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Evaluating a Structural Model Forecast: Decomposition Approach

František Brázdik, Zuzana Humplová, and František Kopřiva *

Abstract

When presenting the results of macroeconomic forecasting, forecasters often have to explain the contribution of data revisions, conditioning information, and expert judgment updates to the forecast update. We present a framework for decomposing the differences between two forecasts generated by a linear structural model into the contributions of the elements of the information set when anticipated and unanticipated conditioning is applied. The presented framework is based on a set of supporting forecasts that simplify the decomposition of the forecast update. The features of the framework are demonstrated by examining two forecast scenarios with the same initial prediction period but different forecast assumptions. The full capabilities of the decomposition framework are documented by an example forecast evaluation where the forecast from the Czech National Bank's Inflation Report III/2012 is assessed with respect to the updated forecast from Inflation Report III/2013.

Abstrakt

Při prezentaci výsledků makroekonomické prognózy musí prognostici často vysvětlovat příspěvky revizí dat, podmiňujících informací nebo expertních úprav k aktualizaci prognózy. V této práci představujeme obecný způsob, kterým je možné rozložit rozdíly mezi dvěma prognózami vytvořenými lineárním strukturálním modelem do příspěvků prvků informační množiny prognózy při aplikaci podmiňujících informací provedené v očekávaném i neočekávaném módu. Prezentovaný systém rozkladu je založen na souboru podpůrných prognóz, které rozklad aktualizace prognózy zjednodušují. Vlastnosti tohoto systému demonstrujeme ukázkou rozkladu rozdílu dvou prognóz se stejným počátečním obdobím predikce, avšak založených na rozdílných předpokladech. Plné možnosti navrženého způsobu rozkladu prezentujeme pomocí příkladu hodnocení prognózy ze Zprávy o inflaci České národní banky III/2012, která je vyhodnocena vzhledem k aktualizované prognóze ze Zprávy o inflaci III/2013.

JEL Codes: C53, E01, E47.
Keywords: Data revisions, DSGE models, forecasting, forecast revisions.

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Nontechnical Summary

In the contemporary monetary policy framework, considerable intellectual activity and computational power is devoted to forecasting the future trajectories of economic variables. Macroeconomic forecasts based on structural models with forward-looking model-consistent expectations are used extensively in the modern process of monetary policy decision making.

As a macroeconomic forecast should provide answers to many questions, it is important to support its presentation with a transparent quantification of its driving forces. Thus, the forecast update analysis has to explain how the newly available data (releases and revisions) and assumptions about the future development of the forecasted variables are reflected in the identification of structural shocks and unobserved variables. Forecasters require an elaborate examination of the contributions of the forecast update in order to interpret the new data and improve the quality of their outputs. Examining the contributions of new information improves forecasters' understanding of the underlying shocks present in the economy.

We support our presentation of a forecast with an analysis of the responses of the forecasted trajectories to changes in subsets of newly collected information on a regular basis. For this purpose, we develop a framework that is used for the analysis of forecast updates. A detailed description of the framework forms the main part of this paper.

Forecast accuracy evaluation has been a part of the forecasting process of the Czech National Bank (CNB) since the Quarterly Projection Model was introduced in 2002 (Beneš et al., 2003). The introduction of the g3 model framework (Andrle et al., 2009) in 2008 and its further development required more advanced evaluation techniques. This paper describes the up-to-date methodology and its implementation into the CNB's forecasting process to handle the tasks of forecast updating and forecast accuracy analysis. The presented framework is more general and complex than previous approaches and delivers more detail into the forecast evaluation.

This paper describes the CNB's forecasting process in general state-space form, which features model-driven predictions based on a structural model and expert judgment applied in both anticipated and unanticipated mode. We also present details on, and the assumptions of, the solution method based on likelihood maximization, which is used to solve for the forecast trajectories. This provides the rationale for the ordering of information sets in the decomposition procedure, which itself is based on the projection update elasticities.

We demonstrate the features of the framework by identifying the driving forces behind the differences between two alternative forecast scenarios. Also, as forecasts are usually created periodically, it is of interest to examine the driving forces behind the updates and evaluate the performance of the forecast over some period of time. We therefore present the results of a forecast evaluation exercise where the CNB's forecast released in Inflation Report III/2012 is analyzed with knowledge of the forecast released in Inflation Report III/2013. This evaluation enables us to learn how well our forecast performed in confrontation with the data and what lessons may lead to improvements in our future forecasts.

We believe that the presented forecast evaluation methodology will help improve future CNB forecasts by identifying the main sources of forecast errors and by telling us more about the data and model properties. The results provide forecasters with hints for further refining the forecasting framework.

1. Introduction

The modern view on the transmission mechanism of monetary policy emphasizes that monetary policy actions have significant effects on the economy through expectations. As Svensson (2005) summarizes, effective implementation of monetary policy requires effective communication of the central bank's forecast. Hence, the role of central bank communication is to explain and justify the central bank's decisions to the public, thereby purposefully influencing their expectations about future developments.

In the forward-looking monetary policy of Czech National Bank (CNB), the CNB's monetary policy decisions are supported by its own forecast. This raises many questions about the construction of the forecast and its consistency over time. Acceptance of the forecast may be hampered by the inclusion of conditioning information that can often be considered opaque. This opacity is the basis for the critique of forecast communication by Heilemann (2002). Therefore, CNB supports its communication by examining forecast updates and evaluating the forecast every forecast round. This has helped it document and support the inclusion of conditioning information in its forecast since the introduction of the structural model forecast.

In this paper, we present the general framework and its assumptions used for decomposing differences between two conditional forecasts based on a linear structural model. Though the framework is based on the projection update elasticities, the novelty lies in the presence of conditioning applied in anticipated mode. We also demonstrate the use of this framework in the forecasting process.

The motivation for the development of a general decomposition framework originated from the state of the available tools, which handled similar problems using incompatible approaches, thus limiting their applicability. These tools were subject to many constraining assumptions, so inconsistencies between decomposition methodologies were present. The new framework delivers more flexibility and consistency than the former ones that accompanied the previously used Quarterly Projection Model (Beneš et al., 2003) and the currently used g3 model (Andrle et al., 2009). The list of advances includes consistency of the model used in the identification and prediction phase and the possibility of applying conditioning information in anticipated and unanticipated mode.

Regular examination of forecast updates and forecast accuracy allows forecasters to learn about the properties of the model, data revisions, and conditioning information. Moreover, the learning process enhances forecasters' notion of expert judgment. As Goodwin (2000) points out, the need for explanation of the conditioning information used in forecasts helps reduce forecasters' overreaction to random movements in the data. Also, to address the opacity of such conditioning, Heilemann (2002) suggests that the prediction process should start with a number of test runs to examine the effects of assumptions and updates on the forecast. He points out that these test runs help increase the transparency of the forecasting process by demonstrating the role of the assumptions in the prediction. Furthermore, the repetitious analysis of forecast updates helps improve the narrative of the forecast, which is important for delivering high-quality forecast reports.

The evaluation of forecast accuracy has been a focus of attention since the early 1970s (e.g. Mincer and Zarnowitz, 1969) as a vital component of the empirical work of econometricians, and we agree that, as in Todd (1990), forecast revisions should be analyzed to help forecasters and forecast users evaluate and justify the forecasting process. The main stream of literature on forecast accuracy and forecast update evaluation puts great emphasis on the statistical properties of forecasts based on the evaluation of forecast errors. Some of the forecast evaluation exercises only require moments from the predictive distribution, quantiles, confidence intervals, or the probability that the variables take some value (e.g. Christoffel et al., 2010; Mincer and Zarnowitz, 1969).

However, statistical moment-based forecast evaluation is not capable of explaining the story behind the differences in forecasts, of or delivering answers about the origins of deviations from the observed data as well as the future propagation of those deviations. Moreover, we believe that the complexity of conditioning (e.g. the use of anticipated information) creates a difficulty for evaluating forecast properties via traditional methods such as those described in Mincer and Zarnowitz (1969). Therefore, as central bank forecasters, we consider the evaluation of forecast performance by forecast error statistics (e.g. West, 2006; Antal et al., 2008) to be insufficient.

Improving the understanding of forecast properties has motivated decomposition analysis since the early days of forecasting with structural models, as discussed by Todd (1990). Todd (1990) presents an algorithm based on partitioning of the forecast information set. However, his procedure is set up in a one-step-ahead framework that lacks the possibility of implementing expert judgment. Inspired by his approach and the work by Andrle (2013), we develop a general decomposition framework which allows us to analyze the contributions of information set elements to the prediction trajectory. To our knowledge, there is no such publicly available and complex analysis that can be performed on a linear structural model with expert judgment applied in both anticipated and unanticipated modes.

In the next section, the CNB's forecasting process, which is based on an advanced structural model, is presented. This is followed in the third section by solution of the model prediction. In the fourth section, the methodology for examining the forecast update is described, and in the fifth section, applications of this general framework (scenario analysis and forecast evaluation) are demonstrated.

2. Structural Model Forecast

First, we introduce our notation and describe the forecasting process, which is based on the use of a structural model in linear form. We present a CNB implementation of the forecasting process represented in the general form of a structural model in state-space representation, as our goal is to develop a framework with a minimal set of assumptions. Further, we describe the components and phases of the forecast.

The terms “forecast” and “prediction” are generally considered to be synonyms. However, we follow the definition of Mincer and Zarnowitz (1969), who use the term “forecast” to describe the set of predictions produced by the prediction method. So, predictions of variables are elements of the forecast.

Our forecasting framework is built around a linear structural model expressed in the following state-space form:

$$Y_t = \mathbf{C}X_t + \mathbf{D}\xi_t \quad (1)$$

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t, \quad (2)$$

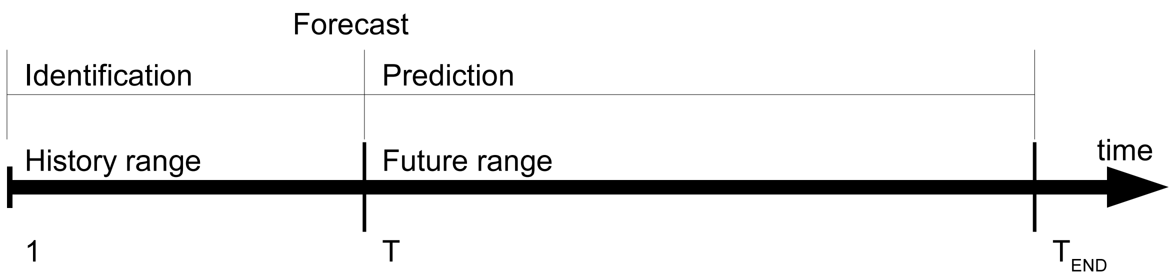
where Y_t is an $(n_y \times 1)$ vector of observed variables (observables/measurables), X_t denotes an $(n_x \times 1)$ vector of transition (state) variables, and ξ_t and ε_t are, respectively, $(n_\xi \times 1)$ and $(n_\varepsilon \times 1)$, vectors of measurement and structural shocks.

The shocks are independent and identically distributed random variables from the normal distribution with zero mean. Matrices $\mathbf{A},\mathbf{B},\mathbf{C}$, and $\mathbf{D}$ are known matrices based on the structural model and its parameters of size $n_x \times n_x, n_x \times n_\varepsilon, n_y \times n_x, and n_y \times n_\xi$. Further, the model given by the system of Equations 1 and 2 will be augmented with additional equations to allow for implementation of expert judgment.

To describe the phases of the forecasting exercise, we start with the definition of information set I_t in period t. Information set I_t includes the past and current values of the observable variables. It may also include the future values for outlooks without any constraint on their observability. For the information sets we assume that $I_t \supseteq I_k$, for $t \geq k$, so forecasters accumulate knowledge about the past forecasts and data revisions.

As the information sets are updated by revisions and enlarged by new observations, these information set updates are the driving forces of the forecast updates.

Figure 1: Forecast Phases



The construction of the CNB forecast at time T based on information set I_T has two phases: identification of the initial conditions and solution of the prediction problem. Figure 1 shows the timing of these two phases. In the forecasting process, period T is known as the end of history (generally, the end of the available data),[1] while period T_{END} is usually some distant period known as the end of the prediction computation.

The first phase of the forecast is identification of the initial state (cyclical position) based on the history up to period T. The data from period 1 (the start of the data used) up to the end of history T are used in combination with expert judgment to identify the initial state of the prediction. As the technique based on the use of a structural model and the Kalman smoother is used for identification of the initial state, identification is often referred to as filtration and the history range as the filtration range.[2]

The results of the initial state identification enter the prediction phase as the starting point. In the prediction phase, expert judgment and outlooks are used to condition the prediction. The future range thus refers to the set of periods from $T+1$ to the end of the prediction computation T_{END}. The number of periods $T_{END} - (T+1)$ is also known as the prediction span, as in Mincer and Zarnowitz (1969).

[1] Usually only higher-frequency data (e.g. the exchange rate, the interest rate or the inflation rate) is already available at the end of history. To balance the panel of data, lower-frequency data enter in the form of a data estimate and are subject to update when a new data release occurs.

[2] We should point out here the mismatch between the naming convention and the tool actually used. The Kalman smoother is used to identify the initial conditions, but application of is often referred to as filtration.

The identification of the prediction's initial state should reflect the forecaster's view on the current position of the economy in the cycle. As this view tries to capture many expert opinions, expert judgment has to be applied in the process of initial state identification. This expert judgment is referred to as the identification tunes and integrates information that is not captured by the model mechanisms. The identification tunes impose constraints on the estimation of state variables or shock realizations to reflect expert opinions.

The expert judgment imposed in the identification phase is implemented by augmenting the state-space representation with new time-varying restrictions on the observable variables.[3] That is, the measurement Equation 1 of the model is augmented by a vector of identification tunes $Y^J_{t|T}, (n_{y^J} \times 1)$, and the restrictions imposed between observed variables and unobserved states are described by the matrices $\Gamma_{t|T}, (n_{y^J} \times n_x)$ for each period $t \in \langle 1, \dots, T \rangle$:

$$\begin{bmatrix} Y_t \\ Y^J_{t|T} \end{bmatrix} = \begin{bmatrix} \mathbf{C}X_t \\ \mathbf{\Gamma}_{t|T}X_t \end{bmatrix} + \begin{bmatrix} \mathbf{D}\xi_t \\ \mathbf{\Delta}_{t|T}\nu_t \end{bmatrix} \quad (3)$$

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t. \quad (4)$$

The presented extension exposes unobserved elements of the state-space system to forecasters, so expert judgment can be applied as the observation of the variable. As the identification tunes are imposed in the period of interest, the expert judgment series is observed only in these periods, while the rest of the corresponding additional measurement series has missing values. The implementation of expert judgment in the identification phase is based on the use of a filter that is able to handle missing observations. See, for example, Harvey (1989) for more details on the implementation of such a filter.

Uncertainty about expert judgment can also be present. It arises from shocks $\nu_t, (n_{y^J} \times n_{y^J})$ with a covariance matrix $\mathbf{\Delta}_{t|T}, (n_{y^J} \times n_{y^J})$. In our implementation of the forecasting process, we focus only on expert judgment in the form of hard tunes (hard conditioning) as introduced by Waggoner and Zha (1999) and described by Beneš et al. (2010). Therefore, we assume no uncertainty about the filter judgment, so $\mathbf{\Delta}_{t|T}\nu_t = 0$.[4] In our forecasting framework, we use matrices $\mathbf{\Gamma}_t$ to impose the one-to-one judgment–variable relation, implying that $\mathbf{\Gamma}_t$ is the identity matrix in this simple case.

The identification tunes implementation, given by Equation 3, is flexible enough to implement conditioning on the value of a state variable (the elements of X_t), or on the value of a single structural shock (an element of ε_t). This flexibility originates from the equivalence implied by the linearity of the restrictions in the measurement block given by Equation 3. Due to the nature of the Kalman smoother, the identification tunes are implemented in the form of unanticipated shocks. The initial state for the prediction phase is estimated by applying the structural model given by the system of Equations 3–4 using the Kalman smoother on the data up to period T.

In the second phase of the forecasting exercise, prediction trajectories are computed. In this phase, the initial state from the identification phase is used to construct a prediction over the future range $\langle T+1, \dots, T_{END} \rangle$. The prediction trajectories are a function of the initial state and are conditioned on the assumption regarding the trajectories of exogenous variables (outlooks) and the expert judgment available in the information set I_T.

[3] The detailed implementation of expert judgment in the CNB's structural model environment is described by Andrle et al. (2009) and examples are presented by Brůha et al. (2013).

[4] The introduction of expert judgment is based on Doran (1992), where the augmented system of measurement equations constrains the estimated state variables, so that expert judgment on state variables is delivered.

In general, these outlooks and expert judgment applied over the future range are called prediction tunes. Forecasters' assumptions about the prediction tunes originate from the information set I_T and can be revised together with any future updates of the information set.[5]

In the prediction phase, there are two modes for applying prediction tunes over the future range. From the model agent point of view, prediction tunes can be applied in unanticipated or anticipated mode. Prediction tunes applied in anticipated mode over the future range $\langle T+1,\ldots,T_{END}\rangle$ allow the behavior of model agents to be affected as from period $T+1$, as model agents are forward looking and anticipate these shocks as from the first prediction period. In contrast, prediction tunes applied in unanticipated mode affect model agents' behavior only from the period in which they were applied. To implement prediction tunes in both modes, the state-space system is augmented with the linear restrictions and shocks $\overline{\varepsilon}_t$ anticipated at time T. In our implementation of the forecasting process, we stress the fact that prediction tunes applied in anticipated mode do not change over the future range, so no expectation shocks are present. The absence of expectation shocks originates from our need for transparency when the resulting prediction has to be interpreted and presented.

Augmenting the state space of the basic model given by Equations 1–2 with the sequence of constraints and shocks creates the following general form of the prediction problem:

$$
\begin{aligned}
Y_t &= \mathbf{C}X_t + \mathbf{D}\xi_t && (5)\\
X_t &= \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t + \mathbf{B}\overline{\varepsilon}_t && (6)\\
\mathbf{Z}_{t|T}X_t &= R_{t|T} + \mathbf{\Lambda}_t\mu_t && (7)\\
\overline{\mathbf{Z}}_{t|T}X_t &= \overline{R}_{t|T} + \overline{\mathbf{\Lambda}}_{t|T}\overline{\mu}_{t|T}, && (8)
\end{aligned}
$$

where vectors and matrices with bars refer to expert judgment applied in anticipated mode.

In this general augmented system, $\mathbf{Z}_{t|T}$ $(n_r \times n_x)$ and $\overline{\mathbf{Z}}_{t|T}$ $(n_{\overline{r}} \times n_x)$ are fixed matrices that, together with the vectors of constants $R_{t|T}$ $(n_r \times 1)$ and $\overline{R}_{t|T}$ $(n_{\overline{r}} \times 1)$, define the restrictions on the variables imposed by implementing the outlooks and expert judgment for periods $t \in \langle T+1,\ldots,T_{END}\rangle$. The linear constraints imposed by matrices $\mathbf{Z}_{t|T}$ and $\overline{\mathbf{Z}}_{t|T}$ usually have a straightforward structure, as the usual restriction binds one shock and one variable.

As in the application of identification tunes, prediction tunes can be applied with some uncertainty in the most general case. This uncertainty originates from the presence of shocks $\mu_t, (n_\mu \times 1)$ and $\overline{\mu}_{t|T}, (n_{\overline{\mu}} \times 1)$ with a covariance structure described by matrices $\mathbf{\Lambda}_{t|T}$ $(n_\mu \times n_\mu)$ and $\overline{\mathbf{\Lambda}}_{t|T}$ $(n_{\overline{\mu}} \times n_{\overline{\mu}})$. Such mode of tune application allows for some flexibility in deviating from the tunes applied. However, for the sake of clear forecast interpretation, in our application we assume no uncertainty about prediction tunes, so $\mathbf{\Lambda}_{t|T}\mu_{t|T} = 0$ and $\overline{\mathbf{\Lambda}}_{t|T}\overline{\mu}_{t|T} = 0$. Implementing prediction tunes without any uncertainty is known as hard tunes conditioning, as defined by Beneš et al. (2010).

[5] The CNB's forecast is conditioned on the trajectories for the following variables: the foreign demand, inflation, and interest rate paths; the inflation target trajectory; the outlook for administered prices; the government spending prediction; and the near-term forecast for inflation and the exchange rate for the first quarter of the prediction. The prediction is created under the assumption of endogenous monetary policy responses derived from the monetary policy rule of the model. As monetary policy operates via setting a trajectory for the nominal interest rate in a regime of inflation targeting, many may regard this forecast as unconditional. However, our forecast is conditioned on the outlooks and expert judgment. The uncertainty about the outlooks included in the information set I_T and expert judgment are described by creating alternative forecast scenarios. More information on the role of scenarios in the forecasting process can be found in Brůha et al. (2013).

When solving the prediction problem, prediction tunes that are described by the constraints given by Equations 7 and 8 are reflected in the predictions of unanticipated structural shocks ε_t and anticipated structural shocks $\overline{\varepsilon}_{t|T}$ for $t \in \langle T+1, \ldots, T_{END} \rangle$. The prediction phase problem, described by Equations 5–8 for $t \in \langle T+1, \ldots, T_{END} \rangle$ with the initial state given by the result of the identification phase, can be viewed as the constrained optimization problem of finding the likelihood-maximizing paths for the state variables. The process of solving the forecast problem conditioned by the constraints given by Equations 7–8 is described in the following section.

In the CNB's implementation of the conditional forecast, we map one variable to one structural shock in the given period of time. As pointed out by Andrle et al. (2009), the expert choice of the variable-shock pair is a crucial decision in the forecasting process and is known as the forecast plan. The use of one-to-one (injective) mapping originates from the interpretation approach used for writing the inflation report, as it allows us to suppress non-uniqueness problems and provides more details in the explanation of the forecast. In our view, this form of conditioning implementation also increases the consistency of the CNB forecast with the experts' view on future developments in the economy and with the behavior of economic agents making their decisions with regard to anticipated developments.

The structure of the forecast problem given by Equations 5–8 allows for a very broad structure of conditioning. Also, as in the initial state identification, expert judgment applied via the series of structural shocks ε_t and $\overline{\varepsilon}_t$ is equivalent to conditioning applied to the variables associated via the linear restrictions.

The two-phase forecasting exercise given by the identification and prediction problem allows us to define the forecast as a structure of time series. The forecast produced at time T conditional on the information set I_T is a structure of time series ${}_T\mathbb{F}(I_T) = \{{}_T\mathbf{Y}, {}_T\mathbf{Y}^J, {}_T\boldsymbol{\xi}, {}_T\mathbf{X}, {}_T\boldsymbol{\varepsilon}, {}_T\overline{\boldsymbol{\varepsilon}}\}$, where ${}_T\mathbf{Y}$ is a matrix of observed variables including their prediction ${}_T\mathbf{Y} = (Y_1, \ldots, Y_T, Y_{T+1}, \ldots, Y_{END})$, ${}_T\mathbf{Y}^J$ is a matrix of identification tunes ${}_T\mathbf{Y}^J = (Y^J_{1|T}, \ldots, Y^J_{T|T})$, and $\mathbf{X}_T$ is a matrix of unobserved state variables ${}_T\mathbf{X} = (X_1, \ldots, X_T, X_{T+1}, \ldots, X_{END})$. To avoid loss of information when assessing the forecast trajectories' forecast structure, the forecast also includes shocks, so ${}_T\boldsymbol{\xi}$ is a matrix of measurement shocks ${}_T\boldsymbol{\xi} = (\xi_1, \ldots, \xi_T, \xi_{T+1}, \ldots, \xi_{END})$, ${}_T\boldsymbol{\varepsilon}$ is a matrix of unanticipated structural shocks ${}_T\boldsymbol{\varepsilon} = (\varepsilon_1, \ldots, \varepsilon_T, \varepsilon_{T+1}, \ldots, \varepsilon_{END})$, and ${}_T\overline{\boldsymbol{\varepsilon}}$ is a matrix of anticipated structural shocks ${}_T\overline{\boldsymbol{\varepsilon}} = (\overline{\varepsilon}_{T+1}, \ldots, \overline{\varepsilon}_{END})$.

In the forecast ${}_T\mathbb{F}(I_T)$, the values for the time series for periods $t \in \langle 1, \ldots, T \rangle$ originate from the initial state identification as defined by Equations 3 and 4 and the values for $t \in \langle T+1, \ldots, T_{END} \rangle$ form the solution to the prediction problem given by Equations 5 and 8. A prediction trajectory is therefore a $T_{END} \times 1$ vector ${}_Tx(I_T)$ from forecast ${}_T\mathbb{F}(I_T)$. An element of the prediction trajectory ${}_Tx_h(I_T)$ is the prediction stated at period T for period h, $h \in \langle 1, \ldots, T_{END} \rangle$ and based on information set I_T.

Forecast ${}_T\mathbb{F}(I_T)$ cannot be viewed as a mechanistic one, as it is conditioned on judgment and outlooks imposed by forecasters. This judgment is based on expert views regarding recent developments and on knowledge of the model properties.[6]

[6] Expert judgment as seen by Svensson (2005) consists of information, knowledge, and views outside the scope of a particular model. Svensson (2005) argues that judgmental adjustments are a necessary and essential ingredient of modern monetary policy.

Since the forecasting exercise has two phases, there are two groups of expert judgment: filter and prediction tunes. As there are differences in the methods used in the identification and prediction phases, there are also differences in expert judgment implementation.

3. Solving the Prediction Problem

The method for solving the prediction problem allows for mixing of unanticipated and anticipated shocks and is based on the seminal works by Blanchard and Kahn (1980) and Klein (2000). The introduction of conditioning into the forecast follows the stream originated by Doan et al. (1983), while the solution method largely builds on the methodology developed by Waggoner and Zha (1999). Implementation details on the introduction of anticipated prediction tunes can be found in Leeper and Zha (2003) and Schmitt-Grohe and Uribe (2008).[7]

The point forecasts based on the linear model conditional on the expert judgment applied in anticipated and unanticipated mode, given by Equations 5 and 8, are constructed by two runs of the general solution procedure. In the first run, judgment in anticipated mode is implemented via the general solution method. In the second round, the general solution method is used to include unanticipated judgment while conditioning on the paths from the first round.

The general solution method has four steps. First, the model solution is constructed by forward expansion, so that the effect of future shocks is retained. Second, the expert judgment is translated to linear constraints on shocks and initial conditions for the constructed model solution. In the third step, the likelihood maximization problem is solved to calculate the values of shocks and initial conditions consistent with the judgment. Finally, the original system is simulated to obtain paths for the variables.

Originating from the notation by Blanchard and Kahn (1980), the model given by Equations 5–6 can be cast in the general form:

$$\widetilde{\mathbf{A}}E[\widetilde{X}_{t+1}|I_t]+\widetilde{\mathbf{B}}X_t+\widetilde{\mathbf{C}}\widetilde{\varepsilon}_t=0, \tag{9}$$

where $\widetilde{X}_t$ is a vector that includes measurement and state variables, $\widetilde{\varepsilon}_t$ is an augmented vector of structural and measurement shocks, and $\widetilde{\mathbf{A}},\widetilde{\mathbf{B}}$, and $\widetilde{\mathbf{C}}$ are matrices that are functions of the model structural parameters. For $t>T$, forward iteration of the model given by Equation 9 delivers a general solution conditional on expectations of future shocks given by:

$$\widetilde{X}_t=\widetilde{\mathbf{F}}X_{t-1}+\widetilde{\mathbf{G}}_0\widetilde{\varepsilon}_t+\sum_{k=1}^{\infty}\widetilde{\mathbf{G}}_kE[\widetilde{\varepsilon}_{t+k}|I_t]. \tag{10}$$

The mean and covariance matrix of the initial condition $\widetilde{X}_T$ originates from the application of the Kalman smoother in the first stage of the forecasting process using the available information. In our forecasting process, it is assumed that the distribution of shocks is normal with zero mean and covariance matrices $\Omega_t=COV(\widetilde{\varepsilon}_t|I_T)$ for $t>T$. Using forward expansion and substitutions, it follows

[7] Our implementation is based on the IRIS toolbox. IRIS is a free, open-source toolbox for macroeconomic modeling and forecasting in Matlab, developed by Jaromír Beneš. IRIS integrates core modeling functions (such as a flexible model file language, simulation, and estimation) with a wide range of supporting features (such as time series analysis, data management, and reporting) in a user-friendly command-oriented environment. The toolbox and its documentation are available at `http:\\www.iris-toolbox.com`.

that each value of $\widetilde{X}_T$ is a linear function of $\widetilde{X}_T$, structural shocks, and expectations thereof. In our forecasting process, the forecast conditioning is added in form of a sequence of linear constraints:

$$\widetilde{\mathbf{Z}}_{t|T}\widetilde{X}_t = \widetilde{\mathbf{R}}_{t|T}, \tag{11}$$

where $\widetilde{\mathbf{Z}}_{t|T}$ and $\widetilde{\mathbf{R}}_{t|T}$ are matrices defining the constraints for $t > T$. This allows us to transform the problem of finding the likelihood-maximizing paths for the variables of the model given by Equations 5–6 subject to the constraints given by Equations 7–8 into the problem of finding likelihood-maximizing values for $\widetilde{X}_T$ and the sequence of shocks $\widetilde{\varepsilon}_t$, subject to the constraint given by the sequence of Equation 11. Solving for $\widetilde{X}_T$ and the sequence of shocks $\widetilde{\varepsilon}_t$ and constraints can be converted into a likelihood-maximization problem by stacking these sequences into vectors.

Generally, the solution depends on the infinite sum of conditional expectations. We use T_{END} as the cut-off point, as beyond this point our forecast does not contain any conditioning information, so the shocks beyond this point are considered to be zero (the mean of their distribution). The simplifying assumption taken to compute our forecast trajectory is stated as follows: $E[\varepsilon_{T_{END}+k}|I_T] = E[\varepsilon_{T_{END}+k}|I_{T+1}] = \cdots = E[\varepsilon_{T_{END}+k}|I_{T_{END}}] = 0$ for $k > 1$.

An interesting fact about the likelihood-maximizing solution is that for the shocks there will be no change in the conditional expectations, and this will make them equal to the realizations of ε_t, so $E[\varepsilon_t|I_T] = E[\varepsilon_t|I_{T+1}] = \cdots = E[\varepsilon_t|I_{t-1}] = \varepsilon_t$ for $t > T$. Also, as we assume shocks from the normal distribution, the solution to the likelihood-maximization problem coincides with the mean of the distribution of the stacked vector conditional on the linear constraint.

Finally, after the optimal solution to forecasting problem is obtained, the system is simulated by plugging it into Equation 12 for periods $t, t \in \langle T+1, \ldots, T_{END}\rangle$:

$$\widetilde{X}_t^* = \widetilde{\mathbf{F}}X_{t-1}^* + \widetilde{\mathbf{G}}_0\widetilde{\varepsilon}_t^* + \sum_{k=T+1}^{T_{END}} \widetilde{\mathbf{G}}_k\widetilde{\varepsilon}_k^*. \tag{12}$$

So, performing two runs of the general solution procedure allows us to create forecast ${}_T\mathbb{F}(I_T)$, while we also keep the trajectories of the forecast that does not include expert judgment applied in unanticipated mode.[8]

4. Forecast Update Decomposition

As presented above, every forecast is driven by the elements of the information set, e.g. the observed data, the filter, and the prediction tunes. As the information set used for conditioning a forecast is updated over time, forecasters respond by updating the forecast to reflect new information. Thus, several prediction trajectories for the same variable are available over the period of time considered.

The dissemination of the updated forecast raises questions about the contributions of new elements of the information set to the changes in the forecast trajectories. In order to find answers, forecasters would like to identify which elements of the information set contributed to the particular forecast updates, as mentioned by Andrle et al. (2009) (see Section 6.5) and by Todd (1990). Moreover, a

[8] In our implementation, the final forecast ${}_T\mathbb{F}(I_T)$ and the forecast without unanticipated judgment are stored as a set of trajectories of the variables and shocks as a series of complex numbers.

forecast is often judged not only on its accuracy, but also on how intuitively it explains its updates. Therefore, the purpose of the forecast update decomposition is to provide additional insights into the forecast and the properties of the forecasting process and also to improve understanding of the structural model used.

Early versions of our decomposition tools were implemented with the introduction of the Quarterly Projection Model (Beneš et al., 2003) into the forecasting framework of the CNB. The most noticeable limitation of these tools originated from sequential evaluation of the elements of the information set, leading to results that were conditional on the ordering. Another drawback stemmed from the QPM framework, which did not allow for mixing of conditioning in anticipated and unanticipated mode. Since the current forecasting framework (Andrle et al., 2009; Brůha et al., 2013) is much more advanced than the previous one, we are motivated to create a more general decomposition framework that meets our needs.

The current decomposition procedure decomposes the forecast update into components identified with the direct and indirect effects of the updates of information set elements. The goal is to analyze the difference between the prediction trajectories of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$, where $T_O < T_N$.

Figure 2: Time Conventions

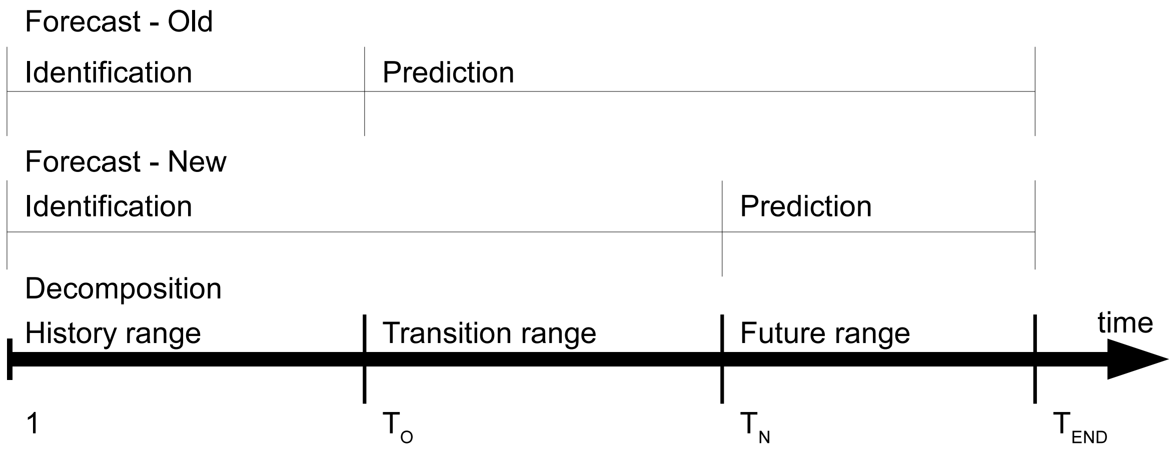


Figure 2 shows the timing of the two forecasts under analysis. Each of the forecasts has its own identification and prediction phase. Figure 2 defines the ranges of interest in the forecast update decomposition. Range $\langle T_O+1,\ldots,T_N\rangle$ denotes the transition range, which corresponds to the intersection of the prediction of the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$ and the identification of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$. The history range $\langle 1,\ldots,T_O\rangle$ denotes the intersection of the two forecasts' initial state identification phases. The future range $\langle T_N+1,\ldots,T_{END}\rangle$ is the intersection of the prediction phases of the two forecasts analyzed.

The forecast update decomposition identifies the contributions of the updates of the elements of the information set to the difference between the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$.

If $T_O < T_N$, then a time shift is present between the forecasts and the prediction from the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$ has to be compared with the identification of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$. The decomposition of the forecast update is based on the partitioning of the information set update from I_{T_O} to I_{T_N}

into disjoint subsets while keeping in mind the difference between the identification and prediction methodology.

To examine the contributions of the information set elements, we use a complex but still general procedure based on partitioning the information set into subsets. This partitioning procedure exploits properties of the forecasting process and divides the examination process into several steps. These steps are based on supporting forecasts used to identify the contributions of the information set elements to the forecast update. The creation of these supporting forecasts exploits the linearity of the model, as it implies that the construction of a prediction is additive with respect to the information set elements. The additivity property allows us to express the differences between the New and Old forecasts as the sum of the differences between the New forecast and the supporting forecast, and the supporting forecast and the Old forecast.

Generally, decomposition is a non-linear problem, as shown by Todd (1990). However, Andrle (2013) shows that in the case of a linear model, independent normally distributed shocks, and the use of a multivariate linear filter (such as the Kalman filter/smoother), decomposition is a linear problem and can be solved numerically by an iterative process that sequentially analyzes the forecast elements. Therefore, under the assumption of a linear state-space model, a linear multivariate filter, and the same model parametrization for both forecasts, the forecast decomposition analysis is also a linear problem.

The role of the supporting forecast in the decomposition of the forecast update between the New forecast trajectory ${}_{T_N}x_h(I_{T_N})$ and the Old forecast trajectory ${}_{T_O}x_h(I_{T_O})$ is based on the following scheme:

$$ {}_{T_N}x_h(I_{T_N}) - {}_{T_O}x_h(I_{T_O}) = ({}_{T_N}x_h(I_{T_N}) - {}_{T}\,x_h(I^S)) + ({}_{T}x_h(I^S) - {}_{T_O}x_h(I_{T_O})), \tag{13} $$

where ${}_{T}x_h(I^S)$ is the forecast trajectory from the supporting forecast ${}_{T}\mathbb{F}(I^S)$ based on the information set I^S with the end of history in period T. In this simplified decomposition scheme, we have $I_{T_O} \subseteq I^S \subseteq I_{T_N}$ and T is either T_N or T_O depending on the construction of I^S.

In the forecast update examination process, the decomposition procedure has to cope with the inclusion of expert judgment in anticipated mode, revisions, and the change from the identification to the prediction phase. Hence, the decomposition procedure has to exploit a rich structure of supporting forecasts to extract the effects of the information set elements on the prediction trajectories considered. Taking into account the simple step described by Equation 13, the decomposition has the following complex form:

$$ \begin{aligned} {}_{T_N}x_h(I_{T_N}) - {}_{T_O}x_h(I_{T_O}) &= ({}_{T_N}x_h(I_{T_N}) - {}_{T_1}x_h(I^{S_1})) + ({}_{T_1}x_h(I^{S_1}) - {}_{T_2}x_h(I^{S_2})) + \\ &+ ({}_{T_2}x_h(I^{S_2}) - {}_{T_3}x_h(I^{S_3})) + ({}_{T_3}x_h(I^{S_3}) - {}_{T_4}x_h(I^{S_4})) + \\ &+ \cdots + \\ &+ ({}_{T_{K-1}}x_h(I^{S_{K-1}}) - {}_{T_K}x_h(I^{S_K})) + ({}_{T_K}x_h(I^{S_K}) - {}_{T_O}x_h(I_{T_O})), \end{aligned} \tag{14} $$

where supporting forecasts ${}_{T_1}x_h(I^{S_1}),\ldots,{}_{T_K}x_h(I^{S_K})$ are used to extract specific groups of information. As $I_{T_N} \supseteq I_{T_O}$, supporting information sets I^{S_i} are constructed so that $I_{T_N} \supseteq I^{S_i}$ for all $i = \{1,\ldots,K\}$. In the scheme given by Equation 14, each term in brackets shows how a subset of the information set (forecast component) would have changed the forecast trajectory.

Partitioning the update of the information set from I_{T_N} to I_{T_O} into subsets is the core of the decomposition analysis, and the supporting information sets I^{S_i}, $i = \{1,\ldots,K\}$ are the building blocks of the algorithm. The supporting information sets I^{S_i} are used to partition the update of the information set from the time perspective with respect to the phases of the forecasting process. As set I^{S_i} includes aggregates of variables, it can be partitioned further into the disjoint sets $I^{S_{ij}}$, $j = \{1,\dots,J\}$ with respect to the variables. So, the information set $I^{S_{ij}}$ allows us to examine the effect of the time subset i of a specific variable j over the periods covered by the aggregate information set I^{S_i}.

This aggregate set usually covers multiple periods, therefore $I^{S_{ij}}$ can be partitioned further so that the information subset $I^{S_{ijl}}$ identifies the effect of a specific variable in time period l.

For the sake of clarity of the decomposition algorithm, we explain the construction of the supporting information sets I^{S_i}, $i = \{1,\dots,K\}$, because the search for the effect of a particular variable in a given time period is dependent on this set. For the reader's convenience, we describe the crucial sets in steps. Partitioning the supporting information set I^{S_i} into the disjoint elements $I^{S_{ijl}}$ then involves a very straightforward cycle through all periods and variables included in the aggregate.

1. **Removing new unanticipated judgment on future range: New forecast (with expert judgment both anticipated and unanticipated) $\Longleftrightarrow$ New forecast without unanticipated expert judgment on future range** The decomposition algorithm starts with the forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and moves toward replication of ${}_{T_O}\mathbb{F}(I_{T_O})$ by altering the information sets used to create the forecasts. The last component added to the forecast is expert judgment on the future range applied in unanticipated mode, so the first supporting information set I^{S_1} is constructed from I_{T_N} by removing this expert judgment from the prediction phase. The first supporting forecast based on I^{S_1} is constructed with its identification phase ending in period T_N and without expert judgment applied in unanticipated mode, so ${}_{T_N}\mathbb{F}(I^{S_1}) = \{{}_{T_N}\mathbf{Y}, {}_{T_N}\mathbf{Y}^J, {}_{T_N}\boldsymbol{\xi}, {}_{T_N}\mathbf{X}(I^{S_1}), {}_{T_N}\boldsymbol{\varepsilon}(I^{S_1}), {}_{T_N}\overline{\boldsymbol{\varepsilon}}\}$, where ${}_{T_N}\boldsymbol{\varepsilon}(I^{S_1}) = (\varepsilon_1,\dots,\varepsilon_{T_N})$ and ${}_{T_N}\mathbf{X}(I^{S_1})$ is the matrix of state variables that is the solution to the identification and prediction phase of the forecast. The differences in the forecast trajectories ${}_{T_N}x_h(I_{T_N}) - {}_{T_N}x_h(I^{S_1})$ describe the effect of the expert judgment in unanticipated mode applied over the future range.

2. **Removing new anticipated judgment on future range: New forecast without unanticipated expert judgment on future range $\Longleftrightarrow$ New forecast without expert judgment on future range** The second supporting information set I^{S_2} is constructed from I^{S_1} by the removal of the expert judgment applied in anticipated mode over the future range, so $I^{S_1} \supseteq I^{S_2}$. In this step of the decomposition algorithm, ${}_{T_N}\boldsymbol{\varepsilon}(I^{S_1}) = {}_{T_N}\boldsymbol{\varepsilon}(I^{S_2})$ and ${}_{T_N}\overline{\boldsymbol{\varepsilon}}(I^{S_2}) = \emptyset$ is used to create the following supporting forecast ${}_{T_N}\mathbb{F}(I^{S_2}) = \{{}_{T_N}\mathbf{Y}, {}_{T_N}\mathbf{Y}^J, {}_{T_N}\boldsymbol{\xi}, {}_{T_N}\mathbf{X}(I^{S_2}), {}_{T_N}\boldsymbol{\varepsilon}(I^{S_2}), {}_{T_N}\overline{\boldsymbol{\varepsilon}}(I^{S_2})\}$, where ${}_{T_N}\mathbf{X}(I^{S_2})$ is the corresponding matrix of state variables. The differences in the trajectories of the forecasts ${}_{T_N}\mathbb{F}(I^{S_2})$ and ${}_{T_N}\mathbb{F}(I^{S_1})$ identify the effects of expert judgment applied in anticipated mode over the future range $\langle T_N + 1,\dots,T_{END}\rangle$.

3. **Removing new judgment on transition range: New forecast without expert judgment on future range $\Longleftrightarrow$ New forecast without expert judgment on future and transition range** After removing the expert judgment applied in the prediction phase of the New forecast, the decomposition algorithm shifts its focus to the transition range. The goal is to identify the effects of the expert judgment applied with respect to the newly released data. Hence, the expert judgment of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ applied in the identification phase over the periods $\{T_O + 1,\dots,T_N\}$ is removed from the information set I^{S_2} and the subsequent set I^{S_3}, such that $I^{S_2} \supseteq I^{S_3}$, is constructed. By creating the supporting forecast ${}_{T_N}\mathbb{F}(I^{S_3}) = \{{}_{T_N}\mathbf{Y}, {}_{T_N}\mathbf{Y}^J(I^{S_3}), {}_{T_N}\boldsymbol{\xi}(I^{S_3}), {}_{T_N}\mathbf{X}(I^{S_3}), {}_{T_N}\boldsymbol{\varepsilon}(I^{S_3}), \emptyset\}$, where ${}_{T_N}\boldsymbol{\varepsilon}(I^{S_3}) = ({}_{T_N}\varepsilon_1,\dots,{}_{T_N}\varepsilon_{T_O})$ is the matrix of shocks identified in the forecast constructed in period T_N, we are able to identify the effect of the transition range expert judgment on

the identified initial state used in the prediction phase. Comparison of the trajectories of the forecasts ${}_{T_N}\mathbb{F}(I^{S_3})$ and ${}_{T_N}\mathbb{F}(I^{S_2})$ allows us to identify the propagation of expert judgment ${}_{T_N}\boldsymbol{\varepsilon} = ({}_{T_N}\varepsilon_{T_O+1}, \ldots, {}_{T_N}\varepsilon_{T_N})$ to the prediction, thus the contributions to the update of the forecast trajectories over the future range are also identified.

4. **Removing new judgment on history range: New forecast without expert judgment on future and transition range $\Longleftrightarrow$ New forecast without expert judgment** The fourth supporting information set completes the removal of the expert judgment applied in the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$. The set I^{S_4} is constructed from I^{S_3} by omitting the remaining expert judgment applied in the identification phase over the periods $\{1, \ldots, T_O\}$, so $I^{S_3} \supseteq I^{S_4}$. Identification of the effect of the expert judgment from the information set I_{T_N} is finalized by creating the supporting forecast ${}_{T_N}\mathbb{F}(I^{S_4}) = \{{}_{T_N}\mathbf{Y}, \emptyset, {}_{T_N}\boldsymbol{\xi}(I^{S_4}), {}_{T_N}\mathbf{X}(I^{S_4}), {}_{T_N}\boldsymbol{\varepsilon}(I^{S_4}), \emptyset\}$, where ${}_{T_N}\boldsymbol{\varepsilon}(I^{S_4}) = \emptyset$, so there is no expert judgment applied. The forecast ${}_{T_N}\mathbb{F}(I^{S_4})$ is an expert judgment-free (unconditional) version of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$, but the information set I^{S_4} still includes the new data (revisions and releases) collected after the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$ was constructed.

5. **Removing newly released data and time shift: New forecast without expert judgment $\Longleftrightarrow$ New forecast without expert judgment and newly released data** In the construction of the fifth supporting forecast, we exploit the consistency of the model applied for the identification and prediction phase to alter the end of the history period. The information set I^{S_5} is constructed from I^{S_4} by removing the observations used in the identification over the transition range, so the observed data set becomes ${}_{T_N}\mathbf{Y}(I^{S_5}) = ({}_{T_N}Y_1, \ldots, {}_{T_N}Y_{T_O})$. The set I^{S_5}, $I^{S_5} \subseteq I^{S_4}$, does not contain all the data observed at time T_N, as the data for periods $\{T_O + 1, \ldots, T_N\}$ are replaced with missing values. The model consistency over the forecast phases, along with the properties of the Kalman filter and its ability to handle missing values, implies equivalence between the forecast ${}_{T_N}\mathbb{F}(I^{S_5}) = \{{}_{T_N}\mathbf{Y}(I^{S_5}), \emptyset, {}_{T_N}\boldsymbol{\xi}(I^{S_5}), {}_{T_N}\mathbf{X}(I^{S_5}), \emptyset, \emptyset\}$ and the forecast ${}_{T_O}\mathbb{F}(I^{S_5}) = \{{}_{T_O}\mathbf{Y}(I^{S_5}), \emptyset, {}_{T_N}\boldsymbol{\xi}(I^{S_5}), {}_{T_O}\mathbf{X}(I^{S_5}), \emptyset, \emptyset\}$. This equivalence allows us to replicate the forecast trajectories ${}_{T_N}x_h(I_{S_5})$ with the forecast trajectories ${}_{T_O}x_h(I_{S_5})$. So, the following steps of the decomposition algorithm are based on the forecasts with the end of history T_O.

6. **Replacing new revisions with old data on history range: New forecast without expert judgment and newly released data $\Longleftrightarrow$ Old forecast without expert judgment** After the last element of the end of the identification phase of the forecast is shifted from period T_N to period T_O, the last component of the information set I_{T_N} consists of revisions of the observations over the history range $\langle 1, \ldots, T_O \rangle$. So, the sixth aggregate supporting information set I^{S_6} is constructed from I^{S_5} by reverting from the observations collected in I_{T_N} to the observations from the information set I_{T_O}, where ${}_{T_O}\mathbf{Y}(I^{S_6}) = ({}_{T_O}Y_1, \ldots, {}_{T_O}Y_{T_O})$ and $I^{S_5} \supseteq I^{S_6}$. Using the supporting forecast ${}_{T_O}\mathbb{F}(I^{S_6}) = \{{}_{T_O}\mathbf{Y}, \emptyset, {}_{T_N}\boldsymbol{\xi}(I^{S_6}), {}_{T_N}\mathbf{X}(I^{S_6}), \emptyset, \emptyset\}$ and its forecast trajectories unravels the effects of the data revisions.

7. **Adding old judgment on history range: Old forecast without expert judgment $\Longleftrightarrow$ Old forecast without expert judgment on transition and future range** The following supporting simulations focus on reconstruction of the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$. As I^{S_6} contains the data for the identification phase, I^{S_7} is constructed by adding the expert judgment over the history range used in the construction of the Old forecast, so $I^{S_7} \supseteq I^{S_6}$. The supporting forecast ${}_{T_O}\mathbb{F}(I^{S_7}) = \{{}_{T_O}\mathbf{Y}, {}_{T_O}\mathbf{Y}^J, {}_{T_O}\boldsymbol{\xi}(I^{S_7}), {}_{T_O}\mathbf{X}(I^{S_7}), \emptyset, \emptyset\}$ is used to identify the effects of the expert judgment for the initial state identification (the effect on the forecast trajectories over the history range) and its propagation to the prediction phase (the effect on the forecast trajectories over the transition and future range).

8. **Adding old anticipated judgment on transition and future range: Old forecast without expert judgment on transition and future range $\Longleftrightarrow$ Old forecast without unanticipated**

expert judgment on transition and future range The forecast based on set I^{S_7} replicates the identification phase results of ${}_{T_O}\mathbb{F}(I_{T_O})$. I^{S_8} is augmented by adding expert judgment in anticipated mode, so $I^{S_8} \supseteq I^{S_7}$. The supporting forecast ${}_{T_O}\mathbb{F}(I^{S_8}) = \{{}_{T_O}\mathbf{Y}, {}_{T_O}\mathbf{Y}^J, {}_{T_O}\boldsymbol{\xi}, {}_{T_O}\mathbf{X}(I^{S_8}), \emptyset, {}_{T_O}\overline{\boldsymbol{\varepsilon}}\}$ and the forecast trajectory differences ${}_{T_O}x_h(I^{S_7}) - {}_{T_O}x_h(I^{S_8})$ identify the contributions of the expert judgment applied in anticipated mode when constructing the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$.

9. **Adding old unanticipated judgment on transition and future range: Old forecast without unanticipated expert judgment on transition and future range $\Longleftrightarrow$ Old forecast (with expert judgment both anticipated and unanticipated)** The decomposition algorithm is completed by adding the expert judgment applied in unanticipated mode in the prediction phase. So, the set I_{T_O} is obtained in this step and the forecast ${}_{T_O}\mathbb{F}(I_{T_O})$ is replicated. The supporting forecast ${}_{T_O}\mathbb{F}(I^{S_8})$ is compared against the forecast ${}_{T_O}\mathbb{F}(I_{T_O}) = \{{}_{T_O}\mathbf{Y}, {}_{T_O}\mathbf{Y}^J, {}_{T_O}\boldsymbol{\xi}, {}_{T_O}\mathbf{X}, {}_{T_O}\boldsymbol{\varepsilon}, {}_{T_O}\overline{\boldsymbol{\varepsilon}}\}$ to identify the contributions of expert judgment in unanticipated mode.

As mentioned above, each of the aggregate supporting information sets I^{S_i}, $i = \{1, \ldots, K\}$ can be further partitioned to reflect the structure of expert judgment. This detailed partitioning can provide more details on the period-by-period effect of the forecast element under scrutiny.

5. Decomposition Analysis

First, we demonstrate the features of the decomposition framework by decomposing the difference between two forecast trajectories into the contributions of new information as the simplest case. Further, we use the CNB's forecasts presented in Inflation Report III/2012 and Inflation Report III/2013 to demonstrate the use of the framework in the complex case of forecast evaluation.

5.1 Alternative Forecast Scenarios

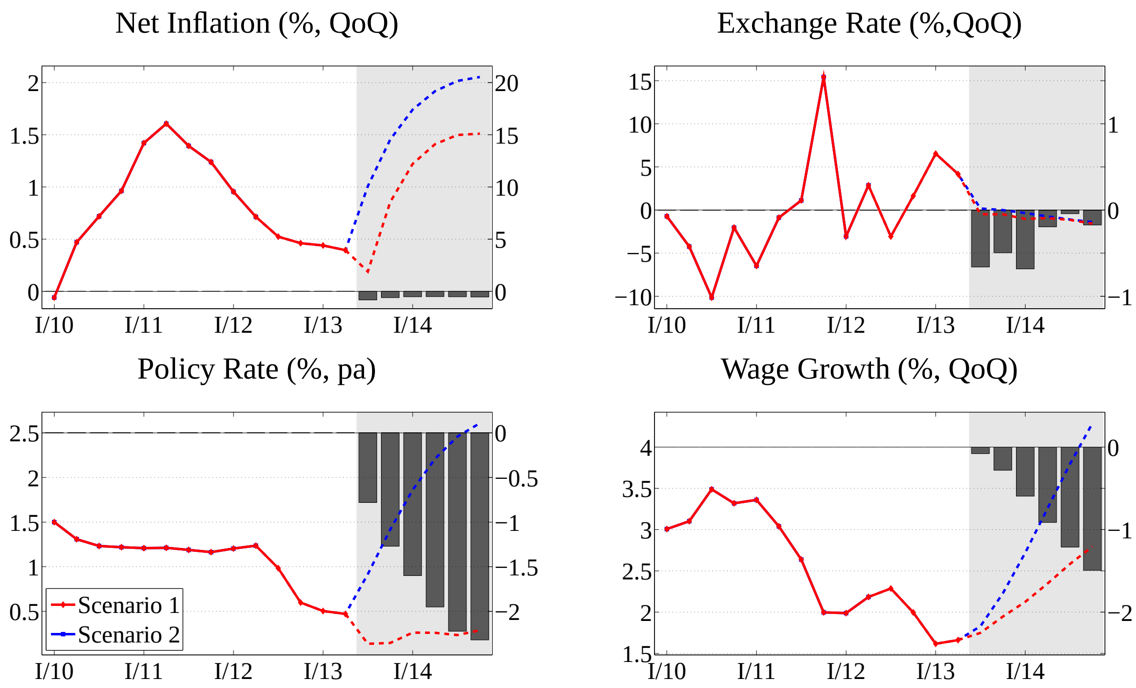
We begin with a comparison of a forecast scenario that uses the set of conditioning information ${}_T\mathbb{F}(I_{T,1})$ (Scenario 1) and a forecast scenario without any application of conditioning information ${}_T\mathbb{F}(I_{T,2})$ in the prediction (Scenario 2).

In our example, Scenario 1 is represented by the baseline scenario of the CNB's forecast released in Inflation Report III/2013. Scenario 1 is created by conditioning on the outlooks for nominal government consumption, administered prices, the external environment outlook (inflation, the short-term interest rate, demand), and the one-quarter-ahead outlook for domestic inflation and the exchange rate. In the forecasting process, the external environment outlook is implemented in anticipated mode.

Scenario 2 is a fictional forecast created with the same information set, but it does not use any conditioning information over the future range. The role of this comparison in the forecasting process is to identify the driving forces of the prediction story delivered by the assumptions applied.

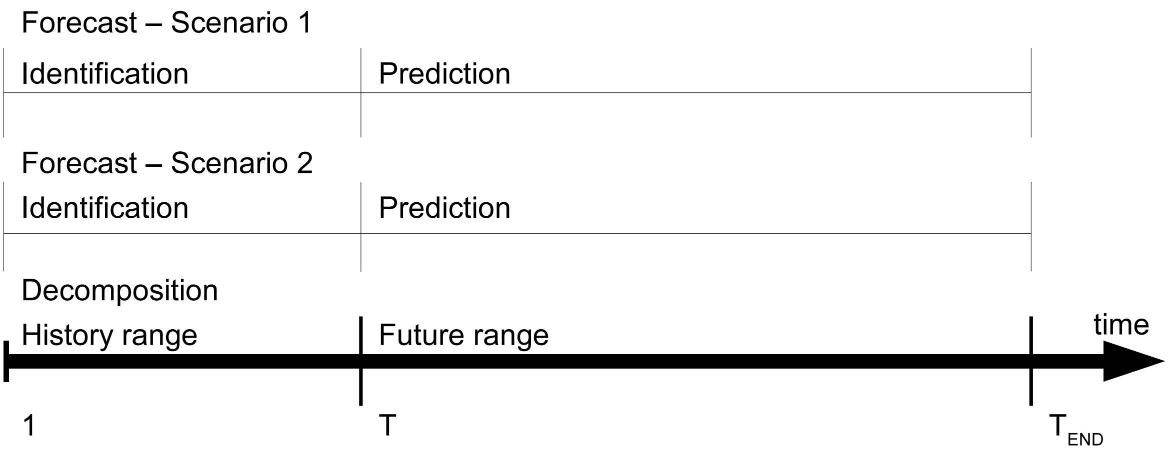
Figure 3 shows the trajectories of the variables of interest for Scenario 1 and Scenario 2. In the graphs, the white area represents the history range (up to the second quarter of 2013) and the shaded background indicates the future range (from the third quarter of 2013), while the bars indicate the differences between the trajectories considered. The same initial state is used in both scenarios, so there is no difference observable over the history range.

Figure 3: Scenario Comparison – Data



In general, we consider two alternative forecast scenarios ${}_T\mathbb{F}(I_{T,1})$ and ${}_T\mathbb{F}(I_{T,2})$. There is no time shift between these two forecasts; however, $I_{T,1} \supseteq I_{T,2}$. In our example, the extra information included in $I_{T,1}$ describes the expert opinion on the trajectories of some of the variables.

Figure 4: Scenario Comparison



The two alternative forecast scenarios, with a prediction span from period $T+1$ to T_{END}, can easily be compared and their differences analyzed, as these scenarios have the same range for initial state identification and for prediction. The scheme for evaluation of the two scenarios is presented in Figure 4. The simplicity of this case originates from the fact that there is no overlap between the identification and prediction part and the decomposition problem breaks down into a simple task also known as alternative scenario decomposition, as presented in Andrle et al. (2009). This process is heavily used during the standard CNB forecasting process due to improved understanding of the driving forces of the forecast trajectories. The core of the exercise involves computing the model's elasticities to changes in the model variables. These elasticities are evaluated for each time period in the future range. The overall response of a prediction trajectory is then computed as the sum of the responses to the conditioning information groups.

Figure 5: Scenario Comparison – Contributions

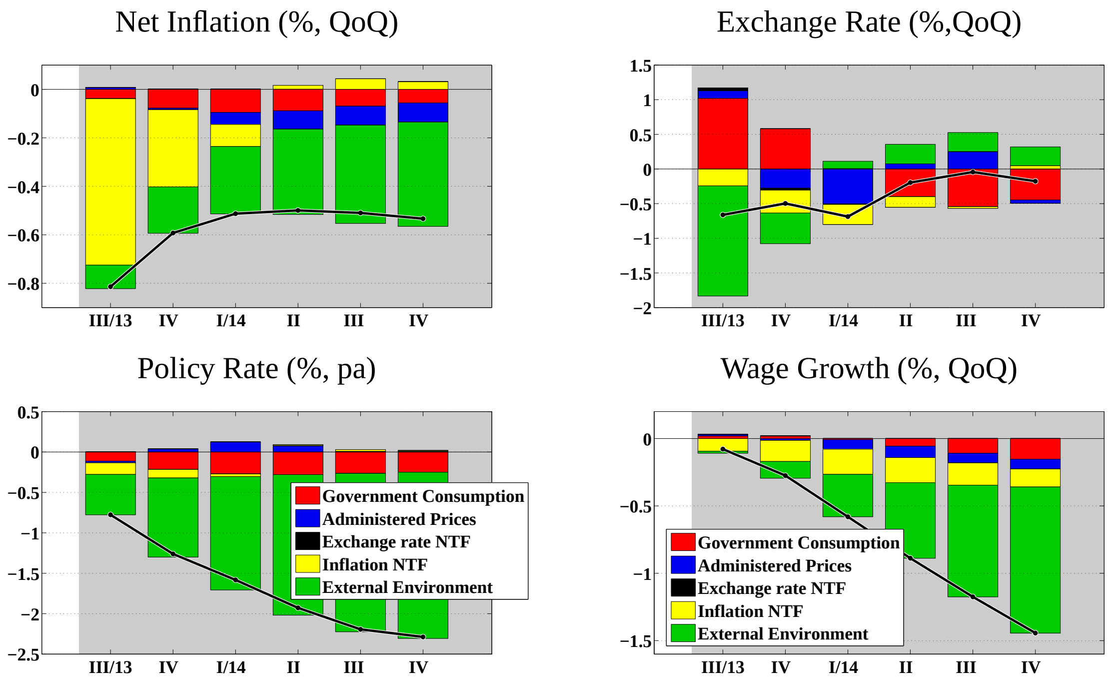


Figure 5 shows the results of applying the decomposition approach for the alternative scenario analysis. As there is no difference in the identification phase, only the future range (from the third quarter of 2013) is shown. The differences (Scenario 1–Scenario 2) between the trajectories shown in Figure 3 are decomposed into the contributions of the forecast elements, while the solid line shows the difference. A brief assessment of the contributions reveals that the major driving force of the forecast is the outlook for the external environment.

5.2 Forecast Evaluation

The extensive capabilities of our evaluation framework are clearly demonstrated when the framework is applied to decompose the difference between two forecasts which were created in different periods of time.

In the production of the new forecast ${}_{T_N}\mathbb{F}(I_{T_N})$, its stability in comparison to the previous forecast ${}_{T_O}\mathbb{F}(I_{T_O})$, where $T_N = T_O + 1$, is of high importance. Although this type of assessment is an example of general decomposition, the current comparison concentrates mainly on the impact on the future range. This assessment is known as forecast update analysis.

However, our framework can be also applied to examine the actual–predicted data variation. To demonstrate its use, details of our methodology are provided for the Inflation Forecast Evaluation exercise.[9] This exercise is conducted on a quarterly basis and we are interested in identifying the

[9] The Inflation Forecast Evaluation is a regular exercise that is a part of the forecasting process. It takes the form of a report and provides an assessment of the old forecast, created 6 quarters ago, and its deviation from the latest

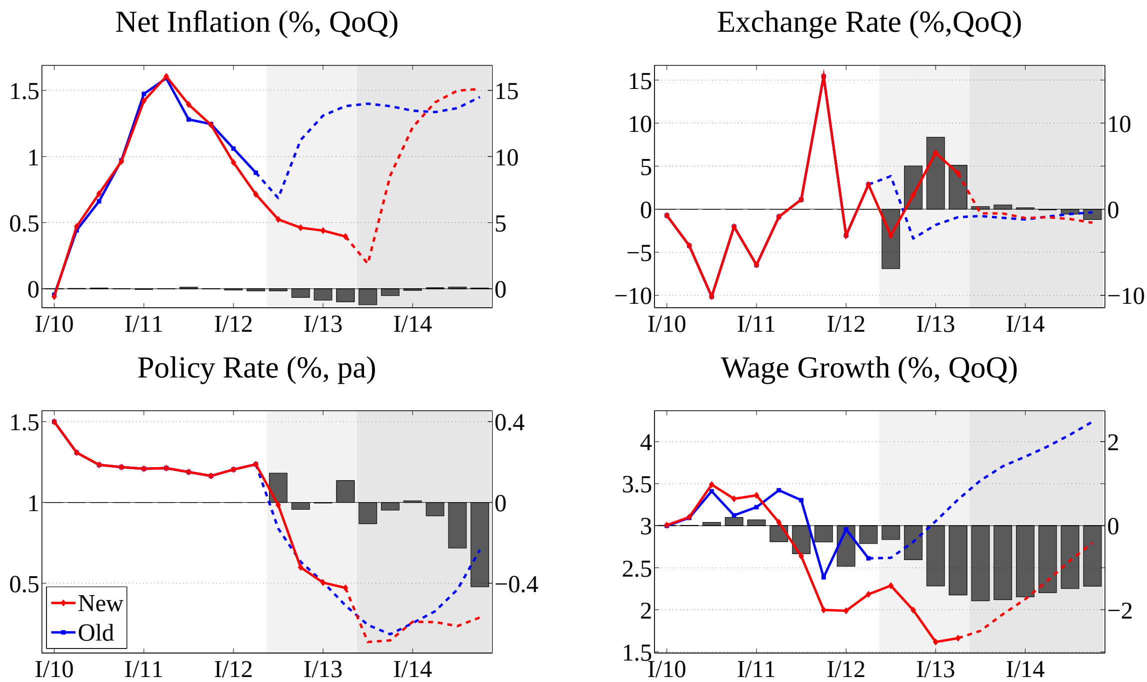
sources of the medium-term differences between the New and Old forecasts, with a focus on the transition range, as it includes the latest data releases. Nevertheless, the decomposition is also provided on the history and future ranges.

The goal of the Inflation Forecast Evaluation is to identify the contributions of newly acquired elements of the information set I_{T_N} to the update of the forecast trajectories. Knowledge of the propagation of information helps us improve the quality of future forecasts, as we learn about the sensitivity of the forecast to its assumptions. We focus on the inflation prediction due to the inflation-targeting nature of the CNB's monetary policy. The results of the evaluation also enhance the transparency and consistency of the forecasting process and serve as a measure of monetary policy performance.

Figure 2 shows the general timing scheme for two forecasts created at different points of time: New $({}_{T_N}\mathbb{F}(I_{T_N}) = \{{}_{T_N}\mathbf{Y}, {}_{T_N}\mathbf{Y}^J, {}_{T_N}\boldsymbol{\xi}, {}_{T_N}\mathbf{X}, {}_{T_N}\boldsymbol{\varepsilon}, {}_{T_N}\overline{\boldsymbol{\varepsilon}}\})$ and Old $({}_{T_O}\mathbb{F}(I_{T_O}) = \{{}_{T_N}\mathbf{Y}, {}_{T_O}\mathbf{Y}^J, {}_{T_O}\boldsymbol{\xi}, {}_{T_O}\mathbf{X}, {}_{T_O}\boldsymbol{\varepsilon}, {}_{T_O}\overline{\boldsymbol{\varepsilon}}\})$. Here, the New forecast data is available up to period T_N and the New forecast prediction starts in period $T_N + 1$. Similarly, the Old forecast data is available up to period T_O and the Old forecast prediction starts in period $T_O + 1$.

The information set of the New forecast I_{T_N} enriches the Old forecast information set I_{T_O} by the release of new data for the periods from $T_O + 1$ to T_N and by data revisions up to period T_O. Also, the expert judgment (the identification and prediction tunes and the outlooks) for the prediction can be updated, reflecting either observed data revisions or expert information updates.

Figure 6: Forecast Evaluation – Trajectories



The trajectories from the forecasts analyzed are presented in Figure 6. In our example, the Old forecast (the blue line) is represented by the forecast released in the third quarter of 2012 (Inflation

data vintage. The focus is on assessing the accuracy of the forecast. The Inflation Forecast Evaluation also features an analysis of the monetary policy decisions made over the period T_O–T_N.

Report III/2012) and uses the data up to the second quarter of 2012 (T_O). The New forecast (the red line) shows the trajectories from the forecast released in the third quarter of 2013 (Inflation Report III/2013). The New forecast uses the data up to the second quarter of 2013 (T_N). The Inflation Forecast Evaluation takes place in $T_N + 1$, after the data for 4 quarters have been collected. The graphs show the history range (the dark shaded area) up to period T_O, the transition range (the light shaded area) $\langle T_O + 1, T_N \rangle$, and the future range from period $T_N + 1$.

The task of the forecast update analysis is to explain the role of the forecast elements and their contributions to the New–Old forecast difference. This task is complicated, as the difference in the initial prediction periods has to be considered. This means that the results of the identification phase of the New forecast have to be compared with the prediction phase of the Old forecast. The complication arises especially from the presence of prediction tunes that are applied in anticipated mode and the forward-looking nature of the model used. At this point, we exploit our knowledge of the elements of the forecast.[10]

In the former specification of the decomposition methodology, starting from the period of use of the Quarterly Projection Model (QPM) framework (Beneš et al., 2003) and also covering the use of the current g3 model, the forecast evaluation was conducted by means of a "what if" analysis. In this analysis, forecasters recreated the Old forecast using the actually collected data in the forecasting process for the identification phase and as the conditioning information in the prediction phase. The analysis consisted of two stages. In the first stage, the data update over the history range and the actual data observations over the transition range in the role of outlooks were used to create a fictional forecast, labeled the "hypothetical forecast with up-to-date knowledge." Then, the differences between the fictional forecast and the Old forecast were examined to assess the contributions of the various information groups to the shift in trajectories. These contributions were analyzed by sequential inclusion of the new data, so the contributions were not independent of the choice of the order for information inclusion. This created a very strong limitation for the interpretation of the results. Very good knowledge of the model responses was necessary to understand the results of the analysis. This requirement, and the dependence on the ordering of the information, limited us in delivering an evaluation of the forecast to a wider audience.

In the second stage of the evaluation in the former framework, the analysis was focused on the deviations between the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and the fictional forecast ${}_{T_O}\mathbb{F}(I_{T_N})$. This stage was focused on missing structural shocks that were omitted or that we formed wrong expectations about while preparing the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$. The drawback of the old framework was that the missing structural shocks could not have been identified because of inconsistences between the New and the fictional forecasts in their assumptions. Consequently, the presentation of this step was very demanding and suffered heavily from the problem of subjective interpretation, as recent economic developments had to be related to the model variables, which required a deep knowledge of both the economy and the structure of the model.

The improved version of the Inflation Forecast Evaluation provides the analysis in one stage and is fully model based. The principal value added of the suggested procedure is that the decomposition is reduced to a technical computation which is independent of forecasters' views. Moreover, missing structural shocks can be identified, which can help in interpreting the results.

Contrary to the computation itself, interpretation remains largely a subjective matter. Since the decomposition provides the impact of every single observed or exogenized (either a shock or an

[10] That is, as forecast creators, we have knowledge about the counterpart identification tunes in the Old forecast.

outlook) variable in every period of time on all the model state variables, it ends up providing hundreds of contributions to the New–Old forecast difference even for a small model. Hence, in order to analyze and interpret the results effectively, we have to aggregate the individual contributions into a reasonable number of groups. The grouping depends primarily on the purpose of the analysis and can vary substantially for different exercises. Although there are no restrictions on grouping, there are some natural ways suggested by the decomposition procedure, such as grouping by type of forecast element (e.g. keeping observations and tunes separate) or time perspective (e.g. separating shocks that occurred in the history, transition, or future range). Other ways of grouping may follow economic interpretation (e.g. groups of foreign variables, real economy variables, monetary policy variables, technology variables, prices). In practice, we predefined several standard sets of groups for every decomposition exercise, as this seemed most appropriate and helpful for that particular analysis, and kept them unchanged over time. This standardization helps us limit subjectivity in interpretation and enhances the consistency of the analysis over time.

The capabilities of the new framework allow us, but do not require us, to keep the form of the Inflation Forecast Evaluation and present its results in two parts. Due mainly to storytelling consistency with the old version, we continue to interpret the results in this way, keeping two views of the variation of the forecasted trajectories, although the computation is different from the previously used approach. Firstly, the forecast update view is used, where we explain the New–Old forecast difference with the updates in the assumptions that were imposed to create the forecasts. Secondly, the Inflation Forecast Evaluation offers a detailed analysis of the model dynamics through the differences in the remaining shocks identified by the model. This second view is helpful in identifying structural shocks that the forecasters could not have anticipated when the forecast was created.

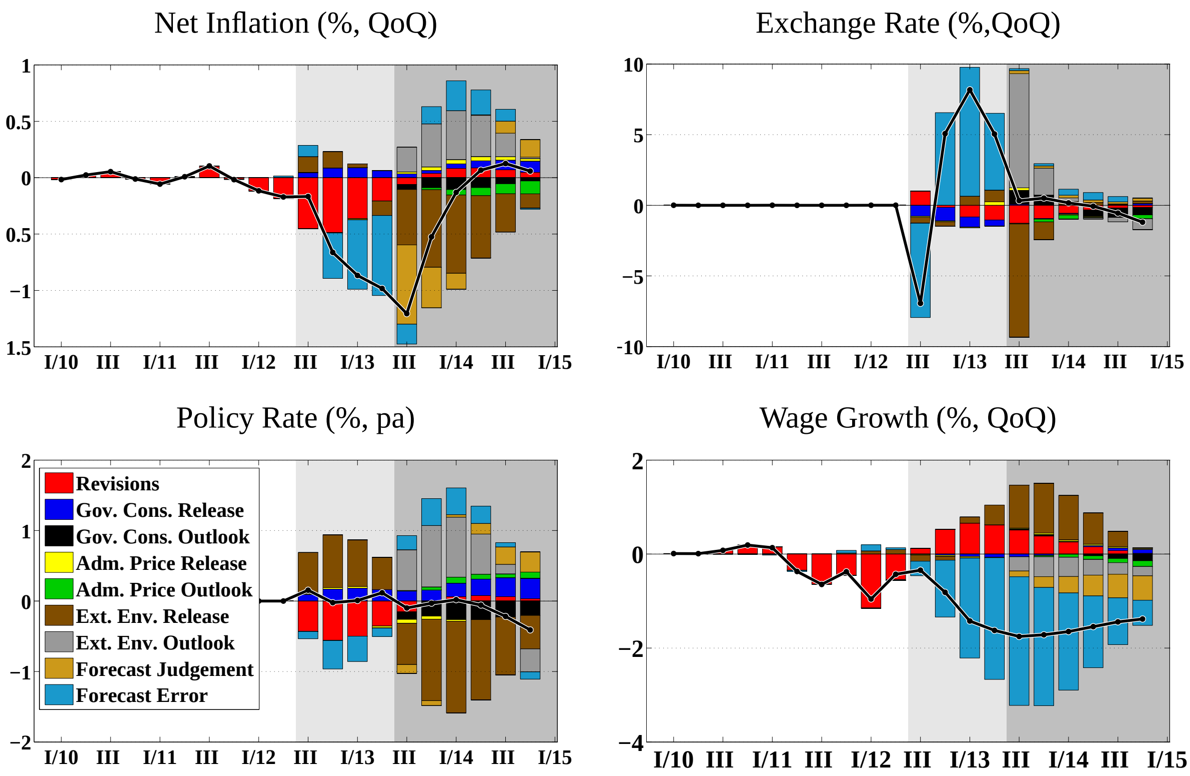
5.3 Forecast Evaluation: Variables View

In the first part of the forecast evaluation, the effect of model changes, data revisions, and updates of outlooks contributing to the difference between the New forecast and the Old forecast is analyzed. The variables which form the conditioning information for the forecast can be distributed into several subgroups mostly according to the source of the underlying data. The usual subgroup under consideration is the foreign environment outlook, represented by the trajectories of foreign demand, the interest rate, and inflation. The outlooks for domestic variables such as administered prices and government consumption form other subgroups. Figure 7 demonstrates the results of identification of the contributions to the variations between the trajectories of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$ as shown in Figure 6.

The presented decomposition framework does not allow for changes in the model between the New and Old forecasts. In practice, when a model change is present in the evaluation, the initial step of the evaluation is to switch to the new model. The Old forecast is recreated with the updated version of the model and for the rest of the analysis this forecast is used as a replacement for the Old forecast. This delivers linearity of contributions to our analysis. Unless there is a substantial change in the model parameters, it usually makes only a small or zero contribution to the difference between the New and Old forecasts. In addition, this contribution covers possible numerical imprecisions.[11] As we assumed no model change in our example for the purposes of this presentation, the contribution of the model change is zero.

[11] The standard procedure within our forecasting process is to extend the weights of the inflation components in the prediction computation to include the last observed value. This model parameter update usually has a negligible effect on the predicted trajectories.

Figure 7: Forecast Evaluation – Contributions



The presentation of the decomposition usually follows the timing of the forecast elements. The data revisions affect both considered forecasts over the history range. Therefore, the contribution of data revisions to the New–Old forecast difference originating in data revisions over the history range usually follows the model change contribution. Data revisions affect the identification of the initial state of the forecasts and usually show a hump-shaped response due to the presence of rigidities in the variables. The plots in Figure 7 show two patterns over the history range depending on the nature of collection of the variable. For variables such as the exchange rate change and the policy rate there are no revisions present, as these are precisely measured by market readings.

The presented results show that the revisions imply lower inflation growth and a lower policy rate. Contrary to this, wage growth was revised upwards. Our knowledge of the data and the ability to break down the revisions group into a single variable contribution reveal that the low inflation and policy easing are a response to the downward revision of economic activity over the history range. These downward revisions also lead to depreciation of the currency, as shown by the positive contribution to the exchange rate change over the initial periods of the transition range.

The contribution of data released over the transition range is also analyzed. The motivation for the inclusion of this group is to analyze the precision of the outlooks used in the forecast and their influence on the forecast trajectories.

As mentioned in the description of the forecasting process, our forecast is conditioned on the trajectories of several outlooks. These outlooks can be split into outlooks for foreign (Foreign Environment Outlook group) and domestic variables (Government Consumption, Administered Prices).

The plots in Figure 7 show that the use of actually observed data instead of outlooks compensate for the effect of revisions over the transition range, as the lower foreign inflation and economic activity will slow down domestic economic activity. The composition of the release groups is mirrored in the outlook groups. The outlook groups represent the update of the variables used for conditioning the forecast over the future range.

The forecast judgment group shows the contribution of updates of the prediction tunes in both forecasts over the future range. The contribution of this group reflects the updates of the forecasters' views on recent developments in the economy.

The forecast error group, as shown in the plots in Figure 7, covers the contributions of domestic observable variables. These variables are used in the identification stage of the New forecast ${}_{T_N}\mathbb{F}(I_{T_N})$ and the shocks identified are compared with the shocks implied by the prediction from the Old forecast ${}_{T_O}\mathbb{F}(I_{T_O})$. The contributions of this group reflect the misalignment between the forecast and the observed data. In the interpretation of the forecast error contributions, we usually break down the group into the individual contributions of the variables for the purposes of detailed analysis of their propagation over the transition range.

Although the presented groups are standard aggregations of the variables we use in the Inflation Forecast Evaluation, our tool enables us to identify the contributions of each forecast element. As mentioned earlier, identification can even be done on a period-by-period basis. This ability allows us to focus on the precise details and their propagation over the forecasts considered.

5.4 Forecast Evaluation: Structural Shocks View

As stated in the description of the forecasting process, conditioning on variables is equivalent to conditioning on structural shocks. Our general framework is based on this equivalence, therefore the differences between forecasts ${}_{T_N}\mathbb{F}(I_{T_N})$ and ${}_{T_O}\mathbb{F}(I_{T_O})$ can also be interpreted as differences in structural shocks. The role of the second view of the Inflation Forecast Evaluation is to provide a detailed examination and help interpret the contribution of the forecast error.

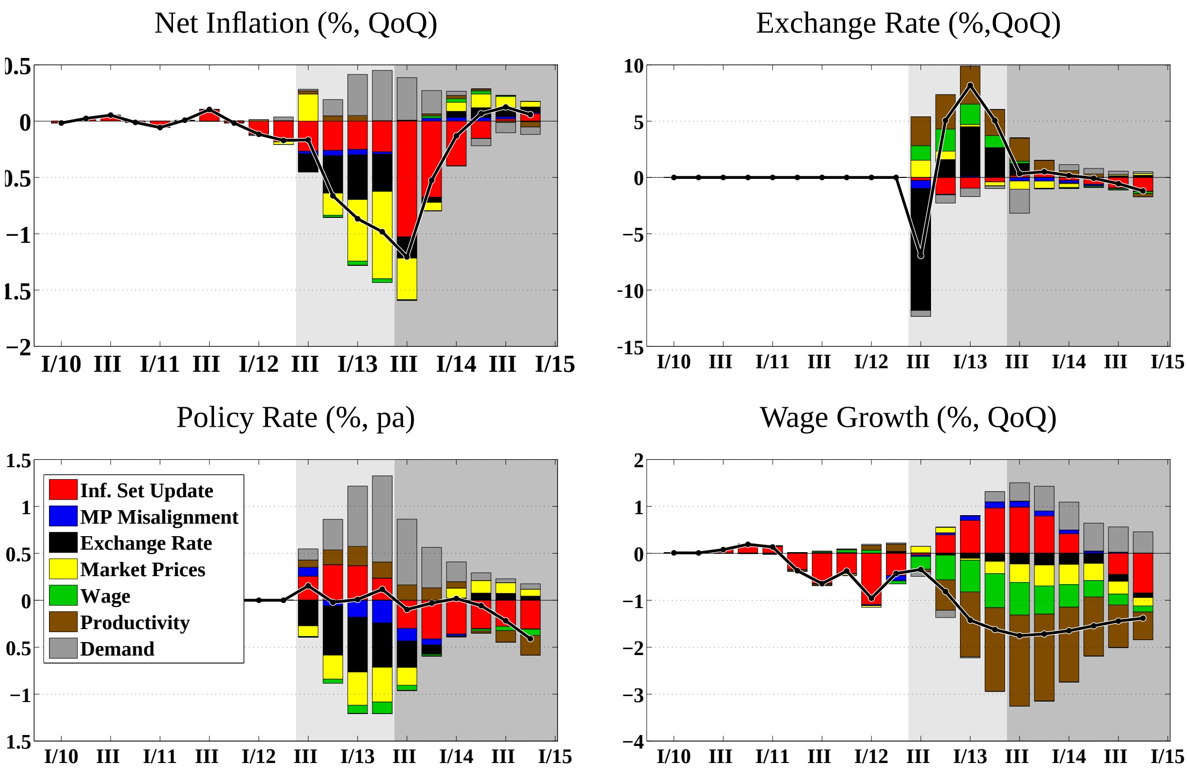
In our standard forecast evaluation process, shocks are separated into six groups: Monetary Policy Misalignment, Exchange Rate (a shock to uncovered interest rate parity), Market Prices (shocks to pricing markups and prices), Wage, Productivity (shocks that increase productivity and affect supply), and Demand. The Information Set Update group covers the effects of the information set update, which was analyzed in the first step of the forecast evaluation.

In the evaluation, we consider the contributions of shocks to be an indication of missing information from the ex-post view rather than forecasters' mistakes. Specifically, in the case of monetary policy, the presence of non-zero monetary policy shocks indicates too loose or too tight policy from the ex-post view. The preference for using the interpretation as missing information is supported by the fact that data collected in the evaluation period T_N are subject to revisions and forecasters cannot forecast these.

The decomposition of the New–Old forecast difference, plotted in Figure 6, into the contributions of structural shocks is presented in Figure 8.[12] The demanding part of the examination of missing structural shocks is to interpret those shocks and build a credible story based on the model

[12] Readers should note that the decomposed difference is the same as the one considered in the variable view of the forecast evaluation as shown in Figure 7.

Figure 8: Missing Structural Shocks



mechanism. The case shown in Figure 8 indicates that monetary policy was more expansionary than the model-based forecast would imply. This is consistent with the negative contribution of the policy shock (MP Misalignment) to the difference in net inflation. The significant appreciation of the exchange rate in the first quarter of 2012 (Exchange Rate) also contributed significantly to low inflation. Even the subsequent depreciation was not able to return the exchange rate closer to the Old forecast trajectories.

The presented decomposition results also indicate that the forecasters in the Old forecast were not expecting the negative shocks to prices (Market Prices) that were identified in the creation of the New forecast. The slowdown of the economy is consistent with the positive contribution of technology shocks, as the slower growth of productivity is not able to eliminate the growth in production factor prices. The decrease in productivity resulting from the economic slowdown (Productivity) is reflected in a negative contribution to wage growth. Slower technology growth and positive cost-push shocks at the beginning of the transition range support the depreciation (positive change) of the exchange rate.

In the process of developing the macroeconomic story, we try to identify reflections of the observed events over the transition range. As mentioned earlier, the identification of missing structural shocks can be done in fully detailed mode, too. This detail of disaggregation is used for further development of the economic story presented in the Inflation Forecast Evaluation. Also, the results from this exercise are used in planning future upgrades of the structural model used. Too large missing shocks or persistent sequences of omitted shocks can direct our attention to an absent mechanism or feature of the model. This often leads to improvements in the structure of the model and also helps validate the model used.

6. Conclusions

Stimulated by the criticism that conditional forecasts from structural macroeconomic models are not transparent, we present a decomposition framework that enables forecasters to quantify the contributions to forecast updates. Approaches based on projection update elasticities, as described in the literature, do not take into account the use of expert judgment applied in anticipated mode. Although our decomposition approach used in the past coped with this complication, the resulting identification of contributions was significantly limited and conditional on the ordering of the model variables, which used to hamper interpretation.

Following Todd (1990), Andrle et al. (2009), and Andrle (2013), we developed a forecast update decomposition framework that can be applied to decompose the differences between two forecasts generated by any linear model. Its design is based on a set of partial decompositions that enable us to identify the effects of specific groups of forecast elements even when the filtration and projection ranges differ. The main advantage of the presented framework is its versatility, as it covers a variety of decomposition problems.

The novelty of the framework lies in its ability to provide decompositions even when expert judgment is simultaneously applied in anticipated and unanticipated modes, while the contributions are independent of ordering. This framework supports transparent presentation of macroeconomic forecasts based on a structural DSGE model under the assumptions applied in the CNB forecasting process.

Starting with the simplest case, the flexibility of the framework is demonstrated by using it to analyze the differences between two forecast scenarios. Applying the decomposition methodology enables us to identify the contributions of, and the propagation of changes in, the forecast elements (e.g. assumptions about foreign variables) to the change in the forecast trajectories.

Further, our framework is used to conduct an ex-post analysis of actual data–forecast variation, known as forecast evaluation. We demonstrated that actual data–forecast variation can be expressed as the sum of the contributions of specific subsets of the information set. These subsets include model and data revisions, data releases, and identification or prediction tunes. Moreover, these elements of forecast revisions can be linked to a specific subset of model variables. The introduction of higher-level aggregation allows us to improve understanding of the results, as concepts such as the foreign economy and regulated prices are intuitive to forecast users.

Forecast evaluation is an important exercise, as it documents the reasons why particular adjustments and revisions are made to forecasts. Keeping track of forecasters' actions allows us to learn from the forecast and actual data misalignment and to avoid overreacting to noise in time series or anticipated events. The presentation of our framework demonstrates how useful it is to understand the forces driving the forecast update. It also shows the advantages of the evaluation framework in the real-time forecasting exercise and explains our motivation for, and interest in, decomposing and evaluating forecasts.

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