RESEARCH ARTICLE

Forecasting inflation: The use of dynamic factor analysis and nonlinear combinations

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Abstract
This paper considers the problem of forecasting inflation in the United States, the euro area, and the United Kingdom in the presence of possible structural breaks and changing parameters. We examine a range of moving window techniques that have been proposed in the literature. We extend previous works by considering factor models using principal components and dynamic factors. We then consider the use of forecast combinations with time-varying weights. Our basic finding is that moving windows do not produce a clear benefit to forecasting. Time-varying combination of forecasts does produce a substantial improvement in forecasting accuracy.

KEYWORDS
dynamic factor models, forecast combinations, Kalman filter, rolling windows, structural breaks

1 | INTRODUCTION

In early 2021, a debate erupted in the United States about the country's prospects for inflation. US consumer prices, which had increased by 1.4% in January 2021, began moving steadily upward, reaching 5.4% in June and 7.0% in December. In a February 2021 column, published in the Washington Post, former Treasury Secretary, Larry Summers, expressed concern that the $ 1.9 trillion American Rescue Plan (amounting to almost 8% of US GDP) then making its way through Congress could "set off inflationary pressures of a kind we have not seen in a generation" (Summers, 2021).[1] Federal Reserve officials, however, expressed little concern about the inflation in early 2021. In late January 2021, Fed Chairman Jerome Powell was quoted saying that "the kind of troubling inflation that people like me grew up with seems far away and unlikely" (quoted from Ip, 2021). That same month, Charles Evans, President of the Chicago Fed, stated: "I'm not worried about inflation going up substantially beyond 2.5 percent. I don't even fear 3 percent" (quoted from Ip, 2021).

In 2022, US inflation continued to rise, peaking at 9.1% in June, before falling somewhat (as of this writing in October 2022) to 8.3% in August.[2] After a succession of forecasts that underpredicted the inflation rate in 2021 and the first half of 2022, in June 2022, Fed Chairman Powell stated, "we understand better now how little we understand about inflation" (quoted from Arnold et al., 2022).[3]

Similar patterns of rising inflation were experienced in the euro area and the United Kingdom during 2021

[1]The American Rescue Plan was enacted into legislation in May 2021. It followed a $ 2.3 trillion (10% of GDP) spending package, the "Coronavirus Aid, Relief, and Economic Security Act," which was signed into law in December 2020.

[2]Federal Reserve officials downplayed the rise in inflation during most of 2021, calling it a "temporary surge." See, for example, Lael Brainard (quoted from Politi & Smith, 2021).

[3]Within the context of the late-1970s and early-1980s, a period marked by high inflation variability, Tobin (1981, p. 391) observed: "We have not done well in modeling the inflation process." More recently, González-Rivera (2013, p. 185) noted: "In fact, inflation rates are notoriously difficult to predict."

and 2022. In the euro area, the year-on-year increase in the harmonized index of consumer prices (HICP) accelerated from 0.9% in January 2021 to 1.9% in June, 5.0% in December, 8.6% in June 2022, and 9.9% in September. In the United Kingdom, the comparable numbers were 0.7% (January 2021), 2.5% (June 2021), 5.4% (December 2021), 9.4% (June 2022), and 8.8% (September). Central bank officials in Europe responded to the rise in inflation in a way that echoed Powell's above remarks. For example, Pierre Wunsch, the governor of the Belgian central bank, was quoted in September 2022 as saying that "we have come to the conclusion that we know much less about inflation drivers than we thought" (Arnold, 2022).

In what follows, we consider the problem of forecasting inflation in the United States, the euro area, and the United Kingdom in the presence of possible structural breaks and changing parameters using monthly data that include much of the recent period of rising inflation. The data sample runs from 1999M1 to 2022M4. We use the month-on-month rate of inflation (i.e., the rate of change between 1 month and the previous month) rather than the change over 12 months, which is a more common definition for inflation. The reason for this is that the annual rate of inflation is made up of the monthly rate over the previous 12 months. It, therefore, has a strong serial correlation property and is relatively easy to forecast. On a monthly basis, the previous 11 monthly changes are known, and it is only the final month that needs to be forecasted. By using the monthly change, we focus on the unknown development in inflation.

The remainder of the paper is structured as follows. Section 2 provides a review of the relevant forecasting literature on inflation. Section 3 discusses the window selection criteria, the factor models, and the time-varying forecast combination technique. Section 4 describes the data we use for each of the currency areas. Section 5 presents the results of the forecasting exercise for the three currency areas. Section 6 concludes.

2 | LITERATURE REVIEW

The recent literature on forecasting has paid considerable attention to the problems posed by structural breaks and parameter instability (Clements & Hendry, 1998; Inoue & Rossi, 2012; Inoue et al., 2017; Rossi, 2013; Stock & Watson, 1996). Typically, these problems are dealt with in the following way. The presence of structural breaks, that is, of abrupt changes, is tested using formal procedures, such as the Bai and Perron (1998) test. If detected, the post-break data are used for estimation. This procedure, however, does not address the possibility of parameter instability, under which the parameters change slowly. To deal with the latter possibility, researchers often use rolling windows, comprising a fixed block of prior observations, at each point of time, under the presumption that recent data are more relevant than distant data for forecasting. Perhaps the key paper in this area is by Pesaran and Timmermann (2007); these authors made extensive use of rolling windows to deal with both structural and parameter change. The intuition here is that we need to balance two forms of bias in our forecasting models: first, the bias that comes from using a sample size that is too small; and second, the bias that comes from using a long sample, which includes structural breaks and changing parameters. Ideally, the length of the moving window should be chosen in the light of these two sources of bias. Other important papers addressing this issue include Swanson (1998), Goyal and Welch (2003), and Molodtsova and Papell (2009). The use of rolling windows, however, leaves open the choice of window length. As Inoue et al. (2017) pointed out, the window size has typically been either arbitrarily determined by forecasters or has been determined based on past experience. We will discuss the various options for achieving window size below. More recent papers that have explored this moving window idea are Medel et al. (2016), Inoue et al. (2017), Hong et al. (2017), and Tang et al. (2021).

We assess the above procedures in the context of forecasting one step ahead monthly inflation rates for three currency areas: the United States, the euro zone, and the United Kingdom. We use a range of methods to select the size of the rolling window and incorporate an array of exogenous information, including factors based on principal components and a dynamic factor technique recently proposed by Gibson et al. (2022), into a variety of autoregressive (AR) models. We then extend our analysis by using the Kalman filter to estimate time-varying combinations of some of the best performing standard models.

Our basic findings are as follows. First, forecasts based on rolling windows do not improve forecasts compared with simple AR models. Second, factor models using principal components also do not show a significant improvement in forecasting compared with simple AR models. Third, significant forecast accuracy is gained using nonlinear forecast combinations.

3 | THE FORECASTING TECHNIQUES

3.1 | Window selection

The underlying data generation process is assumed to be (following Robinson, 1989; Cai, 2007; and Inoue et al., 2017);

$$y_{t+1} = \boldsymbol{x}_t' \boldsymbol{\beta}\left(\frac{t}{T}\right) + \mu_{t+1} \tag{1}$$

where y_{t+1} is the variable we are interested in forecasting; $\boldsymbol{x_t}$ is a $px1$ vector of stochastic regressors; $\boldsymbol{\beta}$ is a $px1$ vector of smoothly time-varying parameters, including the constant (and lagged dependent variables); μ_{t+1} is the disturbance term; and T is the full sample size. Equation (1) is a standard forecasting equation except that the coefficient vector $\boldsymbol{\beta}$ is assumed to change smoothly through time as t moves from 1 to T.

The typical method for dealing with such a situation is twofold; first, we test to see if there is a significant break in the parameters of interest. If there is no break, we use the entire sample period (after an initial training period). If there is a break at time T_b $(1 < T_b < T)$, then we focus on the period after the break. Second, we estimate the forecasting model using ordinary least squares (OLS) with a fixed moving window of data, which is not, of course, a true time-varying estimation process as the underlying assumption of each successive regression from the rolling window is that the true parameter is constant. The intuition, however, is to balance the bias coming from too short a sample for consistent estimation with the bias coming from too long a sample where the true parameter is changing significantly. The choice of the window size is, therefore, crucial. In the past, this balance has been determined in an arbitrary way, but recently, a number of suggestions have been proposed:

1. The post-break method of Pesaran and Timmermann (2007) is to only use the post-break data [T_b+1: T] to estimate the parameters in the forecasting model, where $\widehat{\boldsymbol{\beta}}_{T_b+1:T} = \left(\sum_{i=T_b+1}^{T-1} \boldsymbol{x}_i \boldsymbol{x}_i'\right)^{-1} \left(\sum_{i=T_b+1}^{T-1} \boldsymbol{x}_i y_{i+1}\right)$. Then the forecast is given by $\widehat{y}_{T+1} = \boldsymbol{x}_T' \widehat{\boldsymbol{\beta}}_{T_b+1:T}$.
2. The cross-validation method of Pesaran and Timmermann (2007) (hereafter denoted as the PTCV method) partitions the sample into the estimation period [1:γ] and the validation period [$\gamma+1$: T], where γ is set at $0.75T$ in practice. The last $0.25T$ observations in the validation period are used to compute the pseudo recursive out-of-sample mean squared forecast error (MSFE) starting at a subsample $[\tau : \gamma]$, as

$$MSFE(\tau | T, \gamma) = (T-\gamma)^{-1} \sum_{i=\gamma}^{T-1} \left(y_{i+1} - \boldsymbol{x}_i' \widehat{\boldsymbol{\beta}}_{\tau:i}\right)^2 \tag{2}$$

where $\widehat{\boldsymbol{\beta}}_{\tau:i} = \left(\sum_{j=\tau}^{i-1} \boldsymbol{x}_j \boldsymbol{x}_j'\right)^{-1} \left(\sum_{j=\tau}^{i-1} \boldsymbol{x}_j y_{j+1}\right)$ and τ is assumed to move either from 1 to T_b, or from 1 to $\gamma - \omega$ (whichever is smaller); where ω is the smallest sample size for parameter estimation in the forecasting model, and $\gamma - \omega$ is assumed to be the last possible breakpoint in the data. The former incorporates pre-break observations to estimate the parameters and is known as Pesaran and Timmermann's (2007) cross-validation method with estimated break dates. The latter assumes the break date is unknown, and a minimum of ω observations is needed to estimate the parameters of the forecasting model. When $T_b > \gamma - \omega$, the two approaches yield the same result. The value of τ that yields the smallest MSFE in Equation (2) leads to the optimal sample $[\tau^\star : T]$ for forecasting, where

$$\begin{aligned} \tau^\star &= \arg\min_{\tau} MSFE(\tau | T, \gamma) \\ &= (T-\gamma)^{-1} \sum_{i=\gamma}^{T-1} \left(y_{i+1} - x_i' \widehat{\beta}_{\tau:i}\right)^2 \end{aligned} \tag{3}$$

Then the parameters in the forecasting model are estimated as $\widehat{\beta}_{\tau^\star:T} = \left(\sum_{j=\tau^\star}^{T-1} x_j x_j'\right)^{-1} \left(\sum_{j=\tau^\star}^{T-1} x_j y_{j+1}\right)$, and the forecast is given by $\widehat{y}_{T+1} = x_T' \widehat{\beta}_{\tau^\star:T}$. Both the estimated break date and unknown break date versions are employed with $\omega = 10$.

3. Inoue et al. (2017) suggest selecting the sample size so as to minimize the MSFE, that is to select the window size which minimizes $E\left[\left(y_{T+1} - \widehat{y}_{T+1}\right)^2\right]$, where $\widehat{y}_{T+1} = x_T' \widehat{\beta}_R$ and $\widehat{\beta}_R = \left(\sum_{i=T-R+1}^{T-1} x_i x_i'\right)^{-1} \left(\sum_{i=T-R+1}^{T-1} x_i y_{i+1}\right)$. R denotes the window size. It is equivalent to minimize

$$\left[\widehat{\boldsymbol{\beta}}_{\boldsymbol{R}} - \boldsymbol{\beta}(\mathbf{1})\right]' \boldsymbol{x}_T \boldsymbol{x}_T' \left[\widehat{\boldsymbol{\beta}}_{\boldsymbol{R}} - \boldsymbol{\beta}(\mathbf{1})\right] \tag{4}$$

Because $\boldsymbol{\beta}(\mathbf{1})$ is not feasible, it is replaced by a local linear regression estimate $\widetilde{\boldsymbol{\beta}}(\mathbf{1})$ as

$$\begin{bmatrix} \widetilde{\boldsymbol{\beta}}(\mathbf{1}) \\ \widetilde{\boldsymbol{\beta}}^{(1)}(\mathbf{1}) \end{bmatrix} = \begin{bmatrix} \sum \boldsymbol{x}_t \boldsymbol{x}_t' & \sum \boldsymbol{x}_t \boldsymbol{x}_t' \left(\frac{t-T}{T}\right) \\ \sum \boldsymbol{x}_t \boldsymbol{x}_t' \left(\frac{t-T}{T}\right) & \sum \boldsymbol{x}_t \boldsymbol{x}_t' \left(\frac{t-T}{T}\right)^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum \boldsymbol{x}_t y_{t+1} \\ \sum \boldsymbol{x}_t y_{t+1} \left(\frac{t-T}{T}\right) \end{bmatrix} \tag{5}$$

where $\sum$ represents $\sum_{t=T-R_0+1}^{T-1}$ and R_0 is the estimation window size of $\widetilde{\boldsymbol{\beta}}(\mathbf{1})$. Replacing $\boldsymbol{\beta}(\mathbf{1})$ in Equation (4) with its estimation in Equation (5), and the optimal window size $R^\star$ is given by

$$R^\star = \arg\min_{R} \left[\widehat{\boldsymbol{\beta}}_{\boldsymbol{R}} - \widetilde{\boldsymbol{\beta}}(\mathbf{1})\right]' \boldsymbol{x}_T \boldsymbol{x}_T' \left[\widehat{\boldsymbol{\beta}}_{\boldsymbol{R}} - \widetilde{\boldsymbol{\beta}}(\mathbf{1})\right] \tag{6}$$

Then the parameters in the forecasting model are estimated as $\widehat{\boldsymbol{\beta}}_{\boldsymbol{R}^{\star}} = \left(\sum_{i=T-R^{\star}+1}^{T-1} \boldsymbol{x}_i \boldsymbol{x}_i'\right)^{-1} \left(\sum_{i=T-R^{\star}+1}^{T-1} \boldsymbol{x}_i y_{i+1}\right)$, and the forecast is $\widehat{y}_{T+1} = \boldsymbol{x}_T' \widehat{\boldsymbol{\beta}}_{\boldsymbol{R}^{\star}}$. In practice, R is no less than 20, and R_0 is determined by the cross-validation method with unknown break date, as $R_0 = T - \tau^{\star} + 1$. This window selection method is denoted as Inoue, Jin, and Rossi's (IJR) algorithm in the following discussion. It is based on Inoue et al. (2015).

4. A fixed rolling window with $T = 60$ is also used.

The steps in our analysis are

a. First, we test for parameter constancy on the whole sample period ($T = 60$), using the Bai and Perron (1998) parameter constancy test with 5% significant level. The trimming value is set at $0.15T$.
b. If we fail to reject the constancy of the parameters in (a), we set the sample size to the full sample. If we reject parameter constancy, we then go on to use each of the five-window selection criteria mentioned above.

In addition, we estimate a range of models, as follows: a simple random walk (RW), an autoregressive model with the lags determined by the Akaike information criterion (AIC), an autoregressive model with lags determined by the Bayesian information criterion (BIC), and a range of models with the addition of exogenous variables added as noted below in Section 4. The lags of dependent and exogenous variables are determined by the BIC, and the maximum lag is 3. The maximum number of lags in an autoregressive model is 5.

3.2 | Factor models

In addition to using the above standard models, we estimate two other models, one based on factors using principal components and one based on the dynamic factor analysis. The two approaches we use are principal components and the dynamic factor model of Gibson et al. (2022). Principal components are, of course, well known and will not be further discussed here other than to note that they involve a static set of factors.[4] Gibson et al. (2022) demonstrate how the full set of principal components can be reproduced in the Kalman filter by removing the dynamics in the state equation that generates the factors as state variables. A set of dynamic factors can then be generated from the same Kalman filter setup, except that the state equation is then given a normal dynamic specification. The one step ahead state variables may then be used in a forecasting context. The smoothed state variables at time t would contain information at time $t + 1$ ... T, so this would contain information that would not be available in a real time forecasting exercise.

Gibson et al. (2022) demonstrate that the following Kalman filter set up exactly reproduces standard principal components.

$$\begin{aligned} y_{1t} &= \lambda_1 f_t + \varepsilon_{1t} \\ y_{2t} &= \lambda_2 f_t + \varepsilon_{2t} \\ &. \\ &. \\ &. \\ y_{Rt} &= \lambda_R f_t + \varepsilon_{Rt} \\ \varepsilon_{1t} &\ldots \varepsilon_{R_t} \sim N(0,1) \end{aligned} \tag{7}$$

where

$$\begin{aligned} f_t &= e_t \\ e_t &\sim N\left(0, \sigma^2\right) \end{aligned} \tag{8}$$

and y_{it} are a set of measured variables, in this case, that are being used for the principal component calculations, and f_t is the state variable or the first principal component. This differs from a standard state space in that the state equation is non-dynamic and, hence, mimics the static nature of principal components. Additional principal components are then generated by repeating Equations (7) and (8) but with the measurement equations conditioned on the earlier state variables.

To produce dynamic factors from this setup, all that needs to be done is to generalize the state equations in Equation (8) by adding lags in the usual way. Thus,

$$\begin{aligned} f_t &= \theta(L) f_t + e_t \\ e_t &\sim N\left(0, \sigma^2\right) \end{aligned} \tag{9}$$

where $\theta(L)$ is a lag operator.

3.3 | Time-varying forecast combinations

The final forecast technique that we consider is to use a time-varying forecast combination. It has been well

[4] For a discussion of principal components, see Gibson et al. (2022).

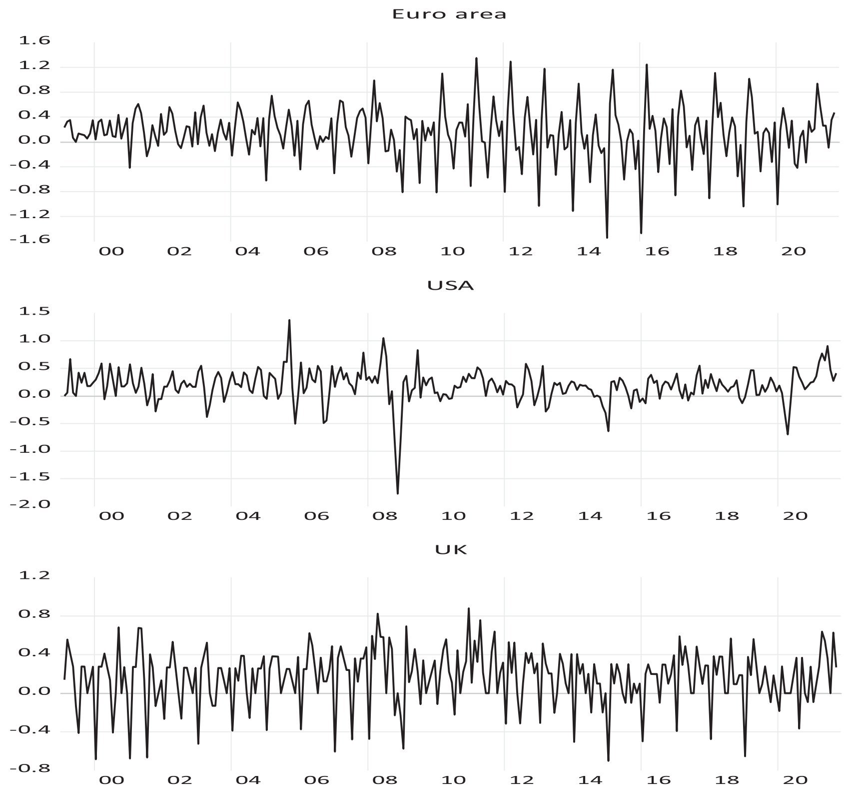

FIGURE 1 Inflation in the euro area, the United States, and the United Kingdom.

known for many years that combining forecasts often acts to produce a forecast with a lower error in variance. Indeed, for an in-sample forecast, it can be demonstrated that a forecast using entire sample and OLS weights must always produce a combined forecast that is either equal in variance or less in variance than the best of the forecasts being combined. This is not, however, true in general for out-of-sample recursive OLS weights although combinations of forecasts still often perform well. In light of this circumstance, Gibson et al. (2020) propose using true time-varying weights (rather than recursive OLS), estimated with the Kalman filter. Here, again, the one step ahead weights must be used in the forecast combination as the smoothed weights would contain information from the future that is unknown at time t. This then can be seen as a generalization of the fixed window techniques described above, as the Kalman filter gives a geometrically declining weights of the parameter estimates from $t = 1 \ldots t_1$, where t_1 is the period being forecast. The rate of the decline is an estimated function of the variance in the state space form. Therefore, rather than using a fixed-window length selected by one of the criteria above, the Kalman filter estimates the speed of the decline based on maximum likelihood.

In using the Kalman filter to approximate any nonlinear form, we make use of the Swamy theorem under which any nonlinear function can be represented by a set of time-varying coefficients.[5] Under this theorem, we do not have to use a particular nonlinear form.

In our set of forecasts, we will take the forecasts from the best of our earlier models and assess if one step ahead Kalman filter weights can produce a better forecast than the models we use to create the combination.

4 | DATA

As mentioned, our focus is on forecasting the monthly rate of inflation for the three currency areas. Inflation is the month-over-month percentage change in the currency union's respective consumer price index.[6] The data are mainly from 1999M1 to 2022M4. Figure 1 displays the data on inflation for the three currency areas.

In Figure 1, we observe a strong seasonal component in the inflation data for the euro zone and the UK. In the forecasting exercises below, we will add a 12th lagged dependent variable to capture the possibility of stochastic seasonality that appears to be present.

[5]See Swamy and Mehta (1975). Granger (2008) provides confirmation of this theorem, although he attributes the proof to Halbert White.
[6]We use month-over-month inflation data because data based on a month in a particular year over the corresponding month of the previous contain a large amount of serial correlation and data that are already known.

As is evident in Figure 1, an important feature of the inflation data is that they are stationary.[7] Consequently, the data differ from corresponding data on inflation from the 1970s and 1980s during which inflation was typically nonstationary. As we discuss below, a reason why some studies have found that rolling windows improve forecasts is that those studies include data that are nonstationary. The link between nonstationarity and the effectiveness of rolling windows is, fundamentally, that a nonstationary process may be viewed as a series of structural breaks (see Hendry & Massmann, 2007, for a discussion of co-breaking and its relationship to stationarity and cointegration). The rolling window technique was developed with a specific objective of dealing with a series subject to structural breaks. If we move the data period from one in which inflation was clearly nonstationary (the 1970s, 1980s, and 1990s) to one where it appears to have become stationary (2000s and 2010s), then there will be less, or even no, substantial structural breaks; hence, the advantage of rolling windows largely disappears.

The data used for the exogenous variables of each currency area differ slightly because of issues of data availability. For the euro zone, we use the following: the euro/pound sterling exchange rate, the euro/US dollar exchange rate, the expected inflation rate, total government spending, industrial production index, the long-term interest rate, the M3 measure of the money supply, the price of Brent crude oil, the price of WTI oil, the output gap, the short-term interest rate, and the unemployment rate. For the United Kingdom, we use the euro/pound sterling exchange rate, the pound sterling/US dollar exchange rate, expected inflation, the government fiscal deficit, government spending, industrial production index, the long-term interest rate, several measures of the money supply (M0, M1, M2, and M3), the Brent crude price of oil, the WTI price of oil, the output gap, real GDP, the short-term interest rate, the unemployment rate, and the aggregate wage rate. For the United States, we use the euro/US dollar exchange rate, the pound sterling/US dollar exchange rate, expected inflation, the government deficit, government spending, industrial production index, the long-term interest rate, the M2 measure of the money supply, the long-term NAIRU, the short-term NAIRU, the Brent crude oil price, the WTI oil price, the output gap, real GDP, the short-term interest rate, the unemployment rate, and the aggregate wage rate. Precise definitions of the variables and the data sources are provided in Appendix A.

[7]Formal tests of stationary are available from the authors.

5 | RESULTS

5.1 | Structural breaks and moving window results

As our main metric for comparing the one step ahead forecasting accuracy of the various models we have outlined, we will use the MSFE. Of the main metrics usually used, the root mean square forecast error will always give the same ranking of the models as the MSFE, so there is little extra information gained by reporting this. The other two main metrics are the percentage mean square forecast error and the percentage root mean square forecast error. These can both give misleading results when the variable under consideration can take the value of zero (as the percentage error then becomes infinite); because inflation on a monthly basis can cross the zero value and some observations are effectively zero, these measures will not be used.

As a basic point of comparison, we begin by reporting the forecasting ability of a simple random walk without drift, and then, the other may be compared with this basic model.

We begin by reporting the results for the United States in Table 1.

The table provides the following information. The first row gives the MSFE from the random walk for the entire period. The second row gives the MSFE for the AR(1) model under five assumptions about the break and the window technique:

1. Fixed uses a fixed rolling window of $T = 60$.
2. Post-break uses all of the data after the break.
3. PTCV unknown uses the PTCV method with an unknown break date.
4. PTCV estimated uses the PTCV method with the break date estimated based on the tests described above.
5. IJR uses the window length that minimizes the MSFE.

The same procedure was followed for the AR model with the number of lags determined by the AIC (row 3) and the BIC (row 4). Finally, the bottom of the table introduces lags of exogenous variable into the models. Tables 2 and 3 below have similar structures.

As reported in Table 1, the best performing model is given by the univariate autoregressive model where the lag selection is made using the BIC. The window length selection makes a little difference with the best model using a fixed window length. The PTCV method with estimated break date does as well as the IJR selection method. A basic finding is that the addition of exogenous

TABLE 1 United States results for the moving window forecasts.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.100				
AR(1)	0.081	0.092	0.083	0.082	0.083
AR (AIC)	0.088	0.164	0.092	0.090	0.095
AR (BIC)	**0.080**	0.093	0.081	0.081	0.080
Variable x	ARX model y(t + 1) = c + aL*y(t) + bL*x(t) + u				
Ex. EUUS	0.082	0.103	0.087	0.087	0.095
Ex. UKUS	0.084	0.127	0.108	0.108	0.110
Expinf	0.084	0.147	0.089	0.089	0.096
Govdef	0.087	0.109	0.093	0.093	0.096
Govspend	0.094	0.110	0.097	0.097	0.099
Ip	0.085	0.168	0.101	0.101	0.108
Ltir	0.085	0.102	0.086	0.086	0.089
M2	0.085	0.149	0.093	0.093	0.098
Nairu_lt	0.085	0.109	0.092	0.092	0.096
Nairu_st	0.087	0.118	0.095	0.095	0.103
Oil_brent	0.085	0.129	0.088	0.088	0.092
Oil_wti	0.085	0.129	0.088	0.088	0.092
Outgap	0.085	0.125	0.093	0.093	0.095
Rgdp	0.085	0.116	0.089	0.089	0.095
Stir	0.085	0.101	0.087	0.087	0.088
Unrate	0.087	0.151	0.095	0.094	0.132
Wage	0.086	0.111	0.090	0.090	0.092

TABLE 2 Euro area results for the moving window forecasts.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.414				
With 12-month inflation lag					
AR(1)	0.076	0.080	0.077	0.077	0.079
AR (AIC)	0.079	0.089	0.079	0.079	0.080
AR (BIC)	0.077	0.081	0.077	0.077	0.079
Variable x	ARX model				
Ex. EUUK	0.082	0.095	0.084	0.084	0.085
Ex. EUUS	0.076	0.096	0.079	0.078	0.084
Expinf	0.080	0.105	0.083	0.082	0.089
Govspend	0.080	0.110	0.083	0.083	0.101
Ip	0.080	0.099	0.083	0.084	0.091
Ltir	0.080	0.103	0.082	0.082	0.085
M3	0.080	0.106	0.083	0.083	0.090
Oil_brent	0.080	0.100	0.080	0.080	0.087
Oil_wti	0.078	0.102	0.079	0.079	0.085
Outgap	**0.074**	0.095	0.080	0.080	0.087
Stir	0.079	0.110	0.081	0.080	0.095
Unrate	0.082	0.110	0.086	0.087	0.097

Note: In this table, a 12th lag of inflation was added to all models to allow for a strong seasonal effect that was present in the data, except for the random walk model.

TABLE 3 United Kingdom results for the moving window forecasts.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.171				
With 12-month inflation lag					
AR(1)	0.054	0.058	**0.054**	0.054	0.054
AR (AIC)	0.056	0.061	0.055	0.055	0.057
AR (BIC)	0.054	0.058	**0.054**	0.054	0.054
Variable x	ARX model				
Ex. EUUK	0.056	0.078	0.056	0.056	0.058
Ex. UKUS	0.054	0.062	0.056	0.056	0.062
Expinf	0.055	0.059	0.057	0.056	0.060
Govdef	0.054	0.067	0.056	0.056	0.058
Govspend	0.057	0.060	0.057	0.057	0.062
Ip	0.057	0.085	0.063	0.063	0.066
Ltir	0.055	0.075	0.056	0.055	0.055
M0	0.057	0.072	0.060	0.059	0.063
M1	0.058	0.061	0.057	0.057	0.058
M2	0.059	0.074	0.058	0.058	0.065
M3	0.059	0.070	0.058	0.058	0.069
Oil_brent	0.057	0.060	0.057	0.057	0.056
Oil_wti	0.054	0.061	0.055	0.054	0.054
Outgap	0.056	0.073	0.070	0.069	0.071
Rgdp	0.057	0.064	0.058	0.058	0.059
Stir	0.057	0.061	0.058	0.058	0.058
Unrate	0.058	0.067	0.061	0.061	0.063
Wage	0.057	0.089	0.056	0.057	0.059

Note: In this table, a 12th lag of inflation was added to all models to allow for a strong seasonal effect that was present in the data, except for the random walk model.

variables does not generally improve the forecasting accuracy.

Table 2 gives the results for the euro area. All models do considerably better than the simple random walk. The best performing model is given by the model with the output gap variable added. The addition of the output gap variable produces a small improvement over the univariate models, although the addition of exogenous variables generally does not improve the forecasting ability of the models. Among the univariate models, the simple AR(1) does better than the more complex AR models. The window selection methods do not produce any improvements.

Table 3 reports the results for the United Kingdom. Again, all models do considerably better than the simple random walk. The best univariate time series model is the AR(1) with all window selection criteria performing in a very similar way. The addition of exogenous information does not improve the forecasting accuracy, although some of the models that include exogenous information do as well as the simple AR(1) model.

5.2 | Factor forecasts

We begin by showing the factors we created from the full set of exogenous variables used in each region. We have chosen to use the first two or four factors—in each case for two reasons: the first two factors explain over 90% of the variation in the data; and using too many factors with their lags starts to impose an undesirable limit on the minimum window size that can be used.

Figures 2 and 3 show the factors for the United States. Table 4 reports the forecasts. In most cases, the dynamic factor models perform better than the principal components. The two-factor models generally do better than the variants using four factors. Overall, the best performing model uses the dynamic factors with two-lagged factors and an AR(1) specification.

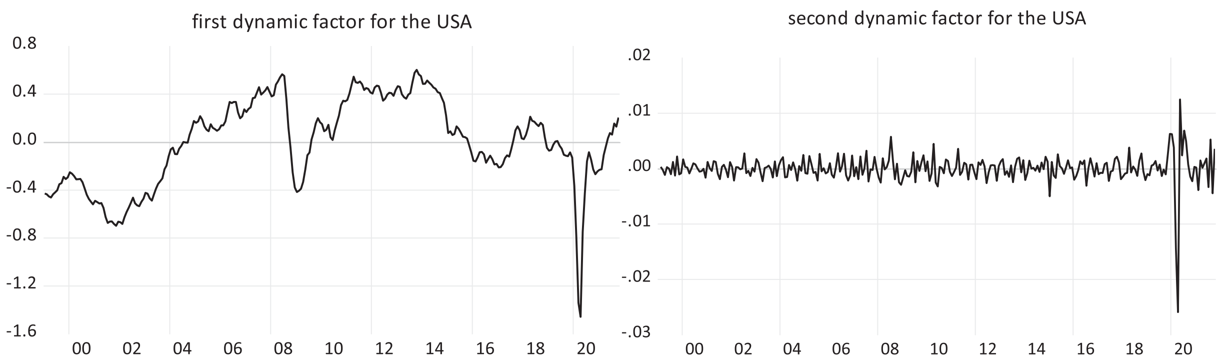

FIGURE 2 The dynamic factors for the United States.

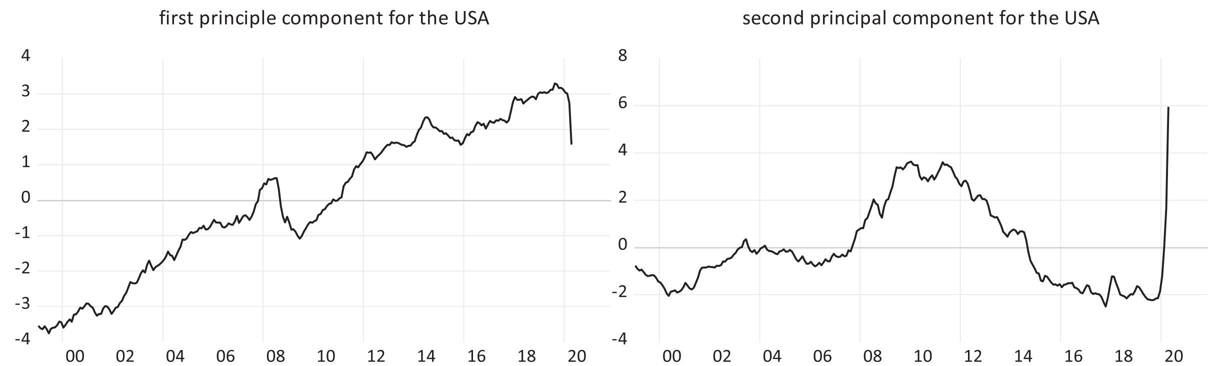

FIGURE 3 The principal component factors for the United States.

TABLE 4 Forecasts for the United States using the factor models.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.100				
2factors	0.105	0.112	0.105	0.106	0.109
2f AR(1)	0.087	0.134	0.100	0.099	0.095
2f AR (AIC)	0.087	0.164	0.092	0.091	0.101
2f AR (BIC)	0.088	0.170	0.100	0.098	0.101
2f(1) AR(1)	**0.081**	0.117	0.074	0.073	0.076
4factors	0.111	0.206	0.121	0.120	0.138
4f AR(1)	0.095	0.209	0.103	0.103	0.109
4f AR (AIC)	0.092	0.279	0.104	0.102	0.115
4f AR (BIC)	0.096	0.283	0.106	0.105	0.127
2pc	0.109	0.127	0.114	0.114	0.113
2pc AR(1)	0.091	0.116	0.095	0.094	0.101
2pc(1) AR(1)	0.086	0.209	0.089	0.088	0.092
4pc	0.121	0.171	0.135	0.135	0.144
4pc AR(1)	0.104	0.200	0.116	0.116	0.140

Figures 4 and 5 display the dynamic factors and principal components, respectively, for the euro area. Table 5 reports the results for the euro area. The factors do not add anything to the forecasting performance relative to the simple AR(1) model. The four-factor models perform worse than the two-factor models and there is little difference between the dynamic factor and the principal component models.

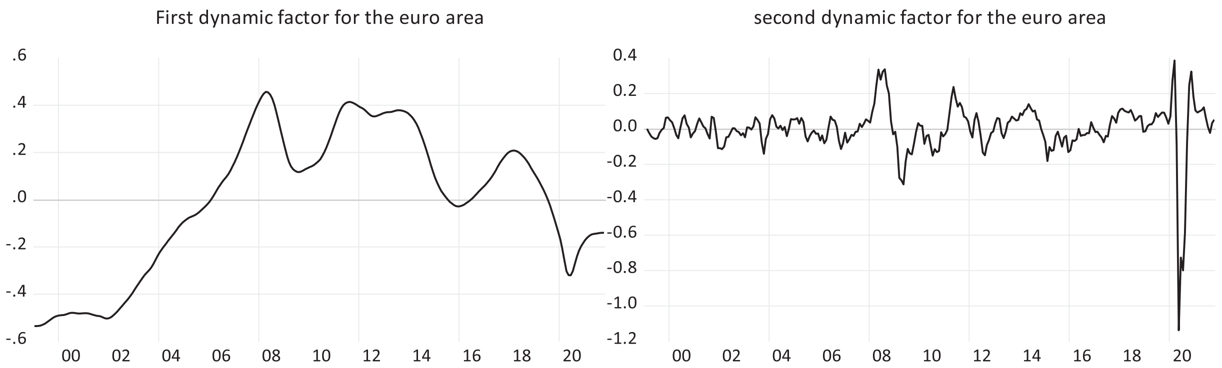

FIGURE 4 The dynamic factors for the euro area.

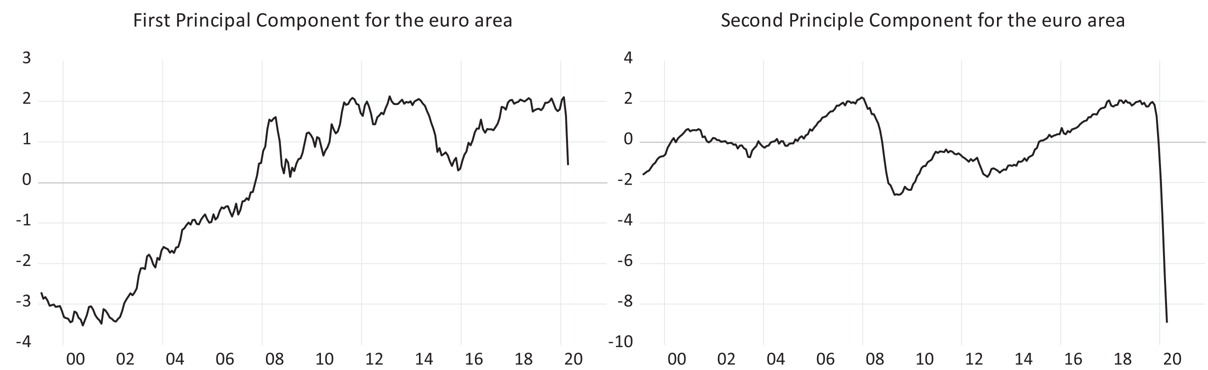

FIGURE 5 The principal components for the euro area.

TABLE 5 Forecasts for the Euro area using the factor models.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.414				
With 12-month inflation lag					
	Factor models				
2f AR(1)	0.084	0.131	0.093	0.094	0.105
2f AR (AIC)	0.087	0.140	0.096	0.097	0.112
2f AR (BIC)	0.086	0.134	0.094	0.096	0.112
2f(1) AR(1)	0.082	0.292	0.086	0.088	0.153
4f AR(1)	0.085	0.294	0.092	0.093	0.139
2pc AR(1)	0.083	0.105	0.091	0.092	0.109
2pc(1) AR(1)	0.081	0.428	0.085	0.084	0.173
4pc AR(1)	0.085	0.205	0.094	0.094	0.200

Note: In this table, a 12th lag was added to all models to allow for a strong seasonal effect that was present in the data with the exception of the random walk model.

Figure 6 shows the dynamic factors for the United Kingdom, and Figure 7 shows the principal components. Table 6 reports the forecasts for the United Kingdom. The best performing model overall is the AR(1) specification with two principal components. Generally, there is not much difference between the performance of the dynamic factors and the principal components.

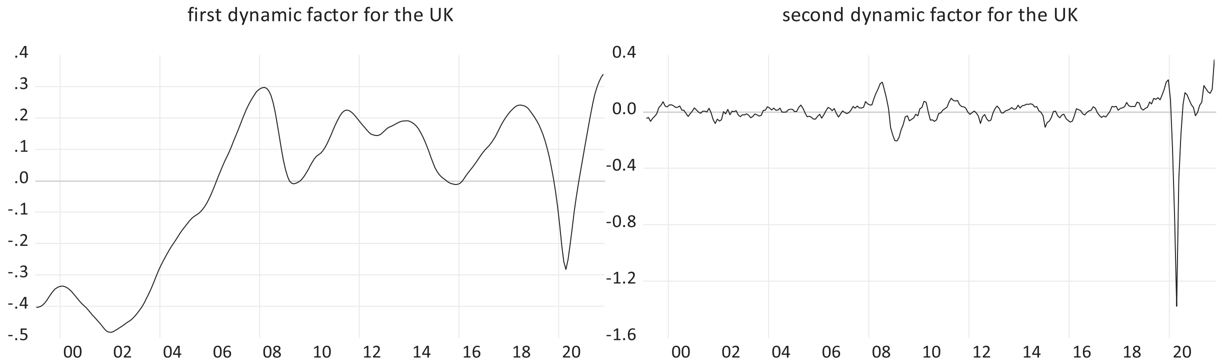

FIGURE 6 The dynamic factors for the United Kingdom.

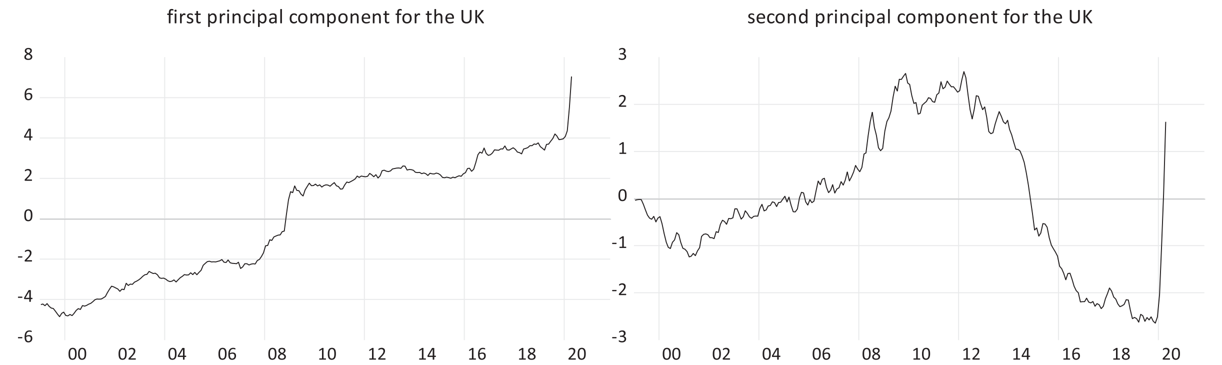

FIGURE 7 The principal components for the United Kingdom.

TABLE 6 Forecasts for the United Kingdom using the factor models.

MSFE	Fixed	Post-break	PTCV unknown	PTCV estimated	IJR
RW	0.171				
With 12-month inflation lag					
	Factor models				
2f AR(1)	0.058	0.068	0.058	0.058	0.068
2f AR (AIC)	0.059	0.087	0.061	0.060	0.072
2f AR (BIC)	0.058	0.068	0.058	0.058	0.068
2f(1) AR(1)	0.059	0.277	0.059	0.059	0.147
4f AR(1)	0.069	0.151	0.075	0.075	0.116
2pc AR(1)	**0.049**	0.081	0.052	0.051	0.061
2pc(1) AR(1)	0.053	0.184	0.059	0.058	0.064
4pc AR(1)	0.058	0.356	0.059	0.058	0.081

5.3 | Combining the forecasts with time-varying weights

We next examine the suggestion of Gibson et al. (2020) to use time-varying combination weights to combine some of the best forecasts together. We will choose the simple AR model with the lowest MSFE, the exogenous variable model with the lowest MSFE, and the factor model with the lowest MSFE and combine them in the following time-varying parameter regression:

$$inf_t = \beta_{1t} inf_{ts,t} + \beta_{2t} inf_{ex,t} + \beta_{3t} inf_{fac,t} + u_t \tag{10}$$

where $\inf_t$ is actual inflation at period t, $\inf_{ts,t}$ is the forecast for inflation at time t made by the best simple

	United States	Euro area	United Kingdom
Best MSFE from the models	0.081	0.074	0.054
Average linear combination	0.080	0.0753	0.0461
OLS linear combination	0.080	0.0726	0.0452
Combined MSFE	0.0689	0.0567	0.0406

TABLE 7 The forecasts from time-varying combinations.

univariate time series model, $\inf_{ex,t}$ is the forecast for inflation at time t made by the best model using an exogenous variable, and $\inf_{fac,t}$ is the forecast for inflation made at time t by the best factor model. Equation (10) is in effect the measurement equation for the Kalman filter. We use a random walk specification for each of the three state equations, as follows

$$\beta_{it} = \beta_{it-1} + \varepsilon_{it} \quad i = 1 \ldots 3 \tag{11}$$

Next, we take the predicted version of the state variables (not the smoothed version as this would contain future information) and use Equation (10) to generate a series of forecast errors. We then simply square these and average them over the estimation period to produce a MSFE to compare with our earlier models. We do this for each of our three regions. As a point of comparison, we also carry out a simple average of the best three forecasts, simple averaging is often found in the literature to perform nearly as well as more complex combination methods. Finally, we also consider a whole sample OLS (linear) combination. This is not a feasible combination technique in practice as the weights are derived from the whole sample. It is, however, a useful comparison as this gives the very best linear combination that it is possible to achieve. The results are reported in Table 7. The average forecasts and the OLS linear combination produce no improvement.

In the case of the United States, the combined nonlinear forecast produces around a 15% reduction in the MSFE, whereas in the case of the other two regions, it produces around a 25% reduction. This represents a considerable increase in forecasting accuracy. The average of the three best forecasts gives a very small improvement over the best of the three, and the OLS weights again provide a small improvement (except in the case of the United States where the OLS combination did not perform any better than the average). The main improvement comes in the nonlinear combination.

5.4 | Discussion

As mentioned, the data on inflation for the period covered in this study are stationary. Likely reflecting this circumstance, forecasts based on rolling windows do not improve forecasts compared with a simple AR model with lags determined by the information criteria. The inclusion of exogenous variables to the AR models, which includes factor analysis, also do not add much value to forecast accuracy, perhaps reflecting the fact that a stationary variable, based on Wold's decomposition theory, can be specified as a suitable moving average (MA) or AR process.

Under the well-established fact that (1) a linear forecast combination can always do at least as well as the best of the individual forecasts, and (2) nonlinear forecast combination should do at least as well as the linear combination—because the nonlinear combination can always select constant coefficients—we would expect the nonlinear forecast combination to produce a substantial improvement. Our findings confirm this expectation.

6 | CONCLUSION

We have considered the problem of forecasting inflation in the United States, the euro area, and the United Kingdom. The forecasting literature has suggested that the problem of changing parameters and structural breaks may be improved by using estimation based on moving windows of the correct length. Various proposals have been made to select the appropriate window length. We extend these methods by considering models that incorporate unobserved factors by using both principal components and dynamic factors to investigate if these extensions improve the ability to forecast. Finally, given the extensive literature on forecast combinations, we consider combining some of the best forecasts using time-varying combination weights.

Our basic findings are as follows. First, for the period covered in our sample forecasts based on rolling windows do not improve forecasting accuracy compared with simple AR models. Second, factor models using principal components or dynamic factors also do not show a significant improvement in forecasting ability compared with simple AR models. Third, significant forecast accuracy is gained using nonlinear forecast combinations. A suggestion for further research is to apply the techniques used in this paper to long data samples that include both stationary and nonstationary data. Another suggestion is to use a Monte Carlo study to investigate the effect of breaks on these techniques.

The main reason for the finding that sophisticated rolling window techniques do not improve forecasts of inflation is that, over the sample we examine, the inflation data are stationary. In this connection, an AR(1) process performs effectively as there are no substantial structural breaks in a stationary process. In contrast, the data period used in the rolling window literature (1970s to 1990s) shows strong nonstationarity and, hence structural breaks. We would speculate that where data for other variables exhibit a pattern of stationarity after having been nonstationary, there would be a similar decline in the usefulness of rolling windows.

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DATA AVAILABILITY STATEMENT

All data are taken from publicly available data sources as defined in the data appendix. The particular vintage of data used in this study is available upon request from the authors.

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APPENDIX A

Data for the United States.

Ex. EUUS	Euro to US dollar exchange rate, average https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html.
Ex. UKUS	US dollars to UK pound Sterling exchange rate, average https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
Govdef	USA government deficit as a percentage of nominal GDP https://fred.stlouisfed.org/series/FGLBAFQ027S
Govspend	Final government expenditure as a percentage of nominal GDP, https://fred.stlouisfed.org/series/W068RCQ027SBEA
Ip	Industrial Production: Total Index, Index 2017 = 100, Seasonally Adjusted, https://fred.stlouisfed.org/series/INDPRO
Ltir	Market yield on US Treasury securities at 10-year constant maturity, percent, https://fred.stlouisfed.org/series/GS10
m2	USA, M2, billions of dollars, monthly, https://fred.stlouisfed.org/series/M2NS
nairu_lt	Noncyclical rate of unemployment, percent, quarterly, not seasonally adjusted https://fred.stlouisfed.org/series/NROU
nairu_st	Natural rate of unemployment (short-term) (DISCONTINUED), percent, quarterly, not seasonally adjusted https://fred.stlouisfed.org/series/NROUST
oil_brent	Crude oil prices: Brent-Europe, dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Crude oil prices: West Texas intermediate (WTI)-Cushing, Oklahoma, dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILWTICO
Outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, "Measuring the Natural rate of Interest: International Trends: International Trends and Determinants"
Rgdp	National Accounts, expenditure, gross domestic product, real, seasonally adjusted, domestic currency, in millions, https://data.imf.org/?sk=4C514D48-B6BA-49ED-8AB9-52B0C1A0179B&sId=1390030341854
Stir	3-month Treasury bill secondary market rate, percent, monthly, not seasonally adjusted, https://fred.stlouisfed.org/series/TB3MS
Unrate	Unemployment rate, percent, monthly, seasonally adjusted, https://fred.stlouisfed.org/series/UNRATE
Wage	Employed full time: Median usual weekly nominal earnings (second quartile): Wage and salary workers: 16 years and over, dollars, quarterly, interpolated to monthly, https://fred.stlouisfed.org/series/LES1252881500Q

Data for the euro area.

Ex. EUUK	Euro to UK pound sterling exchange rate, average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Ex. EUUS	Euro to US dollar, average, https://sdw.ecb.europa.eu/browseTable.do?org.apache.struts.taglib.html
Expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
Govspend	Final consumption expenditure—euro area 19 (fixed composition)—world (all entities, including reference area, including IO), general government, euro, current prices, non transformed data, % of nominal GDP, https://sdw.ecb.europa.eu
Ip	Euro area 19 (fixed composition)—industrial production index, Total industry—NACE Rev2; Eurostat; working day adjusted, https://sdw.ecb.europa.eu
Ltir	Long-term government bond yields: 10-year: Main (including benchmark) for Germany, percent, monthly, not seasonally adjusted, https://fred.stlouisfed.org/series/IRLTLT01DEM156N
m3	M3 for the euro area, National Currency, monthly, not seasonally adjusted, https://fred.stlouisfed.org/series/MABMM301EZM189N
oil_brent	Crude oil prices: Brent-Europe, dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILWTICO
Outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, "Measuring the Natural rate of Interest: International Trends: International Trends and Determinants"
Stir	Euro area (moving concept in the real time database context)-rate: 3-month Euribor (euro interbank offered rate)-euro, average of observations through period, https://sdw.ecb.europa.eu
Unrate	Euro area 19 (fixed composition) as of 1 January 2015; European Labour Force Survey; Unemployment rate; Total; Age 15 to 74; Total; Seasonally adjusted, not working day, https://sdw.ecb.europa.eu

Data for the United Kingdom.

Ex. EUUK	Euro to UK pound sterling exchange rate, average
Ex. UKUS	US dollars to UK pound Sterling exchange rate, average
Expinf	Inflation forecast is measured in terms of the consumer price index (CPI). Source expected inflation, OECD, https://data.oecd.org/price/inflation-forecast.htm
Govdef	Government deficit, net lending (+)/net borrowing (−) as a percentage of GDP - general government, https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/ct8o/ukea
Govspend	Nominal general government final consumption expenditure for Great Britain, domestic currency, quarterly, interpolated to monthly and expressed as a percentage of nominal GDP, https://fred.stlouisfed.org/series/NCGGSAXDCGBQ
Ip	Production of Total Industry in the United Kingdom, Index 2015 = 100, Monthly, Seasonally Adjusted, https://fred.stlouisfed.org/series/GBRPROINDMISMEI
Ltir	Long-term government bond yields: 10-year: Main (including benchmark) for the United Kingdom, percent, monthly, not seasonally adjusted, https://fred.stlouisfed.org/series/IRLTLT01GBM156N
m0	Monthly average amount outstanding of total sterling notes and coin in circulation, excluding backing assets for commercial banknote issue in Scotland and Northern Ireland, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
m1	Monthly amounts outstanding of monetary financial institutions' sterling and all foreign currency M1 (UK estimate of EMU aggregate) liabilities to private and public sectors (in sterling millions) not seasonally adjusted, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp Monthly amounts outstanding of monetary financial institutions' sterling and all foreign currency M1 (UK estimate of EMU aggregate) liabilities to private and public sectors, https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
m2	Monthly amounts outstanding of monetary financial institutions' sterling and all foreign currency M2 (UK estimate of EMU aggregate) liabilities to private and public sectors (in sterling millions) not seasonally adjusted https://www.bankofengland.co.uk/boeapps/database/BankStats.asp

(Continues)

m3	Monthly amounts outstanding of monetary financial institutions' sterling and all foreign currency M3 (UK estimate of EMU aggregate) liabilities to private and public sectors (in sterling millions) not seasonally adjusted https://www.bankofengland.co.uk/boeapps/database/BankStats.asp
oil_brent	Crude oil prices: Brent - Europe, dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILBRENTEU
oil_wti	Dollars per barrel, monthly, https://fred.stlouisfed.org/series/DCOILWTICO
Outgap	The output gap. Estimated by Kathryn Holston, Thomas Laubach, and John C. Williams, Journal of International Economics, 2017, "Measuring the Natural rate of Interest: International Trends: International Trends and Determinants"
Rgdp	Real GDP, National Accounts, expenditure, gross domestic product, real, seasonally adjusted, domestic currency, in millions, https://data.imf.org
Stir	Short-term interest rate, 3-month or 90-day rates and yields: Interbank rates for the United Kingdom, percent, monthly, not seasonally adjusted, https://fred.stlouisfed.org/series/IR3TIB01GBM156N
Unrate	Unemployment rate (aged 16 and over, seasonally adjusted), https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/mgsx/lms
Wage	Average weekly earnings: Whole economy level (£): Seasonally adjusted Total pay excluding arrears, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/timeseries/kab9/emp

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