | 0.17 | 0.14 | 0.20 |
| $\sigma_w$ | invgamma | 0.10 | 2.00 | 0.37 | 0.33 | 0.43 | 0.38 | 0.33 | 0.42 |
| $\mathrm{M}_y$ | normal | 0.10 | 0.20 | | | | -0.03 | -0.07 | 0.00 |
| $\mathrm{M}_\pi$ | normal | 0.10 | 0.20 | | | | -0.02 | -0.04 | -0.01 |
| $K_y$ | normal | 0.10 | 0.20 | | | | 0.00 | -0.15 | 0.16 |
| $K_\pi$ | normal | 0.10 | 0.15 | | | | 0.07 | -0.07 | 0.20 |
| $\Sigma_y$ | invgamma | 0.50 | 0.40 | | | | 0.19 | 0.16 | 0.22 |
| $\Sigma_\pi$ | invgamma | 0.20 | 0.40 | | | | 0.10 | 0.09 | 0.11 |
| $\mathrm{P}_{ya}$ | uniform | -1 | 1 | | | | -0.44 | -0.58 | -0.28 |
| $\mathrm{P}_{\pi p}$ | uniform | -1 | 1 | | | | -0.24 | -0.39 | -0.04 |

Note: fixed values: $\lambda_w = 1.5$, $\varepsilon_w = 10$, $\varepsilon_p = 10$, $\delta = 0.025$, $g_Y$=0.18. Observations from 1984Q1 up to 2008Q3. Posterior distribution computed with the Random Walk Metropolis algorithm with 200000 replications and two chains, with c=0.2.

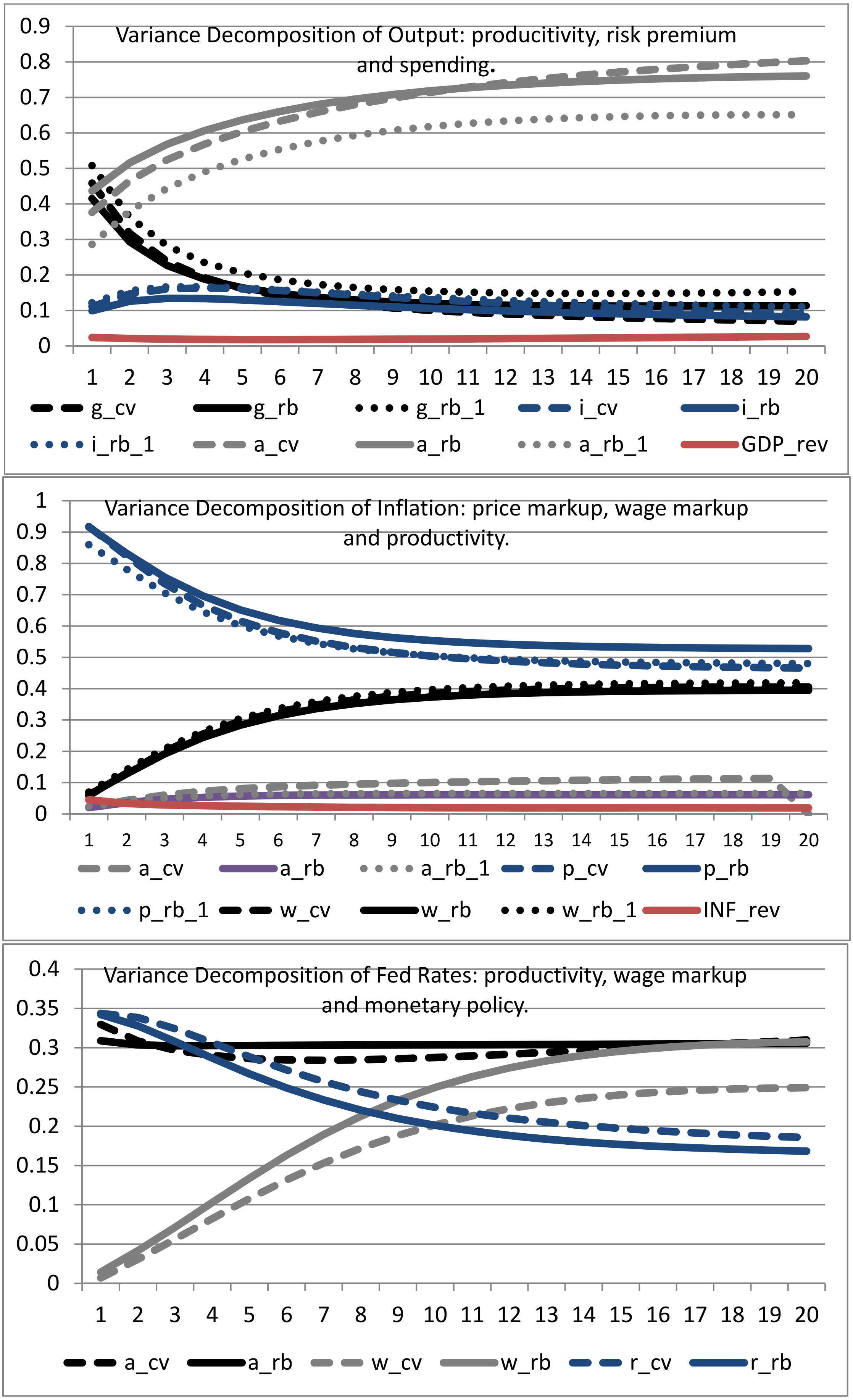
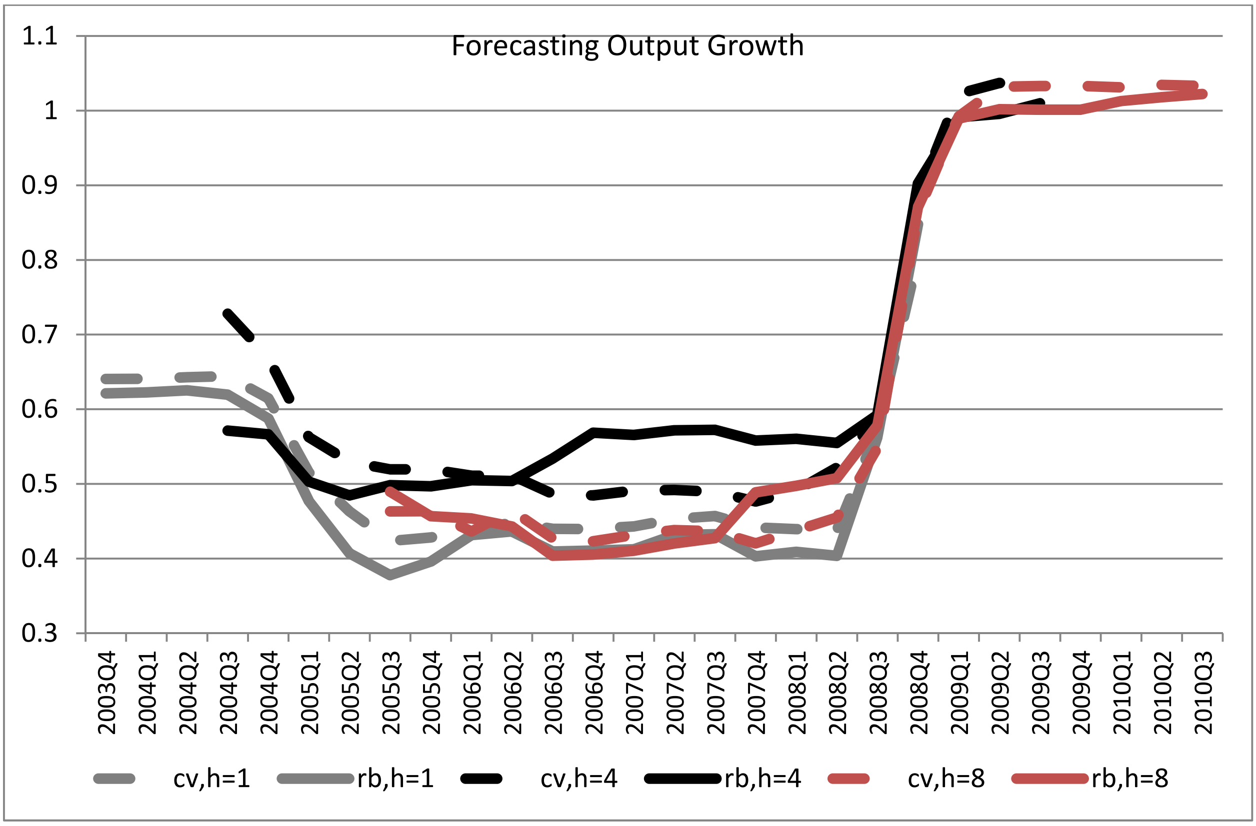



Figure 1: Variance Decompositions computed on the Posterior means (Conventional (_cv), Release-Based (_rb), and released-based first-release (_rb_1)).



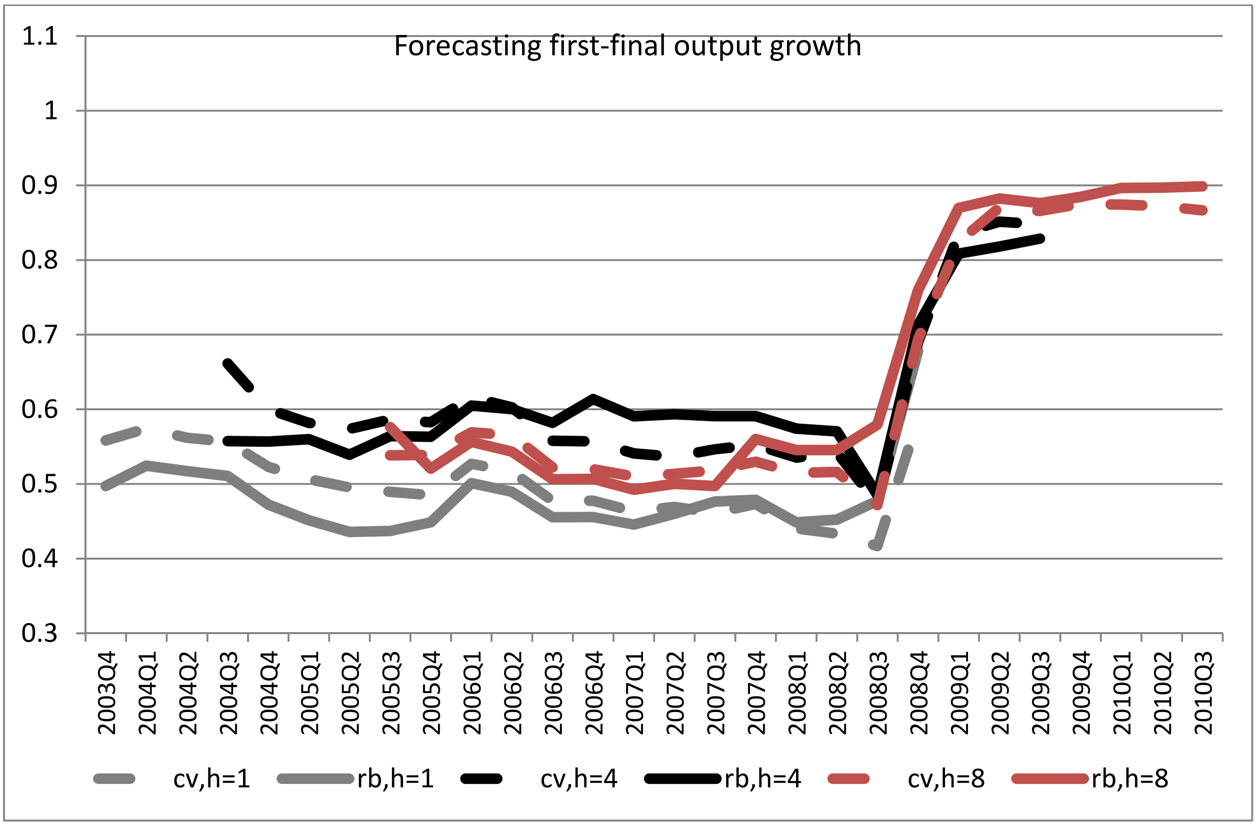
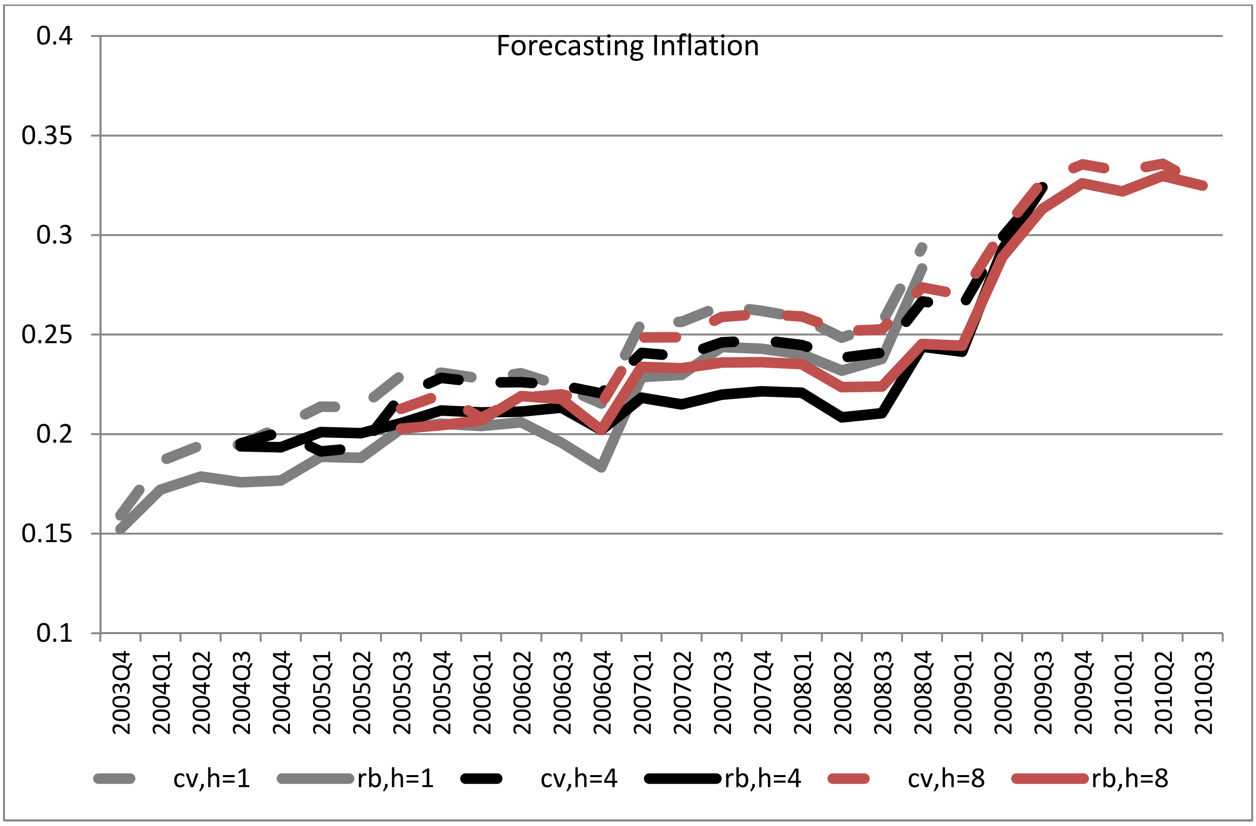




Figure 2: RMSFE over a moving window of 20 (5y) forecasting errors. The date refers to the forecasted observation date at the end of the window. (Note: conventional approach: dashed line).



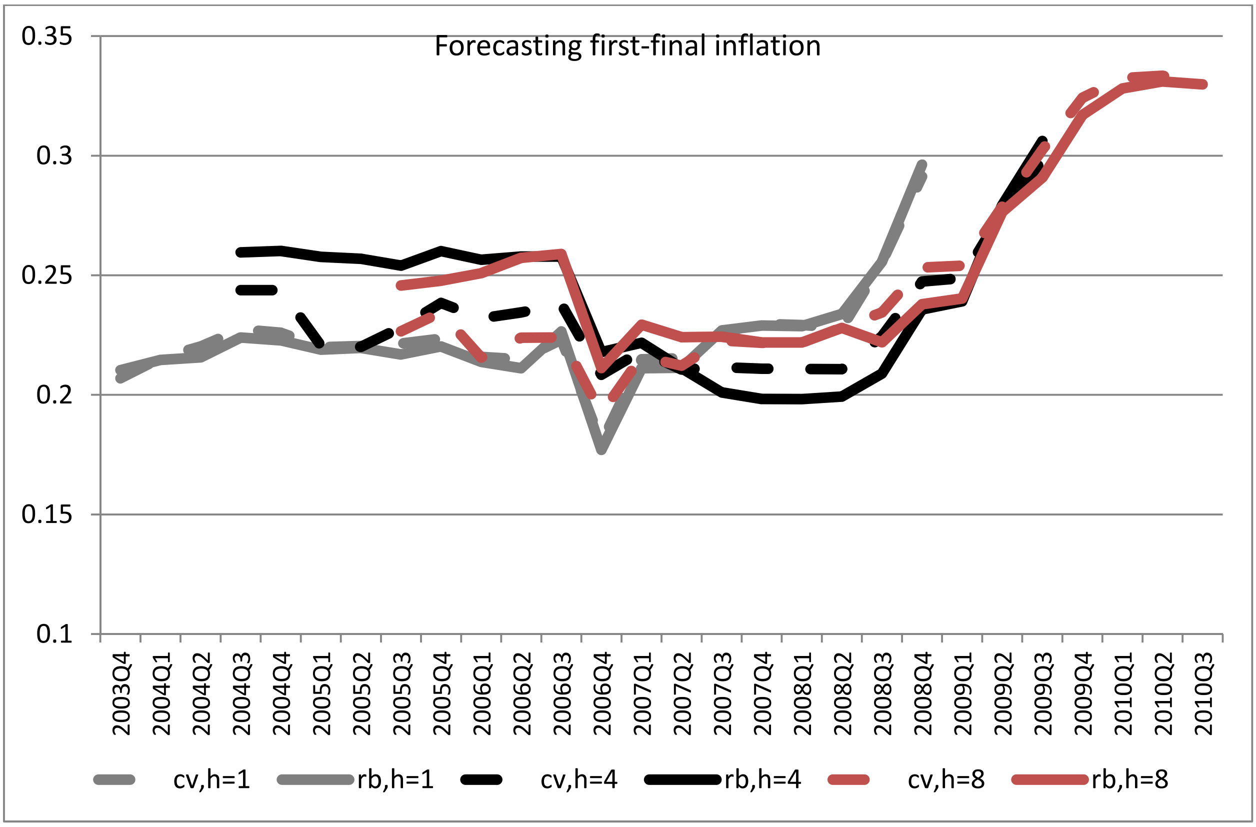
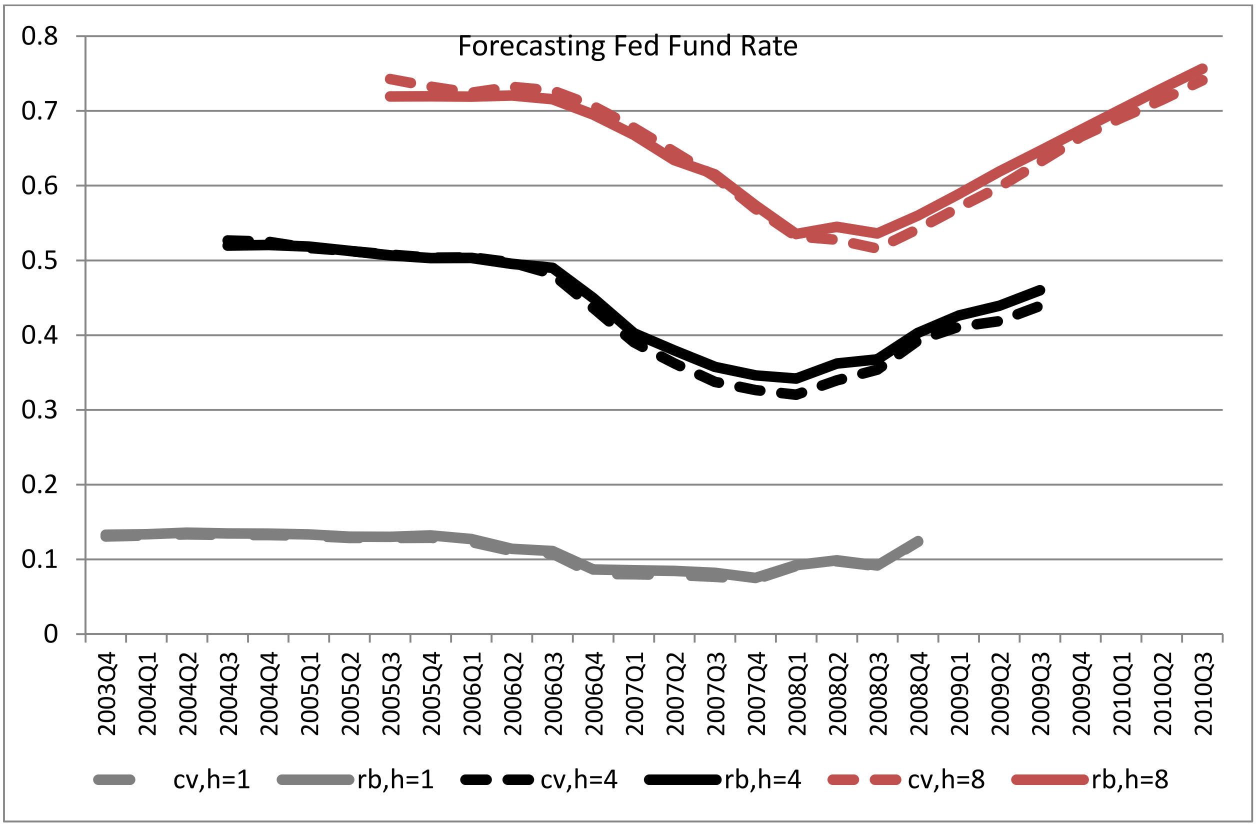




Figure 3: RMSFE over a moving window of 20(5y) forecasting errors. The date refers to the target observation date at the end of the window. (Note: conventional approach: dashed line).



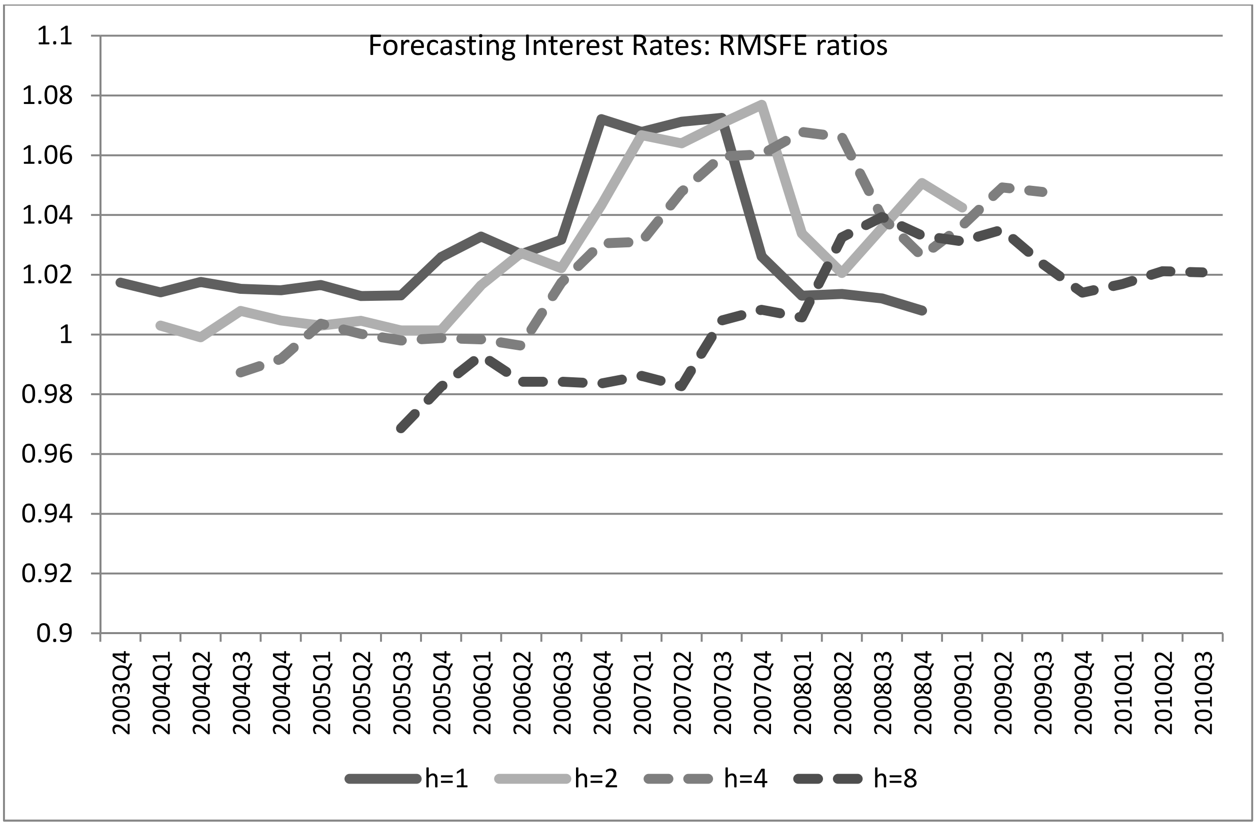




Figure 4: RMSFE over a moving window of 20(5y) forecasting errors. The date refers to the target observation date at the end of the window. (Note: conventional approach: dashed line).

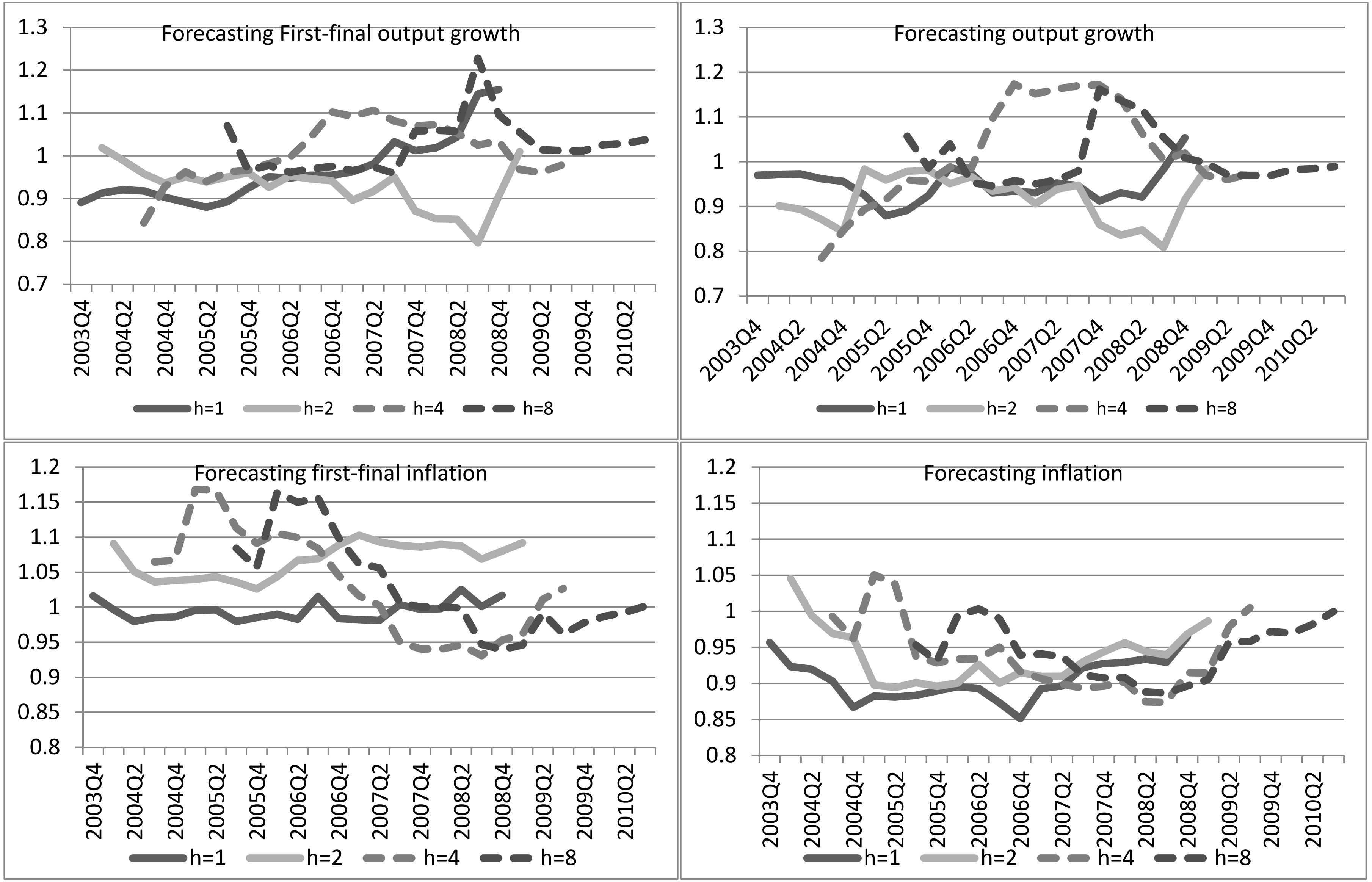



Figure 5: RMSFE ratio of release-based over conventional approach computed over a window of 20 forecasting errors. The date refers to the target observation date at the end of the window.

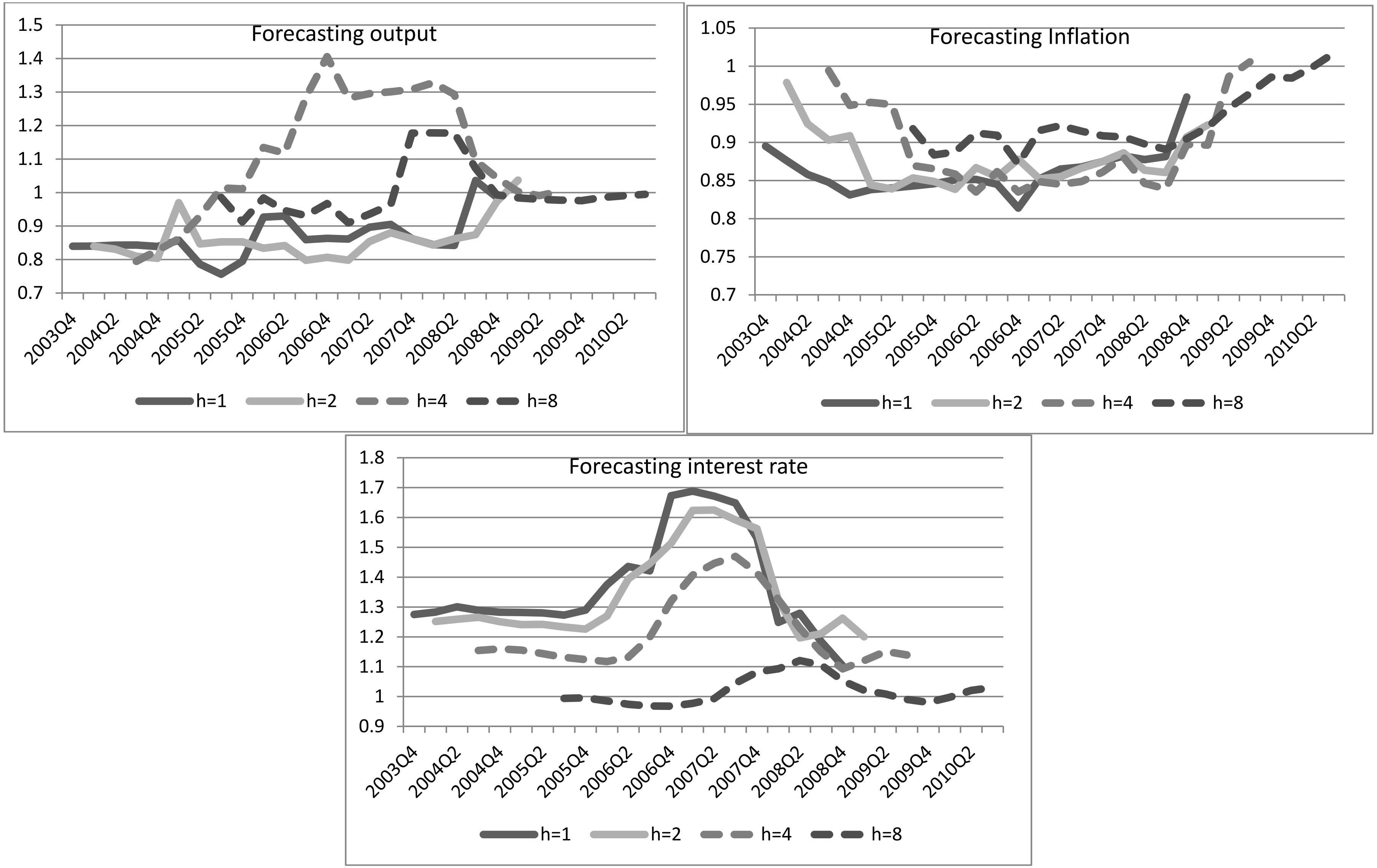



Figure 6: RMSFE ratio of release-based DSGE model over AR(2) (conventional) model computed over a window of 20 forecasting errors. The date refers to the forecasted observation date at the end of the window.

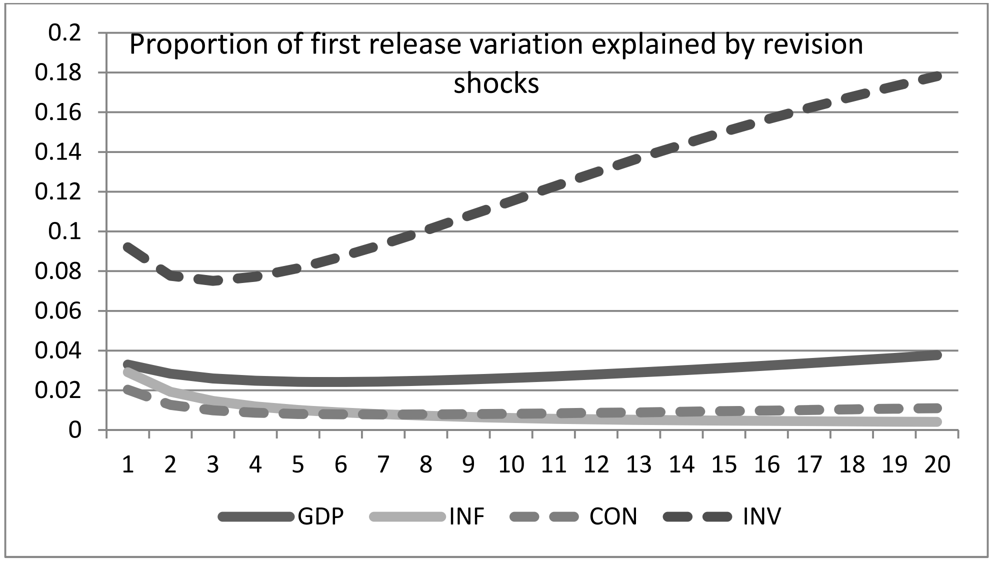



Figure 7: Proportion of the variation of first-releases of Output, Inflation, Consumption and Investment explained by variable-specific data revisions using the released-based DSGE model with four variable-specific revisions.

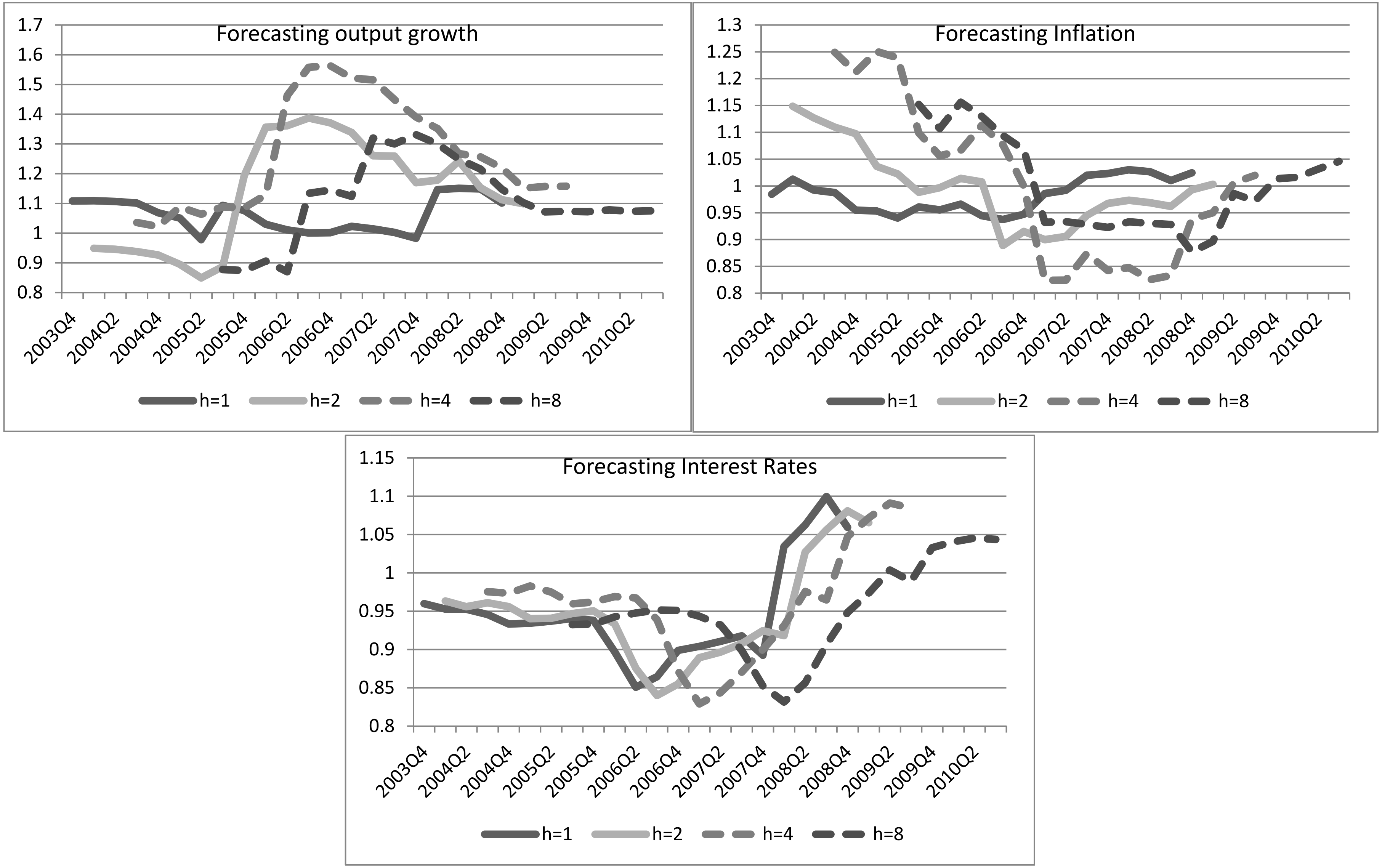



Figure 8: RMSFE ratio of release-based (modelling revision of four variables) over conventional approach computed over a window of 20 forecasting errors. The date refers to the target observation date at the end of the window.

Table A1: Priors and Posteriors Distributions of the Released-Based DSGE Approach modelling data revisions of output, inflation, consumption and investment.

| | Priors | | | Conventional | | | Release-Based | | |
|---|---|---|---|---|---|---|---|---|---|
| | density | Para(1) | Para(2) | mean | 0.05 | 0.95 | mean | 0.05 | 0.95 |
| $\varphi$ | normal | 4.00 | 1.5 | 6.36 | 4.55 | 8.60 | 5.88 | 3.91 | 6.72 |
| $\sigma_c$ | normal | 1.5 | 0.37 | 0.82 | 0.47 | 1.33 | 0.55 | 0.42 | 0.60 |
| h | beta | 0.70 | 0.10 | 0.68 | 0.56 | 0.79 | 0.80 | 0.72 | 0.83 |
| $\xi_w$ | beta | 0.50 | 0.10 | 0.80 | 0.72 | 0.87 | 0.78 | 0.71 | 0.84 |
| $\sigma_l$ | normal | 2.00 | 0.75 | 2.87 | 1.62 | 3.94 | 3.32 | 2.24 | 3.69 |
| $\xi_p$ | beta | 0.50 | 0.10 | 0.87 | 0.83 | 0.91 | 0.82 | 0.80 | 0.89 |
| $\iota_w$ | beta | 0.50 | 0.15 | 0.32 | 0.14 | 0.54 | 0.26 | 0.16 | 0.48 |
| $\iota_p$ | beta | 0.50 | 0.15 | 0.33 | 0.15 | 0.56 | 0.36 | 0.21 | 0.47 |
| $\psi$ | beta | 0.50 | 0.15 | 0.75 | 0.58 | 0.89 | 0.76 | 0.51 | 0.85 |
| $\Phi$ | normal | 1.25 | 0.12 | 1.61 | 1.43 | 1.78 | 1.51 | 1.35 | 1.59 |
| $r_\pi$ | normal | 1.50 | 0.25 | 1.43 | 1.08 | 1.80 | 1.73 | 1.19 | 1.95 |
| $\rho$ | beta | 0.75 | 0.10 | 0.86 | 0.81 | 0.90 | 0.87 | 0.83 | 0.89 |
| $r_y$ | normal | 0.12 | 0.05 | 0.19 | 0.12 | 0.27 | 0.21 | 0.13 | 0.24 |
| $r_{\Delta y}$ | normal | 0.12 | 0.05 | 0.13 | 0.07 | 0.18 | 0.14 | 0.09 | 0.17 |
| $\bar{\pi}$ | gamma | 0.62 | 0.10 | 0.63 | 0.54 | 0.72 | 0.61 | 0.55 | 0.69 |
| $100(\beta^{-1}-1)$ | gamma | 0.25 | 0.10 | 0.24 | 0.12 | 0.40 | 0.28 | 0.17 | 0.39 |
| $\bar{l}$ | normal | 0.00 | 2.00 | -0.35 | -1.49 | 0.66 | -0.02 | -0.86 | 0.51 |
| $\bar{\gamma}$ | normal | 0.40 | 0.10 | 0.38 | 0.29 | 0.46 | 0.42 | 0.39 | 0.45 |
| $\alpha$ | normal | 0.30 | 0.05 | 0.16 | 0.12 | 0.19 | 0.26 | 0.16 | 0.48 |
| $\rho_a$ | beta | 0.50 | 0.20 | 0.97 | 0.92 | 1.00 | 0.94 | 0.89 | 0.96 |
| $\rho_b$ | beta | 0.50 | 0.20 | 0.75 | 0.49 | 0.90 | 0.83 | 0.80 | 0.91 |
| $\rho_g$ | beta | 0.50 | 0.20 | 0.96 | 0.93 | 0.98 | 0.97 | 0.96 | 0.99 |
| $\rho_i$ | beta | 0.50 | 0.20 | 0.66 | 0.47 | 0.80 | 0.37 | 0.22 | 0.50 |
| $\rho_r$ | beta | 0.50 | 0.20 | 0.53 | 0.42 | 0.63 | 0.52 | 0.42 | 0.57 |
| $\rho_p$ | beta | 0.50 | 0.20 | 0.43 | 0.31 | 0.59 | 0.72 | 0.68 | 0.78 |
| $\rho_w$ | beta | 0.50 | 0.20 | 0.63 | 0.34 | 0.85 | 0.62 | 0.45 | 0.81 |
| $\mu_p$ | beta | 0.50 | 0.20 | 0.37 | 0.23 | 0.53 | 0.66 | 0.62 | 0.73 |
| $\mu_w$ | beta | 0.50 | 0.20 | 0.94 | 0.89 | 0.98 | 0.92 | 0.90 | 0.97 |
| $\rho_{ga}$ | beta | 0.50 | 0.20 | 0.29 | 0.15 | 0.42 | 0.29 | 0.14 | 0.33 |
| $\sigma_a$ | invgamma | 0.10 | 2.00 | 0.42 | 0.37 | 0.48 | 0.45 | 0.43 | 0.52 |
| $\sigma_b$ | invgamma | 0.10 | 2.00 | 0.10 | 0.07 | 0.14 | 0.09 | 0.06 | 0.10 |
| $\sigma_g$ | invgamma | 0.10 | 2.00 | 0.40 | 0.35 | 0.45 | 0.39 | 0.36 | 0.43 |
| $\sigma_i$ | invgamma | 0.10 | 2.00 | 0.36 | 0.26 | 0.48 | 0.59 | 0.49 | 0.70 |
| $\sigma_r$ | invgamma | 0.10 | 2.00 | 0.12 | 0.10 | 0.14 | 0.11 | 0.10 | 0.13 |
| $\sigma_p$ | invgamma | 0.10 | 2.00 | 0.15 | 0.13 | 0.18 | 0.19 | 0.15 | 0.21 |
| $\sigma_w$ | invgamma | 0.10 | 2.00 | 0.37 | 0.33 | 0.43 | 0.37 | 0.34 | 0.42 |
| $\mathrm{M}_y$ | normal | 0.10 | 0.20 | | | | -0.04 | -0.06 | -0.01 |
| $\mathrm{M}_\pi$ | normal | 0.10 | 0.20 | | | | -0.01 | -0.04 | 0.01 |
| $\mathrm{M}_c$ | normal | 0.10 | 0.20 | | | | 0.01 | -0.02 | 0.02 |
| $\mathrm{M}_{iv}$ | normal | 0.10 | 0.20 | | | | -0.10 | -0.16 | -0.02 |
| $K_y$ | normal | 0.10 | 0.20 | | | | -0.01 | -0.09 | 0.15 |
| $K_\pi$ | normal | 0.10 | 0.15 | | | | 0.13 | -0.06 | 0.20 |
| $K_c$ | normal | 0.10 | 0.20 | | | | 0.03 | -0.12 | 0.09 |
| $K_{iv}$ | normal | 0.10 | 0.20 | | | | 0.08 | -0.04 | 0.18 |
| $\Sigma_y$ | invgamma | 0.50 | 0.40 | | | | 0.20 | 0.18 | 0.22 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $\Sigma_{\pi}$ | invgamma | 0.20 | 0.40 | | | | 0.10 | 0.09 | 0.11 |
| $\Sigma_{c}$ | invgamma | 0.20 | 0.40 | | | | 0.14 | 0.13 | 0.16 |
| $\Sigma_{iv}$ | invgamma | 0.70 | 0.40 | | | | 0.53 | 0.49 | 0.62 |
| $\mathrm{P}_{ya}$ | uniform | -1 | 1 | | | | -0.45 | -0.52 | -0.29 |
| $\mathrm{P}_{\pi p}$ | uniform | -1 | 1 | | | | -0.28 | -0.36 | -0.11 |
| $\mathrm{P}_{cb}$ | uniform | -1 | 1 | | | | 0.13 | -0.05 | 0.19 |
| $\mathrm{P}_{ivi}$ | uniform | -1 | 1 | | | | -0.27 | -0.36 | -0.12 |

Note: fixed values: $\lambda_w = 1.5$, $\varepsilon_w = 10$, $\varepsilon_p = 10$, $\delta = 0.025$, $g_Y$=0.18. Vintages up to 2008Q4. Posterior distribution computed with the Random Walk Metropolis algorithm with 200000 replications and two chains, with c=0.2.