



# Forecast combinations under structural break uncertainty



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## ABSTRACT

This paper proposes two new weighting schemes that average forecasts based on different estimation windows in order to account for possible structural change. The first scheme weights the forecasts according to the values of reversed ordered CUSUM (ROC) test statistics, while the second weighting method simply assigns heavier weights to forecasts that use more recent information. Simulation results show that, when structural breaks are present, forecasts based on the first weighting scheme outperform those based on a procedure that simply uses ROC tests to choose and forecast from a single post-break estimation window. Combination forecasts based on our second weighting scheme outperform equally weighted combination forecasts. An empirical application based on a NAIRU Phillips curve model for the G7 countries illustrates these findings, and also shows that combination forecasts can outperform the random walk forecasting model.

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## 1. Introduction

The forecasting of economic variables is often complicated by the possibility that the parameters in the underlying data generating process (DGP) might have changed at various points in time over the pre-forecast sampling period. In this paper, we define structural breaks as permanent shifts in the parameters of a DGP, and we focus on the problem that structural breaks often affect forecasts that rely on model estimation. The use of a model estimation window that includes pre-break data can lead to biased out-of-sample forecasts, although the use of pre-break data can also reduce the forecast variance by increasing the estimation sample size. Pesaran and Timmermann (2007) show that if we have information on breaks, such as break points and break sizes, then we can assess the trade-off between the bias and forecast error variance and choose the estimation window that minimizes the out-of-sample mean squared forecasting error. The optimal window often

includes pre-break data. However, as these authors point out, forecasters usually have little knowledge about structural breaks that might have occurred, so that, in practice, it is difficult to take full advantage of the bias–variance trade-off.

Forecast combinations based on observation windows of different lengths can embody a bias–variance trade-off that does not rely on knowledge about structural breaks. This is because the combinations will typically incorporate windows that include pre-break data if a break has occurred. One can improve these combination forecasts by estimating the (last) structural break date, then weighting only those forecasts which are obtained from observation windows that include some of the pre-break data. However, as was demonstrated by Pesaran and Timmermann (2007), forecast combinations that incorporate estimated break dates do not necessarily outperform combinations that use no information on break dates. This is because estimated break dates can be imprecise, and the use of inaccurate estimates of the break dates can be detrimental rather than helpful when choosing estimation windows.

In this paper, we explore the idea that information regarding structural break dates can be used to improve combination forecasts in other ways. We consider two forecast

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weighting schemes that build on this idea. First, we consider a new forecast weighting scheme that is based on by-products of the reverse ordered CUSUM (ROC) structural break test considered by Pesaran and Timmermann (2002). Starting from the most recent observations and going backwards in time, the ROC test is built on a sequence of test statistics that consider each point in the sample as a possible most-recent break point, and we use this sequence of test statistics to weight the associated post-break forecasts. We also consider a simple forecast weighting technique that effectively just places more weight on forecasts which are derived from more recent samples. We compare our proposed combination forecasts with other forecasts that allow for break uncertainty, and find that they perform well in a variety of simulated situations. In particular, we find that, for situations in which breaks are subtle and hard to detect, forecasts based on our first weighting scheme outperform those based on a procedure that simply uses a ROC test to choose and forecast from a single post-break estimation window. Furthermore, forecasts based on our second weighting scheme outperform equally weighted combination forecasts. We use our proposed methods to forecast 12-month inflation changes in G7 countries. For most countries, the use of combination weighting schemes based on ROC test outcomes leads to lower MSFEs than the use of a ROC test to choose a single forecast window, and forecasts based on our second weighting scheme outperform those based on an equally weighted scheme for all countries.

The outline of this paper is as follows. The next section explains the details of some forecasting methods that account for structural break uncertainty, including the new combination weighting schemes. Next, these methods are examined by Monte Carlo simulations in Section 3. We then employ these approaches in Section 4 to conduct an out-of-sample forecasting exercise of 12-month inflation changes based on the NAIRU Phillips curves for G7 countries. Finally, Section 5 concludes.

## 2. Forecasting methods

Assume that the following linear model is subject to  $m$  structural breaks at dates  $T_1, T_2, \dots, T_m$ :

$$y_t = \mathbf{x}'_t \boldsymbol{\beta}_{T_{j-1}+1:T_j} + \sigma_{T_{j-1}+1:T_j} \varepsilon_t, \quad (1)$$

$$j = 1, 2, \dots, m+1 \text{ and } T_{j-1} + 1 \leq t \leq T_j,$$

with  $T_0 = 0$  and  $T_{m+1} = T$ . Here,  $y_t$  is the dependent variable at time  $t$ ,  $\mathbf{x}_t$  is a  $p \times 1$  vector of regressors at time  $t$  that may contain lags of the dependent variable and lagged explanatory variables, and  $\varepsilon_t$  is an innovation with a zero mean and unit variance. The  $p \times 1$  vector  $\boldsymbol{\beta}_{T_{j-1}+1:T_j}$  denotes the values of coefficients of regressors in each segment  $j$  that starts from  $T_{j-1} + 1$  and ends at  $T_j$ , and the parameter  $\sigma_{T_{j-1}+1:T_j}$  measures the standard deviation of the regression error over the time segment  $j$ . The model incorporates  $p+1$  parameters in each of the  $m+1$  regimes. When a structural break occurs, at least some and perhaps all of the current set of  $p+1$  parameters shift permanently until the next breakpoint. For the sake of simplicity, and without loss of generality, the vector of regressors  $\mathbf{x}$  stays the same

across all of the segments. Suppose that we have a sample of  $T$  observations, and we set the minimum acceptable estimation window size  $\underline{w}$  to be at least  $2p$ . The one-step-ahead forecast of  $y_{T+1}$  conditional on information up to time  $T$  is denoted by  $\hat{y}_{T+1}$ . This is computed based on the OLS estimated parameters,  $\hat{\boldsymbol{\beta}}$ .

In the following subsections, we briefly outline the reverse ordered CUSUM (ROC) test, then introduce the newly proposed combination methods that deal with structural break uncertainty.

### 2.1. The ROC test

The reverse ordered CUSUM (ROC) test constitutes the first step of a two stage forecasting strategy introduced by Pesaran and Timmermann (2002). The aim of this strategy is to date the most recent structural break in a time series, then restrict the window for estimating the forecasting parameters to the associated post-break data. As its name suggests, the ROC test is related to the standard CUSUM test developed by Brown, Durbin, and Evans (1975). It differs from the standard CUSUM test in that the test sequence considers possible break points in reverse chronological order, which is achieved by first placing all observations in reverse order, then conducting the standard CUSUM test on the rearranged data set. The test starts with observation matrices  $\mathbf{y}_{T:\tau}$  and  $\mathbf{x}_{T:\tau}$  that are in the format

$$\begin{aligned} \mathbf{y}'_{T:\tau} &= [y_T, y_{T-1}, \dots, y_{\tau+1}, y_\tau], \\ \mathbf{x}'_{T:\tau} &= [\mathbf{x}_T, \mathbf{x}_{T-1}, \dots, \mathbf{x}_{\tau+1}, \mathbf{x}_\tau], \\ &\text{for } \tau = T - \underline{w} + 1, T - \underline{w}, \dots, 2, 1. \end{aligned}$$

The time  $\tau$  in the original sample  $[1 : T]$  is subject to a minimum acceptable estimation window size, so that each observation matrix contains at least  $\underline{w}$  observations. A sequence of least squares estimates of  $\boldsymbol{\beta}$  associated with the reverse-ordered data sets is

$$\begin{aligned} \hat{\boldsymbol{\beta}}^{(R)}_{T:\tau} &= (\mathbf{x}'_{T:\tau} \mathbf{x}_{T:\tau})^{-1} \mathbf{x}'_{T:\tau} \mathbf{y}_{T:\tau}, \\ \tau &= T - \underline{w} + 1, T - \underline{w}, \dots, 2, 1, \end{aligned} \quad (2)$$

and ROC test statistics  $s_\tau$  are constructed using the squares of standardized one-step-ahead recursive residuals  $v_t$  from this sequence using

$$s_\tau = \frac{\sum_{t=\tau}^{T-\underline{w}} v_t^2}{\sum_{t=1}^{T-\underline{w}} v_t^2}, \quad \tau = T - \underline{w}, T - \underline{w} - 1, \dots, 2, 1, \quad (3)$$

where  $v_t$  is computed as:

$$v_t = \frac{y_t - \mathbf{x}'_t \hat{\boldsymbol{\beta}}^{(R)}_{T:t+1}}{\sqrt{1 + \mathbf{x}'_t (\mathbf{x}'_{T:t+1} \mathbf{x}_{T:t+1})^{-1} \mathbf{x}_t}}. \quad (4)$$

The  $s_\tau$  statistics increase as the test sample size increases (and  $\tau$  decreases). The associated lower and upper critical values also increase, and if  $s_\tau$  strays outside the critical bounds, then the first  $\tau$  for which this occurs provides an estimate of the last breakpoint in the sample  $[1 : T]$ .

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