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František Brázdik
Zuzana Humplová
František Kopřiva

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Reviewed by: Marianna Červená (National Bank of Slovakia)
Marcin Kolasa (National Bank of Poland)
Jan Brůha (Czech National Bank)

Project Coordinator: Jan Babecký

Evaluating a Structural Model Forecast: Decomposition Approach

František Brázdik, Zuzana Humplová, and František Kopřiva [*]

Abstract

Macroeconomic forecasters are often criticized for a lack of transparency when presenting their forecasts. To deter such criticism, the transparency of the forecasting process should be enhanced by tracing and explaining the effects of data revisions and expert judgment updates on variations in the forecasts. This paper presents a forecast decomposition analysis framework designed to examine the differences between two forecasts generated by a linear structural model. The differences between the forecasts considered can be decomposed into the contributions of various forecast elements, such as the effect of new data or expert judgment. The framework allows us to evaluate the contributions of forecast assumptions in the presence of expert judgment applied in the expected way. The simplest application of this framework examines alternative forecast scenarios with different forecast assumptions. Next, a one-period difference between the forecasts' initial periods is added to the examination. Finally, a replication of the Inflation Forecast Evaluation presented in Inflation Report III/2013 is created to illustrate the full capabilities of the decomposition framework.

Abstrakt

Makroekonomičtí analytici jsou často kritizováni pro nedostatek transparentnosti ve svých predikcích. Pro odvrácení této kritiky by měla být transparentnost predikčního procesu zvýšena vysvětlením a kvantifikováním příspěvků revizí dat a expertních úprav ke změnám mezi jednotlivými predikcemi. Tato studie popisuje metodu analyzující dekompozice změn mezi dvěma predikcemi vytvořenými lineárním strukturálním modelem. Navržený postup umožňuje rozložit rozdíly v těchto predikcích na příspěvky různých složek predikcí, např. nových dat, revizí nebo expertních úprav, a to i v případě, kdy jsou tyto úpravy modelovány jako očekávané z pohledu ekonomických subjektů v modelu. Při nejjednodušším použití tohoto postupu jsou analyzovány alternativní scénáře prognózy vycházející z různých předpokladů. Dále je analýza rozšířena přidáním rozdílu jednoho období mezi počátečními obdobími prognóz. Nakonec je pro demonstraci plného využití navrženého postupu replikováno Hodnocení plnění inflačního cíle ze Zprávy o inflaci III/2013.

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

[*]František Brázdik, Czech National Bank, Macroeconomic Forecasting Division, frantisek.brazdik@cnb.cz
Zuzana Humplová, Czech National Bank, Macroeconomic Forecasting Division, zuzana.humplova@cnb.cz
František Kopřiva, Czech National Bank, Macroeconomic Forecasting Division, frantisek.kopriva@cnb.cz
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Nontechnical Summary

Macroeconomic forecasts based on structural models with forward-looking model-consistent expectations are used extensively in the process of monetary policy decision making. Therefore, considerable intellectual activity and computational power is devoted to forecasting major economic variables. As an economic forecast should provide answers to many questions, it is important to support its comprehensible presentation with a transparent quantification of its driving forces. We approach this goal by analyzing how changes in various subsets of newly collected information drive the update of the structural model forecast from quarter to quarter. To do this, we develop a framework (a set of assumptions and techniques) that is used in the analysis of forecast updates.

As an economic forecast should provide information about the economy's direction of movement, the timing of turning points, and the magnitude of the change, we are interested in evaluating the forecast with respect to observed data and newly available expert judgment. The forecast update analysis has to explain how the newly available data (releases and revisions) and assumptions regarding the future development of the forecasted variables changed the identification of structural shocks and unobserved variables. Examining the contributions to changes provides the users of forecasts with an understanding of the underlying shocks present in the economy. 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.

In this paper, we briefly summarize the CNB's forecasting process, which is based on a structural model and integrates expert judgment into the model-driven predictions. We believe this approach is superior to simple equation reduced-form models, as the use of structural models delivers more detail and consistency, especially when a complex structural model is employed.

Forecast accuracy evaluation has been a part of the CNB's forecasting process since the Quarterly Projection Model was introduced in 2002 (Beneš et al. (2003)). The switch to the g3 model framework (Andrle et al. (2009)) in 2008 and the further development of this model required more advanced evaluation techniques. This paper describes the newest methodology, recently implemented into the regular forecasting process. It is more general and complex than previous approaches and delivers additional details into the evaluation.

As forecasts are created periodically, it is of interest to examine the driving forces of the forecast update from quarter to quarter. To meet this goal, we present the results of a forecast update analysis where the contributions of assumptions to the differences between the current and previous forecasts are identified. Moreover, as the forecast update is a specific example of a general framework, we also present the results of a real-life inflation forecast evaluation exercise where the CNB's forecast released in Inflation Report I/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 newly developed forecast evaluation methodology helps us 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

Central bank communication is important, especially in the inflation targeting regime. Inflation targeting policy requires a good understanding of the role of the central bank in the monetary transmission mechanism. Forecasters regularly have to clarify and justify the main driving forces of their forecasts to the general public and policymakers in order to achieve their goals. In the communication of decisions, the presentation of macroeconomic forecasts becomes crucial for forming expectations. High-quality inflation reports and credibility of monetary policy appear to be related to the transparency of central bank communication. The supporting role of forecasts in monetary policy decision making raises many questions related to forecast construction and its consistency over time.

The Czech National Bank (CNB), which adopted inflation targeting in 1998, relies on its own forecasts. Therefore, transparency of its forecasts is important for the credibility of its monetary policy decisions. The CNB's official forecast is based on a structural model of a small open economy as described by Andrle et al. (2009). This forecast is conditional on observed data as well as additional assumptions that include the foreign economy, fiscal policy and administered price outlooks, the short-term forecast of the exchange rate and inflation, and expert judgment.

This paper demonstrates the use of a general framework for examining forecast updates and evaluating forecasts. The framework provides forecast users with sufficient detail about the driving forces of the forecast, which, after careful interpretation, offer comprehensive information when policy decisions are communicated. It also allows us to keep a track record of the evaluation of forecast accuracy and to identify assumptions that tend to produce a bias in forecasts.

CNB uses expert judgment to complete its forecast. As Goodwin (2000) indicates, individuals who use judgment to adjust their forecasts tend to overreact to random movements in the data. In order to reduce the bias originating from overreaction, Goodwin (2000) suggests that forecasters should document and provide a rationale for expert judgment used in the forecast creation process. This documentation should be used in determining the origins of forecast errors and possibly reducing forecast errors in the future.

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. The main stream of literature on forecast accuracy evaluation puts great emphasis on the statistical properties of forecasts based on the evaluation of forecast errors. The focus on statistical properties of the forecast originates in researchers' access to components, assumptions, and information on the process of forecast creation.

As in Todd (1990), we agree that forecast revisions should be analyzed to help forecasters and forecast users evaluate and justify the forecasting process. 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 as the focus is on their statistical properties.

Statistical analysis of forecast errors is rather inept at delivering answers about the origins of deviations from the observed data as well as the future propagation of those deviations. 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.

We present a forecast evaluation methodology that is not based on the statistics of forecast errors. As the deficiencies of complex model relationships in describing reality and the importance of judgmental and conditioning information are difficult to separate, our forecast evaluation uses internal knowledge of the elements of the forecast. We exploit knowledge of, and access to, the underlying data of the forecast, the model, and the judgment applied to current and past forecasts.

Our forecast evaluation exercise is in line with the methodology sketched by Todd (1990) for forecast revision analysis. However, we are not able to provide more links to literature, as the published forecast evaluation articles either focus on the statistical properties of forecasts or are not applied in a structural model with forward-looking agents. Therefore, we try to fill the gap in this field and document our approach, which applies the most recent version of the CNB's forecast evaluation framework to three examples based on recently produced forecasts.

Within the presented methodology, we attempt to examine the variations between two forecast simulations generated using the same structural model. These variations are dissected by decomposing the differences in trajectories into the contributions of forecast elements that differ in the two simulations. The simplest example of forecast decomposition is the comparison of two alternative forecast scenarios for the same forecasting exercise. Here, the forecast range does not differ for the two scenarios and the historical observed data on which the forecast is formed are the same. The difference between the two alternative forecast scenarios originates in different forecast assumptions (e.g., the outlook for the foreign economy or expert judgment) and the analysis focuses on the propagation of the differences in the assumptions over the forecast horizon. Moreover, this analysis can be provided in a more complex way while allowing for changes in the initial state of these scenarios.

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Our methodology can be further generalized and used to analyze differences between two forecasts when the initial periods of the predictions differ by more than one period. This analysis also enables forecasters to assess the medium-term difference between the old forecast and the observations. Regular assessment of forecast differences allows forecasters to learn about the properties of the model, data revisions, and expert judgment. Moreover, the learning process enhances forecasters' notion of expert judgment. Also, repetitive analysis of forecast updates helps improve the narrative of the forecast, which is important for delivering high quality inflation reports.

The proposed general methodology is illustrated on the example of an analysis done on a regular basis at CNB – the so-called Inflation Forecast Evaluation. The aim of the evaluation is to compare the six-quarters-old forecast with the currently observed data and identify the contributions of the forecast elements to the deviations from reality. The goal of this analysis is to assess monetary policy performance in meeting the inflation target. It also provides sufficient detail to help identify possible shortcomings in the forecasting process, especially judgmental information and the underlying model structure.

In the next section, the structural model forecasting framework is outlined. We describe the general form of the Czech National Bank's forecasting model, the various phases of constructing the forecast, and the implementation of expert judgment. In the third section, we focus on the forecast update analysis methodology and explain the process whereby differences in forecasts are decomposed into the contributions of the forecast elements. We also describe the methodology of our evaluation framework and present a real-life example. The fourth section applies the update decomposition methodology and demonstrates the use of the framework in the case of the Inflation Forecast Evaluation exercise. The conclusion briefly summarizes the benefits of the general framework for the analysis of forecast variations using a structural model.

2. Modeling and Forecasting Framework

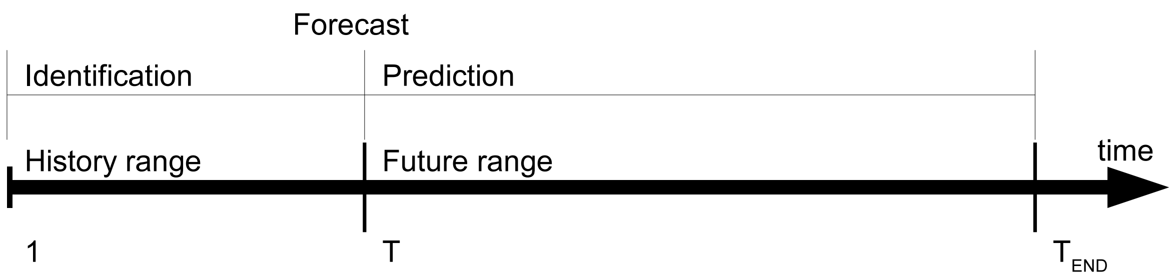
The CNB uses a structural model, known as g3 (Andrle et al., 2009), for its forecasts. This model was adopted for official CNB forecasts in July 2008 and, with ongoing modifications of its tools, parameters, and variable transformations, is still employed in the forecasting process. To provide a generalizing description of the forecasting process, a structural model can be expressed in a state-space representation in the following form:

$$Y_t = \mathbf{C}X_t + \mathbf{D}\xi_t \tag{2.1}$$

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t, \tag{2.2}$$

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 i.i.d. measurement and structural shocks such that $\xi_t \sim N(\mathbf{0}, \mathbf{1}_{n_\xi})$ and $\varepsilon_t \sim N(\mathbf{0}, \mathbf{1}_{n_\varepsilon})$. Matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}$, and $\mathbf{D}$ are known matrices based on the structural model and its parameters of size $n_x \times n_x, n_x \times n_\varepsilon, n_y \times n_x, n_y \times n_\xi$. As the model matrices are constants, the properties of the model do not change over time.

Figure 1: Forecast Phases



A regular forecasting exercise has two main phases, and Figure 1 shows their timing. In the forecasting exercise, period T is known as the end of the history (generally, the end of the available data).[1] The first step of the forecasting process is the identification of the initial state (the cyclical

[1] Usually, at the end of the history, only data based on higher-than-quarterly frequency (e.g. the exchange rate, the interest rate or the inflation rate) is already available. To balance the quarterly frequency of the panel of data, the publication lag has to be taken into account. Therefore, some data points enter the panel in the form of data estimates and are subject to update when a new data release occurs.

position) up to the end of the history T. The data from period 1 (the start of the data) up to the end of the history T and expert judgment are used to identify the initial state of the prediction.[2] The results of the initial state identification enter the prediction phase as a starting point. In the prediction stage, expert judgment and outlooks are used to condition the prediction. The future range thus marks the set of periods from $T+1$ to the end of the prediction computation T_{END}.

The identification of the initial state of the forecast should reflect the forecaster's view on the current position of the economy in the cycle. As this view is more complex than a result obtained by mechanical use of the Kalman filter, expert information is incorporated into 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 expert judgment imposed in the identification phase is integrated into the model by augmenting the state-space representation with new time-varying restrictions on observable variables.[3] That is, the measurement equation 2.1 of the model is augmented by a vector of identification tunes $Y_t^J, (n_{y^J} \times 1)$, and the restrictions imposed between observed variables and unobserved states are described by the matrix $\Gamma_t, (n_{y^J} \times n_x)$:

$$\begin{bmatrix} Y_t \\ Y_t^J \end{bmatrix} = \begin{bmatrix} \mathbf{C}X_t \\ \mathbf{\Gamma}_t X_t \end{bmatrix} + \begin{bmatrix} \mathbf{D}\xi_t \\ \mathbf{\Delta}_t \nu_t \end{bmatrix} \tag{2.3}$$

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t. \tag{2.4}$$

The presented extension provides forecasters with new unobserved elements of the state space system, so expert judgment can be applied. Uncertainty about the expert judgment can be also present. It originates from shocks $\nu_t, (n_{y^J} \times n_{y^J})$ with covariance matrix $\mathbf{\Delta}_t, (n_{y^J} \times n_{y^J})$. However, in our implementation we assume no uncertainty about the identification judgment, so $\mathbf{\Delta}_t \nu_t = 0$.[4] In our forecasting framework, we use matrices $\mathbf{\Gamma}_t$ to impose the judgment–variable relation, and in the simplest case $\mathbf{\Gamma}_t$ is the identity matrix.

The identification tunes implementation structure 2.3 is flexible enough to implement two basic forms of expert judgment. The first form involves conditioning on the value of a state variable (an element of X_t) and the second one on the value of a single structural shock (an element of ε_t). The initial state for the prediction phase is identified by applying the structural model given by the system of equations 2.3–2.4 with the Kalman smoother on the data up to period T. The nature of the reduced form of the structural model fed into the Kalman smoother implies that the identification tunes are implemented in the form of unanticipated shocks.[5]

In the prediction phase of the forecasting exercise, the trajectories of the variables over the future range $\langle T+1, T_{END} \rangle$ are computed. The prediction is created under the assumption of endogenous monetary policy responses.[6] These trajectories of the variables are a function of the initial state and

[2] As the technique used for the identification (the structural model and the Kalman smoother) is based on the Kalman filter, this phase is often called the filtration phase and the history range is the filtration range.
[3] Detailed implementation of expert judgment in a structural model environment is described by Andrle et al. (2009).
[4] The introduction of expert judgment is based on Doran (1992), where simple augmentation of the measurement equation constrains the estimated state variables so that the restrictions on the state variables are satisfied.
[5] We are aware of this limitation of the forecast framework and we are searching for further improvements in this field.
[6] The trajectory for the nominal interest rate follows the endogenous rule. Some forecasters call this type of forecast an "unconditional" forecast. However, our forecast is conditioned on outlooks and expert judgment.

are conditioned on the outlooks for the variables and on expert judgment. The outlooks and expert judgment applied over the future range are called prediction tunes. The CNB's forecast is conditioned on 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. As different assumptions might be used to create a prediction, such forecasts are often referred to as forecast scenarios.

In the prediction phase, there are two modes for applying expert judgment over the future range: unanticipated and anticipated. In our implementation, the prediction process is simplified by the assumption that shocks in the anticipated mode are conditioned on the information available in period T. To implement the prediction tunes in both modes, the state space system is augmented with linear restrictions and anticipated shocks $\overline{\varepsilon}_{t|T}$. Augmenting the state space with new variables and shocks creates the following general form of the prediction problem:

$$
\begin{aligned}
Y_t &= \mathbf{C}X_t + \mathbf{D}\xi_t && (2.5)\\
X_t &= \mathbf{A}X_{t-1} + \mathbf{B}\varepsilon_t + \mathbf{B}\overline{\varepsilon}_{t|T} && (2.6)\\
wrt. & && \\
\mathbf{Z}_t X_t &= R_t + \mathbf{\Lambda}_t \mu_t && (2.7)\\
\overline{\mathbf{Z}}_{t|T} X_t &= \overline{R}_{t|T} + \overline{\mathbf{\Lambda}}_{t|T}\overline{\mu}_{t|T}. && (2.8)
\end{aligned}
$$

Here, vectors and matrices with a bar refer to prediction tunes applied in the anticipated mode. In this general augmented system, $\mathbf{Z}_t, (n_r \times n_x)$ and $\overline{\mathbf{Z}}_{t|T}, (n_{\overline{r}} \times n_x)$ are fixed matrices which, together with the vectors of time-varying parameters $R_t, (n_r \times n_1)$ and $\overline{R}_{t|T}, (n_{\overline{r}} \times 1)$, define the restrictions on the variables representing our judgment for $t > T$. $\mathbf{Z}_t$ and $\overline{\mathbf{Z}}_{t|T}$, together with R_t and $\overline{R}_{t|T}$, bind variables X_t to follow the outlooks and expert judgment. In our implementation, $\mathbf{Z}_t$ and $\overline{\mathbf{Z}}_{t|T}$ are of simple structure such that they bind one variable to one shock. The use of one-to-one mapping removes non-uniqueness problems and improves the explicitness of the story telling. In our view, this form of conditioning implementation increases the consistency of the CNB's forecasts with the experts' view on future developments in the economy and with the behavior of economic agents making decisions with respect to anticipated developments.

Like the identification tunes, the prediction tunes can be applied with some uncertainty in the most general case. This uncertainty originates in the presence of shocks $\mu_t, (n_\mu \times 1)$ and $\overline{\mu}_{t|T}, (n_{\overline{\mu}} \times 1)$ with the covariance structure described by matrices $\overline{\mathbf{\Lambda}}_{t|T}, (n_\mu \times n_\mu)$ and $\overline{\mathbf{\Lambda}}_{t|T}, (n_{\overline{\mu}} \times n_{\overline{\mu}})$. However, in our application, for the sake of interpretation, we assume no uncertainty about the prediction tunes, so $\mathbf{\Lambda}_t \mu_t = \mathbf{0}$ and $\overline{\mathbf{\Lambda}}_{t|T}\overline{\mu}_{t|T} = \mathbf{0}$.

When solving the prediction problem, the prediction tunes that are described by constraints 2.7–2.8 are reflected in the predictions of unanticipated structural shocks ε_t and anticipated structural shocks $\overline{\varepsilon}_{t|T}$. The process of solving the forecasting problem conditioned on constraints 2.7–2.8 involves exogenization of variables and endogenization of structural shocks. The prediction phase problem, described by equations 2.5–2.8 for $t > T$, can be viewed as the constrained problem of optimal least-square projection estimation, and the paths for the state variables are its solution. The adapted solution technique and analytical methods that allow for mixing of unanticipated and anticipated shock trajectories are based on Blanchard and Kahn (1980). Implementation details on the introduction of the anticipated prediction tunes can be found in Beneš (forthcoming) and Schmitt-Grohe and Uribe (2008), where the forward expansion of the state space system is described.

As in the identification, in the CNB's implementation of the conditional prediction we apply conditioning by exploiting one variable and one structural shock relation. Due to this specific form of expert judgment implementation the expert judgment on structural shocks ε_t and $\overline{\varepsilon}_{t|T}$ is equivalent to the expert judgment imposed on the associated variables in the prediction phase. However, the structure of the forecasting problem given by equations 2.5–2.8 still allows for a very broad conditioning structure.

The solution to the prediction problem 2.5–2.8 allows us to define the forecast as a structure of time series. The forecast produced at time T is a structure of time series $\mathbb{F}_T = (\mathbf{Y}_T, \mathbf{Y}_T^J, \boldsymbol{\xi}_T, \mathbf{X}_T, \boldsymbol{\varepsilon}_T, \overline{\boldsymbol{\varepsilon}}_T)$, where $\mathbf{Y}_T$ is a matrix of observed variables $\mathbf{Y}_T = (Y_1, \ldots, Y_T, Y_{T+1}, \ldots, Y_{END})$, $\mathbf{Y}_T^J$ is a matrix of identification tunes $\mathbf{Y}_T^J = (Y_1^J, \ldots, Y_T^J)$, $\mathbf{X}_T$ is a matrix of unobserved variables $\mathbf{X}_T = (X_1, \ldots, X_T, X_{T+1}, \ldots, X_{END})$, $\boldsymbol{\xi}_T$ is a matrix of measurement shocks $\boldsymbol{\xi}_T = (\xi_1, \ldots, \xi_T, \xi_{T+1}, \ldots, \xi_{END})$, $\boldsymbol{\varepsilon}_T$ is a matrix of unanticipated structural shocks $\boldsymbol{\varepsilon}_T = (\varepsilon_1, \ldots, \varepsilon_T, \varepsilon_{T+1}, \ldots, \varepsilon_{END})$ and $\overline{\boldsymbol{\varepsilon}}_T$ is a matrix of anticipated structural shocks $\overline{\boldsymbol{\varepsilon}}_T = (\overline{\varepsilon}_{T+1}, \ldots, \overline{\varepsilon}_{END})$. The terms "forecast" and "prediction" are generally considered to be synonyms. In the terminology in this paper, we follow the definition of Mincer and Zarnowitz (1969), where the term "forecast" is used to describe the set of predictions produced by the prediction method. Here, single predictions are elements of the forecast.

In the forecast $\mathbb{F}_T$, the values for the time series for $t \leq T$ form the solution to the initial state identification problem as defined by equations 2.3–2.4. The values for $t \in \langle T+1, T_{END} \rangle$ form the solution to the prediction problem 2.5–2.8. The interval $\langle T+1, T_{END} \rangle$ is often referred to as the prediction span.

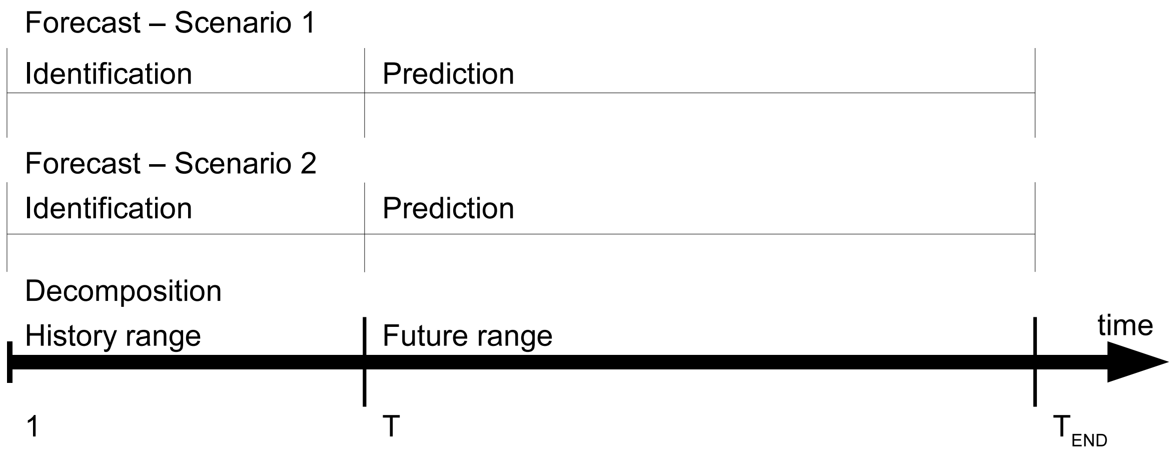
Forecast $\mathbb{F}_T$ cannot be viewed as a mechanical forecast since it is conditioned on the judgment and outlooks imposed by forecasters. This judgment is based on expert views on recent developments and knowledge of the model's properties. Since there are two phases of the forecasting exercise, there are two groups of expert judgment: identification and prediction tunes. As there are differences in the methods used in the identification and prediction phases, there are also differences in the implementation of expert judgment. The complexity of the conditioning on outlooks and expert judgment makes it difficult to evaluate forecasting properties via traditional methods such as those described in Mincer and Zarnowitz (1969).

3. Forecast Update Analysis

In this section, we provide some details about the analysis of forecast updates by decomposing the difference between two forecast trajectories into the contributions of new information. For this exercise, we used the CNB's forecast released in Inflation Report III/2013. First, we demonstrate the decomposition approach by applying it to the analysis of two alternative forecast scenarios. Second, we allow for a one-period time shift between the forecasts examined. We complete our update analysis presentation by considering a complex case of ex-post evaluation of the forecast and the observed data variation.

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 the initial state identification and for the prediction. The scheme for evaluating two scenarios is presented in Figure 2. The simplicity of this case stems from the fact that there is no overlap between the identification and prediction parts.

Figure 2: Scenario Comparison



The acceptance of macroeconometric forecast results is hampered by the inclusion of conditioning information that is often opaque, as mentioned by Heilemann (2002). To face the opacity of conditioning, he suggests that the prediction process should start with a number of test runs to examine the effects of assumptions and updates on the forecast. Heilemann (2002) points out that these test runs help increase the transparency of the forecasting process by demonstrating the role of the assumptions in the prediction.

To demonstrate the capabilities of our evaluation framework, we present a comparison of a scenario that uses a basic set of conditioning information (Scenario 1) and a scenario without any conditioning information (Scenario 2). The role of this comparison in the forecasting process is to identify the driving forces of the prediction story delivered by the assumptions applied. 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. Some expert judgment is also applied. The external environment outlook is simulated in the anticipated mode. So, Scenario 1 is the baseline scenario of the CNB's forecast released in Inflation Report III/2013. Scenario 2 does not use any extra information over the prediction range.

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

In the presented scenario comparison exercise, it is easy to quantify the effects of differences in assumptions on the predicted 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 prediction range. The overall response of a prediction trajectory is then computed as the sum of the responses to the conditioning information groups.

Figure 4 shows the results of applying the decomposition approach for the alternative scenario analysis. As there is no difference in the identification phase, only the prediction 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

Figure 3: Scenario Comparison - Data

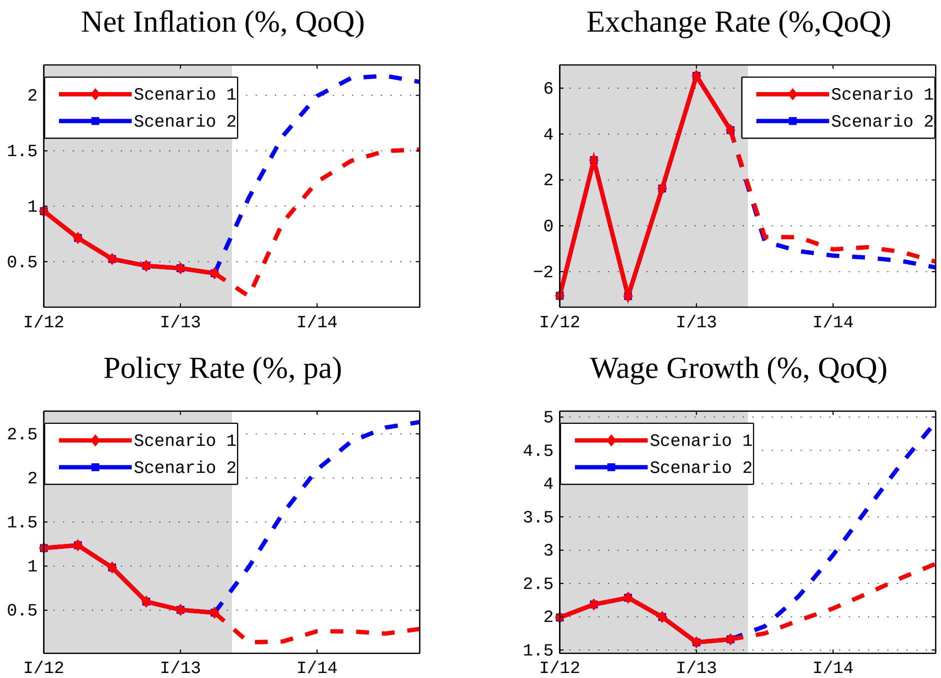
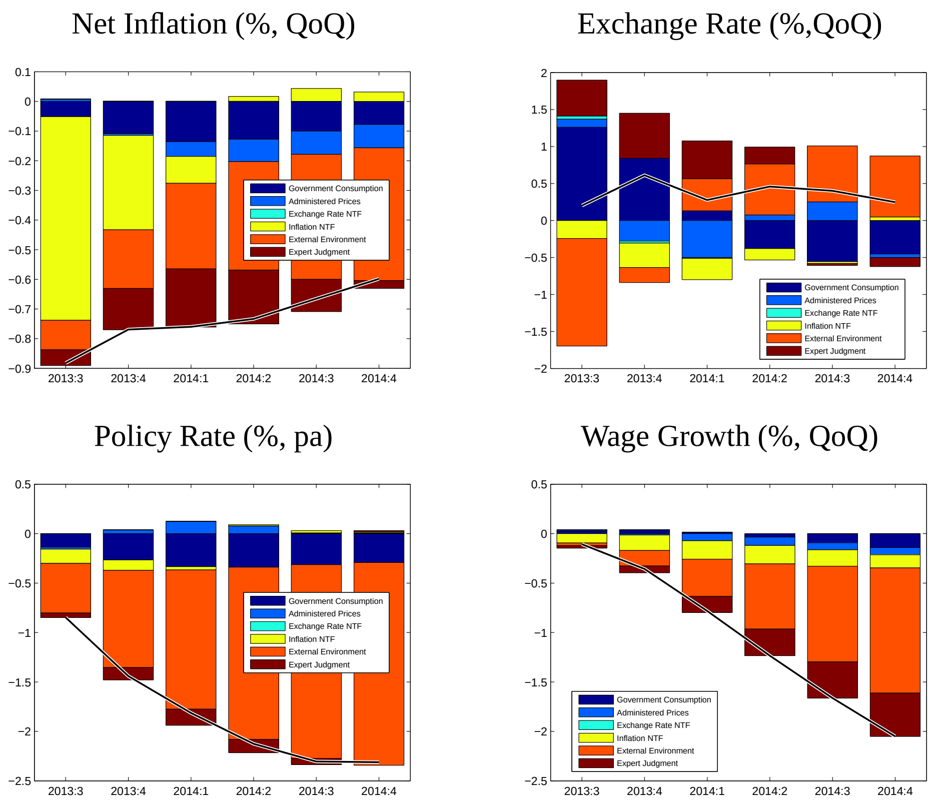


Figure 4: Scenarios Comparison - Contributions

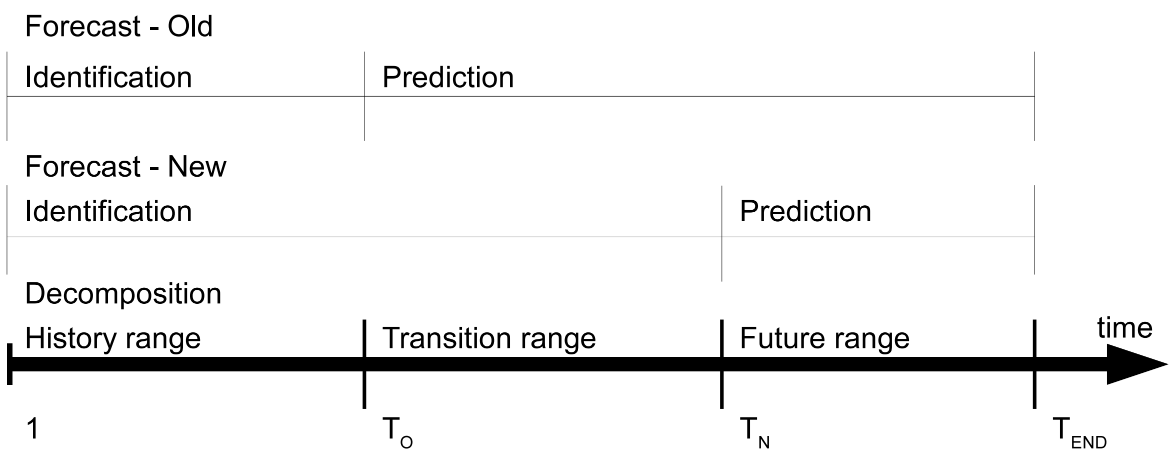


line shows the difference. A brief assessment of the contributions reveals that the major driving force of the forecast is the outlook for the external environment.

The extensive capabilities of our evaluation framework are clearly demonstrated when we compare two forecasts created at different periods of time. More specifically, we focus on two forecasts created in consecutive periods of time, since their comparison is often under scrutiny. In assessing the quality of the new forecast, the quantification of the main driving forces behind the update of the forecast trajectories in comparison with the old forecast is of high importance. Also, demonstrating the role of various forecast assumptions is helpful for presenting the new forecast and defying the "black box" critique. Therefore, we need to examine the effect of the newly applied forecast assumptions and expert judgment in comparison with the forces that drove the old forecast. As we are interested in explaining the contributions of the forecast assumptions in the forward-looking model, the decomposition is more complex than the aforementioned case of the alternative scenario comparison.

Figure 5 shows the time perspective of the two forecasts: New (e.g. the current forecast) and Old (e.g. the previous forecast). Here, to create the Old forecast, data is available up to period T_O (the first quarter of 2013) and the Old forecast prediction starts in period T_O+1. This exercise is a replication of the forecast update analysis as presented in Inflation Report III/2013. As we implicitly assume $T_O < T_N$, the New forecast starts in period T_N+1 (the third quarter of 2013). In the regular forecast update evaluation exercise, Old and New are consecutive forecasts, so $T_O+1 = T_N$. In this example, the end of the forecast computation for both forecasts is in period T_{END}.

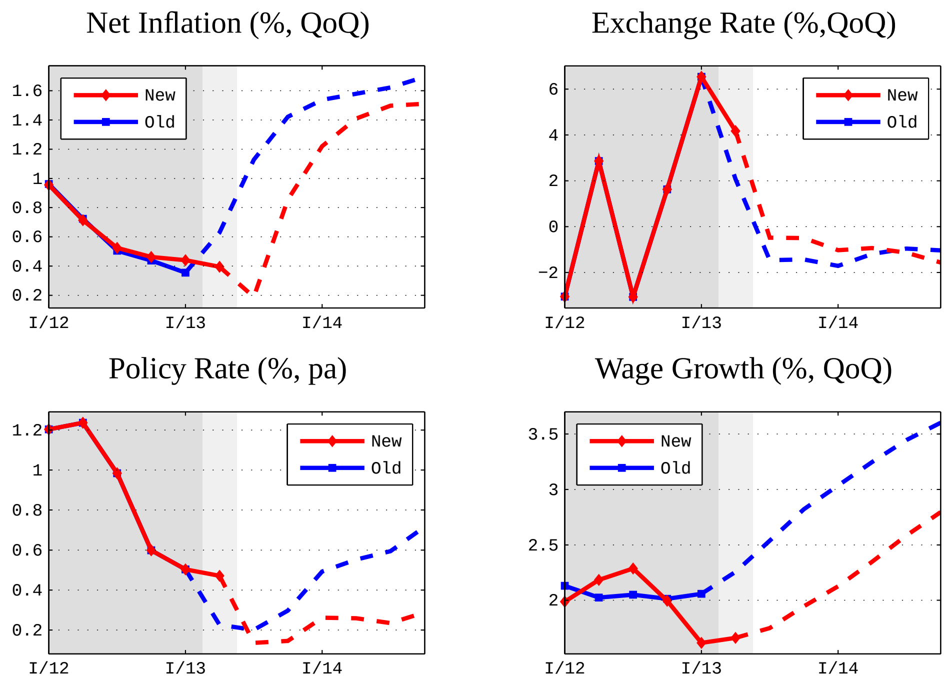
Figure 5: Time Notation



Here, the history of the new forecast includes the release of new data for the periods from T_O+1 to T_N and revisions of data up to period T_O. Also, the assumptions (the identification and prediction tunes and the outlooks) for the prediction can be updated to reflect data revisions.

The task of the forecast update analysis is to explain the role of forecast elements and their contributions to the New–Old forecast difference. This task gets complicated, as the difference in the initial periods of prediction 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 from the presence of prediction tunes that are applied in the anticipated mode and the forward-looking nature of the model used. At this point, we use our knowledge of the elements of the forecast.

Figure 6: New and Old Forecast Trajectories



As the history and prediction are handled differently in the forecasting process, for the purposes of update analysis we define three ranges – history, transition, and future. These ranges refer to specific time spans as shown in Figure 5. The history range denotes all periods with data available for both forecasts, so it starts in period 1 (the period from which all the necessary data started to be collected) and ends at the Old forecast end of the history T_O. The transition range contains periods where observations are no longer available for the Old forecast but are available for the New forecast; it starts at $T_O + 1$ and ends at T_N. The prediction periods for both forecasts, starting at $T_N + 1$ and continuing until the end of the forecast horizon T_{END}, belong to the future range.

Over the history range, observed data is available for both forecasts and can be used to identify the contributions to the initial state and realizations of shocks. Similar consistency is also present over the future range, where only the prediction trajectories are available for analysis.

Over the transition range, the New forecast uses observed data to identify the initial state. However, for the Old forecast only the predicted trajectories are available. This inconsistency over the transition range makes comparing the Old and New forecasts a non-trivial task. Knowledge of the elementary components of the forecasting process and the properties of the model is necessary.

Figure 6 shows the trajectories of the variables of interest for the New and Old forecasts. In the graphs, the dark shaded area represents the history range (up to the first quarter of 2013) and the light shaded area shows the transition range (the second quarter of 2013). The white background indicates the future range (from the third quarter of 2013) of the examined forecasts. The differences observed in the history range stem from data revisions. The most regular revision comes from the update of the seasonal adjustment process, as the seasonal pattern estimate is updated by the new data.

To examine the contributions to the updates of the trajectories, we use a complex procedure that is independent of the model structure. This procedure exploits the properties of the forecasting model and is divided into several steps. These steps are based on supporting simulations used to identify the contributions of the forecast elements, e.g. expert judgment, to the forecast update. The supporting simulations are created by exploiting the linearity of the model, as it implies that the construction of a prediction is additive with respect to its components. 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 simulation and between the supporting simulation and the Old forecast. Generally, the role of the supporting simulation in the decomposition of the forecast update between the New forecast X^N and the Old forecast X^O is summarized in the following scheme:

$$X^N - X^O = (X^N - X^S) + (X^S - X^O), \tag{3.9}$$

where X^S is a supporting simulation. In the process of forecast update evaluation, the supporting simulations provide the basis for comparison and are used to extract the elements of the forecasts. As there might be several elements that contribute to the forecasts, the decomposition process takes the following form:

$$\begin{aligned} X^N - X^O &= (X^N - X_1^S) + (X_1^S - X_2^S) + \\ &+ (X_2^S - X_3^S) + (X_3^S - X_4^S) + \\ &+ \cdots + \\ &+ (X_{K-1}^S - X_K^S) + (X_K^S - X^O), \end{aligned} \tag{3.10}$$

where supporting simulations $X_1^S, \ldots, X_K^S$ are used to extract specific groups of information.

As mentioned in the description of the forecasting framework, forecasts are conditional on the identification and prediction tunes applied. Therefore, to examine the forecast update by the decomposition procedure, the first supporting simulation removes the prediction tunes applied in the New forecast over the future range $\langle T_N + 1, T_{END} \rangle$. This completely removes the New forecast's expert judgment applied in the prediction phase.

The next supporting simulation removes the identification tunes applied in the initial state identification phase of the New forecast over the transition range $\langle T_O + 1, T_N \rangle$. This supporting simulation covers the expert judgment applied to newly released data. Further, to complete the removal of expert judgment, the identification tunes over the history range $\langle 1, T_O \rangle$ are removed in the following supporting simulation.

After the prediction and identification tunes have been removed from the New forecast, we reach the unconditional identification and prediction supporting simulation. In this simulation, the prediction phase still starts in period $T_N + 1$. It should be noted that this unconditional supporting simulation can be replaced with Kalman smoother estimation over the range $\langle 1, T_{END} \rangle$ with the missing data over the future range $\langle T_N + 1, T_{END} \rangle$.

An important element of the creation of the New forecast is the processing of new data releases in the initial state identification phase. The effect of new data releases is evaluated by a supporting simulation that moves the starting point of the prediction phase from period T_N to period T_O. This simulation removes data releases over the transition range $\langle T_O + 1, T_N \rangle$. From this simulation, the decomposition procedure follows the timing of the identification and prediction phase of the Old forecast.

As the basic comparable elements of the forecasting model are shocks and variables, there are two approaches for matching the effects over the transition range. In the case of observed data straightforwardly linked with the state variables, we use state variables as the matching elements of the decomposition. In this case, we try as much as possible to treat the Old forecast as if the prediction was real data and compare it to the observed data available for the New forecast.

Optionally, shocks can be used to match the simulations over the transition range. In this case, the forecast update evaluation is focused on the identification of shocks implied by the observed data used when constructing the New forecast. The shocks identified from the New forecast are compared with the shocks imposed on the Old forecast over the considered range.

The results of the decomposition over the transition range are dependent on the choice of matching scheme (variables or shocks). The choice of approach reflects the focus of the assessment.[7]

After the supporting simulation has removed new data releases, the next simulation removes revisions of data over the history range $\langle 1, T_O \rangle$. After this simulation, no new data is used in the identification or prediction phase and the procedure only considers data available at time T_O for the creation of the Old forecast.

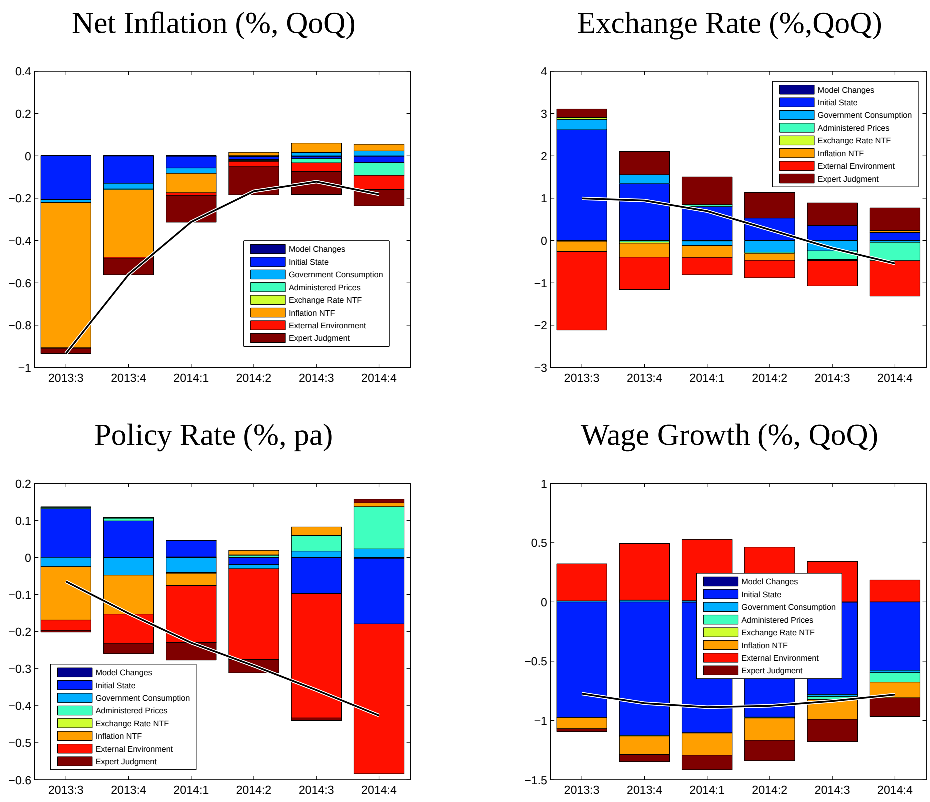
Another three supporting simulations are going to recreate the Old forecast from the data available at time T_O by adding the identification and prediction tunes. Therefore, the next supporting simulation adds the identification tunes used in the Old forecast over the history range $\langle 1, T_O \rangle$. This simulation is followed by a simulation where the prediction tunes from the Old forecast are added over the transition range used in the Old forecast. The final supporting simulation adds the Old forecast prediction tunes over the future range $\langle T_N + 1, T_{END} \rangle$ and thus recreates the Old forecast. Figure 7 demonstrates the results of the forecast update analysis. The New–Old forecast differences between the trajectories shown in Figure 6 are decomposed into the contributions of the forecast elements. Similarly to the comparison of the alternative scenarios, the solid line shows the difference between the trajectories examined. As the purpose of this assessment is to support the presentation of the New forecast, only the decomposition over the future range is shown in Figure 7.

The presented decomposition of the forecast update lists the model changes group. Since the model was not changed, its contribution is nil. All the updates up to and including period T_N are reflected in the contribution of the initial state group, and this includes revisions, data releases, and identification tunes. The initial state group covers all variables and expert judgment updates up to and including period T_N. It can be observed that the change in the wage growth prediction is significantly driven by the data revisions, as can be seen in Figure 6. Due to the forward-looking nature of monetary policy and the presence of rigidities in the model, the impact of initial state revisions either diminishes over time (inflation and the exchange rate) or is hump shaped (wages and the interest rate).

Further, the updates of the outlooks for administered prices and government consumption and the short-term outlooks are shown in the figures. The almost zero revision of the short-term outlook for the exchange rate is due to the accuracy of the Old forecast. As in the case of the scenario comparison, the update of the external environment makes a major contribution to the prediction

[7] In the case of the search for the effects of the data on the business cycle dynamics, the contribution of the variables is the preferred approach as it also identifies the propagation of the observed data or outlooks. When the assessment focuses on the identification of deviations from the business cycle dynamics, the focus is on the contribution of shocks and the matching scheme is based on the linking of the shocks over the history, transition, and future ranges.

Figure 7: Forecast Update - Contributions



trajectory updates. The final contribution represents expert judgment over the future range $\langle T_N + 1, T_{END} \rangle$, which is updated in response to new outlooks and possible data issues.

4. Application: Inflation Forecast Evaluation

In the previous section, our generalized framework was applied to the case of the New–Old forecast update analysis. In the aforementioned analysis, only a one-period difference in the production of the considered forecasts is present. Also, the analysis is focused on the contributions over the future range of the New forecast.

However, our framework can be applied for examining the actual–predicted data variation. To demonstrate the use of it, details of the Inflation Forecast Evaluation exercise are therefore provided.[8] This exercise is conducted on a quarterly basis and we are interested in identifying the sources of the medium-term differences between the New and Old forecasts, with a focus on the transition range, as it includes the most actual data releases.

[8] 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 6-quarters-old forecast and its deviation from the most actual data vintage. The focus is on assessing the accuracy of the forecast by means of a ”what if analysis“. In this analysis, the forecasters recreate 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 Inflation Forecast Evaluation also features an analysis of the monetary policy decisions made over the past 6 quarters.

One of the goals of the Inflation Forecast Evaluation is to identify the contributions of newly acquired elements of the information set 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.

The evaluation of the inflation forecast employs the same methodology as the forecast update analysis described in the previous section. The Old forecast $\mathbb{F}_{T_O}$ is created in period T_O and the New forecast $\mathbb{F}_{T_N}$ in period T_N, where $T_O + 6 = T_N$. The six-period difference is based on the Czech National Bank's stated monetary policy horizon of 6 quarters.

The Old forecast $\mathbb{F}_{T_O}$ is constructed conditional on the data available up to period T_O and the prediction starting in period $T_O + 1$ is conditioned on the information available up to period T_O. Therefore, to stress the information set available, the Old forecast can also be denoted as

$$\mathbb{F}_{T_O|T_O} = (\mathbf{Y}_{T_O|T_O}, \mathbf{Y}^J_{T_O|T_O}, \boldsymbol{\xi}_{T_O|T_O}, \mathbf{X}_{T_O|T_O}, \boldsymbol{\varepsilon}_{T_O|T_O}, \overline{\boldsymbol{\varepsilon}}_{T_O|T_O}).$$

Similarly, in this notation the New forecast can be denoted as

$$\mathbb{F}_{T_N|T_N} = (\mathbf{Y}_{T_N|T_N}, \mathbf{Y}^J_{T_N|T_N}, \boldsymbol{\xi}_{T_N|T_N}, \mathbf{X}_{T_N|T_N}, \boldsymbol{\varepsilon}_{T_N|T_N}, \overline{\boldsymbol{\varepsilon}}_{T_N|T_N}).$$

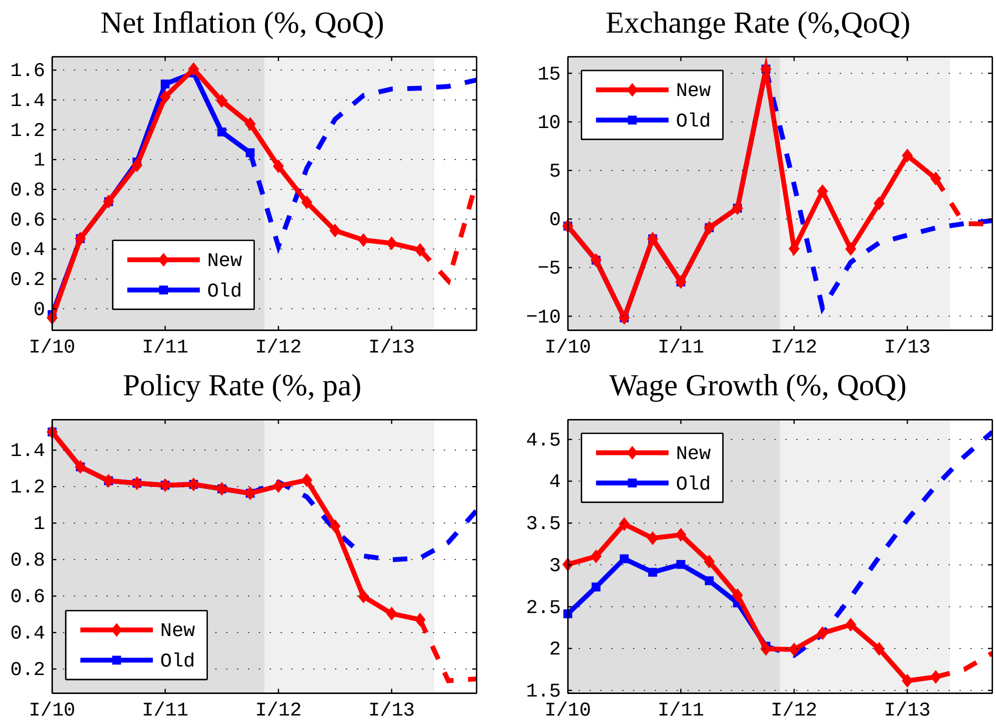
The goal of the forecast evaluation exercise is to examine the variation in the trajectories of the Old forecast $\mathbb{F}_{T_O|T_O}$ and the New forecast $\mathbb{F}_{T_N|T_N}$, with the focus on the transition range $\langle T_O + 1, T_N \rangle$.

A number of events related to the data used in the forecast occur over the transition range. To begin with, the historical data up to period T_O is revised. These revisions would have affected the observations and identification tunes which entered the identification of the Old forecast's initial state. Next, new data for the periods in $\langle T_O + 1, T_N \rangle$ is released and the outlooks for the variables (which enter the forecast as constraints or prediction tunes) are revised. The identification tunes reflect the new data, too. Then, as the outlooks beyond T_N are also updated, the prediction phase reflects this in the new prediction tunes. Moreover, since the structural model employed is subject to continuous testing and refinement, its parameters and/or structure can be updated. Unfortunately, the analysis of model changes is a complex task since it generates non-linearity subject to model changes. Hence, in this paper we assume no model changes between the forecasts under scrutiny.

The trajectories from the two forecasts are presented in Figure 8. The Old forecast (the blue line) represents the forecast released in the first quarter of 2012 (Inflation Report I/2012) and uses the data up to the fourth quarter of 2011 (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 six quarters have been collected. The graphs show the history range (the dark shaded area) up to period T_O (the fourth quarter of 2012), the transition range (the light shaded area) $\langle T_O + 1, T_N \rangle$, and the future range from period $T_N + 1$.

The forecast evaluation methodology, originating in the former Quarterly Projection Model (QPM) framework as presented in Beneš et al. (2003), 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

Figure 8: Forecast Evaluation - Trajectories



of outlooks were used to create a fictional forecast, labeled as the “hypothetical forecast with up-to-date knowledge.’. In the first stage of the evaluation, 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 $\mathbb{F}_{T_N|T_N}$ and the fictional forecast $\mathbb{F}_{T_O|T_N}$. This stage was focused on missing structural shocks that were omitted or we formed wrong expectations about while preparing the Old forecast. Also, the interpretation and presentation of this step was very demanding, as it required deep knowledge of the model structure to understand the impact of the missing structural shocks identified.

The improved version of the Inflation Forecast Evaluation also offers two views on the variation between the Old forecast trajectories and the data released over the transition range. First, the forecast update view is used. In this view, we explain the New–Old forecast difference with the updates in the assumptions that were imposed to create these forecasts. Second, the Inflation Forecast Evaluation offers a detailed view of the model dynamics through the differences in the 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 produced. We keep the two views of the variation of the forecasted trajectories, but they are different from the previously used approach.

Our improved forecast update evaluation framework makes the analysis easier to communicate and more intuitive for the target audience. Also, it is general enough and capable of replicating the results of the old style approach. The capabilities of the new framework allow us, but do not require us, to keep the form of the Inflation Forecast Evaluation and present the results in two stages.

4.1 Information Set Update

In the first stage of the Inflation Forecast Evaluation, the same decomposition methodology as in the forecast update analysis is used. The focus of the evaluation is on the transition range, which is significantly extended. We analyze the variations between the data available for identification of the initial state of the New forecast $\mathbb{F}_{T_N|T_N}$ and the prediction of the Old forecast $\mathbb{F}_{T_O|T_O}$. As mentioned in the description of the forecast update analysis, due to the difference between the identification and prediction methodologies (the presence of anticipated shocks), forecast evaluation is a complex task and the supporting simulations technique is adopted for identification of the contributions to the data–forecast differences.

From the forecasters' point of view, in the Old forecast over the transition range, conditioning information is applied as prediction tunes. In the New forecast over the transition range, new data and expert judgment are applied as identification tunes.

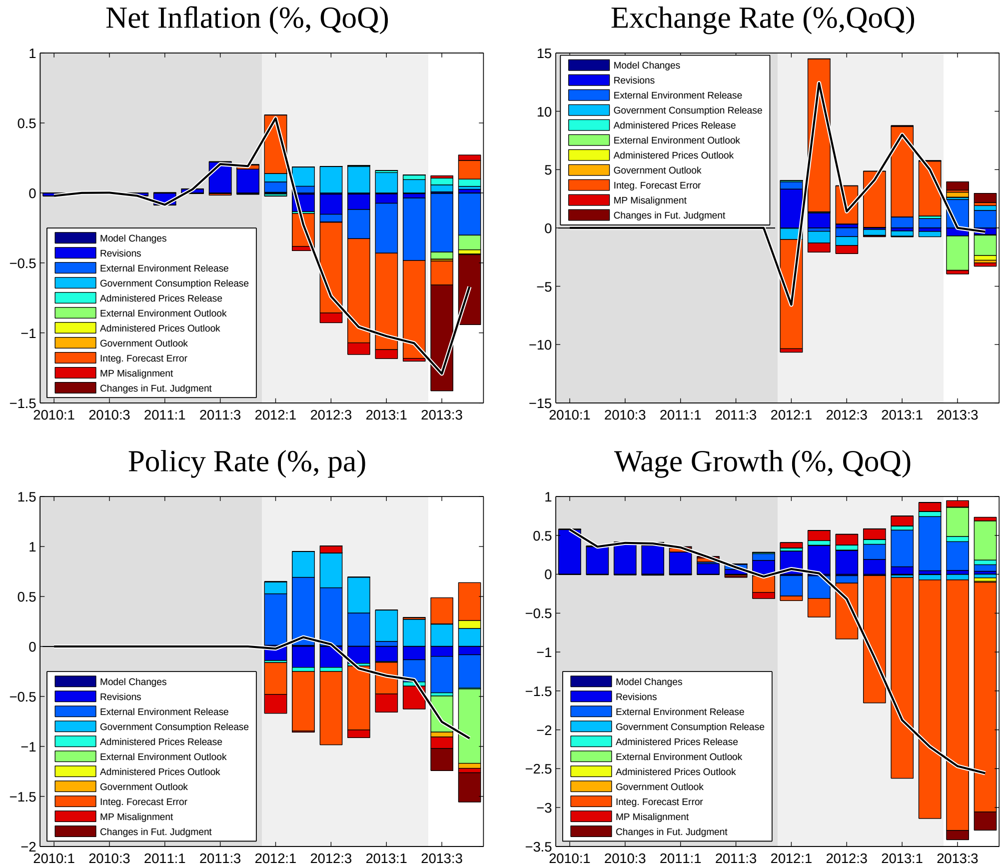
In the first stage of the evaluation, the contributions of model changes, data revisions, and updates of outlooks contributing to the difference between the New forecast and the Old forecast are analyzed. The variables which form the conditioning information for the forecast can be distributed into several subgroups. 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 9 demonstrates the results of identification of the contributions to the variations between the New forecast $\mathbb{F}_{T_N}$ and the Old forecast $\mathbb{F}_{T_O}$ trajectories as shown in Figure 8.

As we assumed no model change for the purposes of this presentation, the contribution of the model change is zero. In the evaluation with model changes present, the initial step of the evaluation is to switch to the new model. The Old forecast is then 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.[9]

The presentation of the decomposition usually follows the timing of the forecast elements. The data revisions enter 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. These 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 9 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, hence a non-zero contribution can be used as a check of the precision of the analysis.

[9] 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 9: Forecast Evaluation - Contributions



The presented results show that the revisions deliver 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.

Next, the contribution of data released over the transition range is analyzed. The motivation for the inclusion of this group is the analysis of the precision of the outlooks used in the forecast and their influence on the forecast trajectories. This group loosely resembles the creation of the fictional forecast in the previously employed methodology of the Inflation Forecast Evaluation as described above.

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 and domestic variables. Foreign variables include the foreign interest rate, the foreign inflation rate, and foreign demand growth (approximated by foreign GDP). The contribution of the release of foreign outlooks (replacing the outlooks with the observed data) is next on the list of forecast elements to analyze. Domestic outlooks are represented by the outlooks for domestic government consumption and administered prices. The plots in Figure 9 show that the use of the actually observed data instead of outlooks contributes to an improvement of the inflation forecast, as the lower foreign inflation and economic activity will slow down domestic economic activity. The release group is followed by the outlooks group, which has a similar composition. This group represents the update of the variables used for conditioning the forecast over the future range.

Further, the forecast error group, shown in the plots in Figure 9, covers the contributions of domestic observable variables. These variables are used in the identification stage of the New forecast $\mathbb{F}_{T_N}$ and are compared with the predictions for these variables from the Old forecast $\mathbb{F}_{T_O}$. 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.

The monetary policy misalignment group identifies the contribution of monetary policy over the transition range to the actual data–Old forecast deviation over the transition range.

The last group identifies the contribution of the updated prediction tunes in both forecasts over the future range. This contribution originates in the update of the forecasters' views on recent developments in the economy.

Although the presented groups are aggregations of the variables, our tool enables us to identify the contributions of each forecast element. The 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 considered forecasts.

4.2 Missing Structural Shocks

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 $\mathbb{F}_{T_N}$ and $\mathbb{F}_{T_O}$ can also be interpreted as differences in structural shocks. The role of the second stage of the Inflation Forecast Evaluation is to help interpret the contribution of the forecast error identified in the first stage.

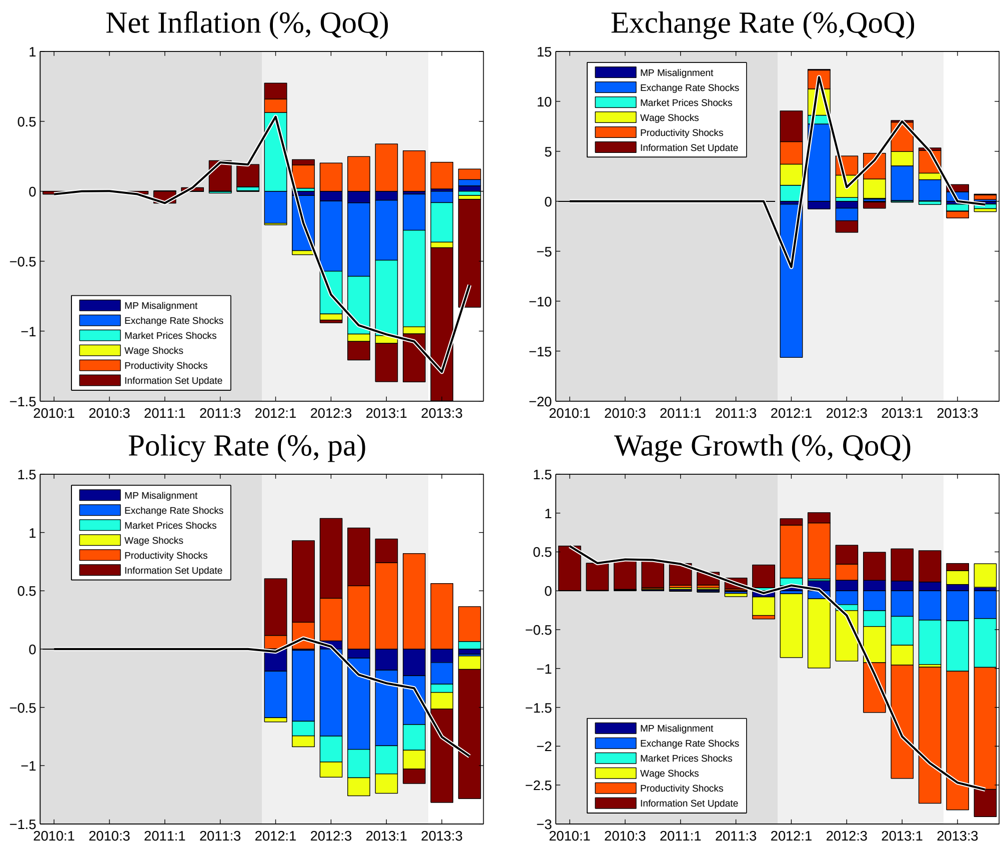
In our standard forecast evaluation process, shocks are separated into six groups: monetary policy misalignment, an exchange rate shock (a shock to uncovered interest rate parity), price shocks (shocks to pricing markups), wage shocks, and technology shocks (shocks that increase productivity and affect the demand for production factors). The sixth group covers the effects of the information set update, which was analyzed in the first stage of the forecast evaluation.

In the evaluation, we consider these 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 the missing information view is also supported by the fact that data collected in the evaluation period T_N are subject to revisions.

The decomposition of the New–Old forecast difference, plotted in Figure 8, into the contributions of structural shocks is presented in Figure 10. This difference is the same as the one considered in the first stage of the evaluation – see Figure 9.

The demanding part of the examination of missing structural shocks is to interpret those shocks and build a credible story based on the model mechanism. The case shown in Figure 10 indicates that monetary policy was more expansionary than the model simulation would imply. This is consistent with the negative contribution of the policy shock (MP Misalignment) to the difference in net

Figure 10: Missing Structural Shocks



inflation. The significant appreciation of the exchange rate in the first quarter of 2012 (Exchange Rate Shocks) 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 Shocks) 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 Shocks) 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 in the first stage, the identification of missing structural shocks can be done in fully detailed mode, too. The contribution of each shock in every period can be identified. 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 missed shocks can direct our attention to a missing mechanism or feature of the model. This often leads to improvements in the structure of the model and also helps validate the model used.

5. Conclusion

Stimulated by the criticism that conditional forecasts from structural macroeconomic models are not transparent, this study demonstrates a framework and tool that enable us to quantify the contributions of updates of forecast elements to the predicted trajectories. This framework is used in the forecasting process to increase the transparency of monetary policy relying on structural DSGE model predictions. The increased transparency of central bank forecasts helps us cope with the ”black box“ accusations of critics favoring small, reductionist textbook models. This work describes various applications and methodology steps of the forecast evaluation tool.

The presented framework and tool are used to explain the variation in the period-to-period forecast update. This facilitates detailed presentations of the forecast update, keeping the forecasting process elaborate yet transparent. The details of the analysis provide users of the forecast with the possibility of tracking down forecast updates to the forecasters' assumptions and hypotheses.

Starting with the simplest case, the flexibility of the presented framework is demonstrated by using it to analyze the differences between two forecast scenarios. Applying the decomposition methodology allows 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.

We also document the use of the decomposition methodology for forecast update analysis in the presence of a time shift. The results of this analysis are used in communicating the forecast, as the decomposition allows us to link the change in forecast elements (e.g. data or expert judgment) to the change in the forecast trajectories.

Further, the presented decomposition framework is general enough to be used to conduct an ex-post analysis of the actual data–forecast variation. We demonstrate that forecast revisions can be expressed as the sum of the contributions pertaining to specific subsets of the information set. These sets include model and data revisions, data releases, and identification or prediction tunes. Moreover, these elements of forecast revisions can be identified with a specific subset of variables in the model used for forecasting. This enables us to compute the contributions of variables relating to the domestic or foreign economy or monetary policy and thus decompose the differences between two forecasts into the contributions of specific elements of the forecast. Our methodology provides elaborate results, as it is able to identify the effects of forecast elements even when the expert information comprises a mixture of anticipated and unanticipated elements.

Forecast evaluation is an important exercise, as it documents the reasons why particular adjustments and revisions are made to forecasts. Keeping track of the forecasters' actions allows us to learn from the forecast and actual data misalignments 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 demonstrates 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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Czech National Bank
Economic Research Department
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 14 278
http://www.cnb.cz
e-mail: research@cnb.cz
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