

Verona, Fabio

Working Paper

From waves to rates: Enhancing inflation forecasts through combinations of frequency-domain models

Bank of Finland Research Discussion Papers, No. 1/2025

Provided in Cooperation with:

Bank of Finland, Helsinki

Suggested Citation: Verona, Fabio (2025) : From waves to rates: Enhancing inflation forecasts through combinations of frequency-domain models, Bank of Finland Research Discussion Papers, No. 1/2025, Bank of Finland, Helsinki,
<https://nbn-resolving.de/urn:nbn:fi-fe202501031242>

This Version is available at:

<https://hdl.handle.net/10419/308098>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Bank of Finland Research Discussion Papers
1 • 2025

Fabio Verona

From waves to rates: enhancing inflation forecasts through combinations of frequency-domain models



Bank of Finland
Research

Bank of Finland Research Discussion Papers
Editor-in-Chief Esa Jokivuolle

Bank of Finland Research Discussion Papers 1/2025
3 January 2025

Fabio Verona:
From waves to rates: enhancing inflation forecasts through combinations of frequency-domain models

ISSN 1456-6184, online

Bank of Finland
Research Unit

PO Box 160
FIN-00101 Helsinki

Phone: +358 9 1831

Email: research@bof.fi

Website: www.suomenpankki.fi/en/research/research-unit/

The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Bank of Finland.

From waves to rates: enhancing inflation forecasts through combinations of frequency-domain models[◇]

Fabio Verona*

Abstract

This paper addresses the challenge of inflation forecasting by adopting a thick modeling approach that integrates forecasts from time- and frequency-domain models. Frequency-domain models excel at capturing long-term trends while also accounting for short-term fluctuations. Combining these models with traditional approaches leverages their complementary strengths, resulting in forecasts that consistently outperform individual methods, especially during periods of heightened inflation volatility. By pooling insights from diverse modeling frameworks, this study provides a robust and effective strategy for improving inflation forecasts across different horizons.

Keywords: inflation forecasting, forecast combination, wavelets, Haar filter, time-varying parameters, Phillips curve

JEL codes: C32, C53, E31, E37, E43, E44

[◇] The views expressed are those of the authors and do not necessarily reflect those of the Bank of Finland. Any remaining errors are the sole responsibility of the authors. We thank Gene Ambrocio, Esa Jokivuolle, and Mikael Juselius for useful comments.

* Bank of Finland – Monetary Policy and Research Department, and University of Porto – *Cef.up* (f8fabio@yahoo.it)

1 Motivation for a new approach to forecasting inflation

The left panels of figure 1 display the annualized one-quarter, one-year, and two-year average Consumer Price Index (CPI) inflation rates in the U.S. (black line), alongside their long-term trend (blue line) and NBER recessions (gray shaded bars). After the disinflation of the 1980s, inflation remained relatively low and stable for about 30 years, punctuated by two notable events: a sharp decline followed by a quick recovery during the 2007-2008 Global Financial Crisis (GFC) and a significant rise and subsequent fall following the COVID-19 recession. The right panels of figure 1 reveal similar patterns for the one-quarter, one-year, and two-year average Personal Consumption Expenditures (PCE) inflation rates.

These inflation dynamics – characterized by slow-moving long-term trends interrupted by abrupt, mean-reverting fluctuations – pose significant challenges for forecasters (e.g., Stock and Watson, 1999). Despite extensive research, forecasting inflation with greater accuracy than simple univariate models remains difficult. The first and most critical step in effective inflation forecasting is to track its slow-moving, time-varying trend accurately (del Negro and Schorfheide, 2013 and Faust and Wright, 2013). However, this alone is insufficient to consistently outperform the benchmark random walk model. The key challenge lies in simultaneously capturing both the slow-moving trend and high-frequency, short-term fluctuations, making it nearly impossible for any single variable or econometric model to consistently excel across all time periods.

This paper advances the development of better inflation forecasting models by adopting a thick modeling approach, as proposed by Granger and Jeon (2004). This approach involves generating multiple model forecasts and pooling the results. Specifically, we construct a suite of forecasting models designed to produce reasonable inflation predictions up to two years ahead. Some models excel at tracking long-term trends, while others focus on short-term fluctuations around these trends. By averaging or combining these forecasts, we aim to enhance the accuracy and robustness of inflation predictions.

This paper makes several contributions to the inflation forecasting literature. First, we include simple bivariate models with financial variables as predictors, which are often overlooked in favor of more

complex models such as VARs, factor models, and term-structure models. This allows forward-looking financial variables to play a more prominent role in the forecasting exercise, addressing a gap left by studies like Stock and Watson (2003), which examined the forecasting power of a large set of asset price variables only up to 1999. Second, we estimate these models using time-varying coefficients (TVC) to assess whether they enhance predictability by effectively capturing the time-variation in the relationship between inflation and its predictors. Third, we incorporate frequency-domain models into our model suite, leveraging their proven ability to capture both long-term trends and high-frequency fluctuations more effectively than traditional time-series approaches, as demonstrated in prior research (e.g., Faria and Verona, 2018 for stock market return and Martins and Verona, 2024 for inflation). Finally, we combine forecasts from these frequency-domain models with those from conventional time-series models to assess the additional value they bring to inflation forecasting, particularly in capturing the nuanced dynamics of inflation over different horizons.

Our main findings are summarized as follows.

1. ***Short-horizon challenges.*** Predicting inflation over short horizons (e.g., one-quarter ahead) is notably harder than at longer horizons (e.g., one or two years). Short-horizon forecasts often produce large errors, particularly around sharp turning points such as the one observed at the onset of the GFC.
2. ***Advantages of time-varying coefficients.*** Models with TVC outperform constant-coefficient models, particularly for CPI inflation forecast. This underscores the importance of accounting for parameter instability.
3. ***Survey-based forecasts.*** The Survey of Professional Forecasters (SPF) produces better one- and two-year forecasts compared to the Michigan Survey of Consumers, which struggles to outperform the benchmark random walk model.
4. ***Frequency-domain models.*** While most frequency-domain models perform comparably to time-domain models, the frequency-domain Phillips curve delivers superior long-horizon CPI inflation

forecasts.

5. ***Combination effectiveness.*** Forecast combinations generally outperform individual models by reducing errors. However, combining all models indiscriminately underperforms compared to the best individual models.
6. ***Trimming the model set.*** Limiting combinations to a subset of four models significantly improves forecasting performance. At short horizons, combinations with time-varying weights excel, while equal-weight combinations perform better at longer horizons.
7. ***Frequency-domain insights.*** Forecast combinations incorporating frequency-domain information outperform time-domain counterparts, especially at longer horizons. The low-frequency component of the term spread emerges as a consistently valuable predictor.

The rest of this paper is organized as follows. Section 2 provides a concise literature review on inflation forecasting. Section 3 describes the data, while section 4 outlines the forecasting models and methodology. Section 5 presents the empirical results, and section 6 concludes.

2 A brief literature review on inflation forecasting

The history of inflation forecasting dates back to early theoretical models like Fisher (1911). However, modern econometric approaches gained prominence during the 1970s and 1980s, driven by works such as Gordon (1977) and Sims (1980). A comprehensive survey of the extensive literature on inflation forecasting is provided by Faust and Wright (2013). Notable recent studies on U.S. inflation forecasting include Berge (2018), Dur and Martínez García (2020), Fulton and Hubrich (2021), and Eugster and Uhl (2024), while studies on Euro area inflation include Hubrich and Skudelny (2017), Jarocinski and Lenza (2018), Banbura and Bobeica (2023), and Huber, Onorante and Pfarrhofer (2024).

The most common methods for inflation forecasting encompass a wide range of techniques. These include time series models (e.g., AutoRegressive Integrated Moving Average (ARIMA) and exponential smoothing like the Holt-Winters method), economic models (e.g., Phillips curve and leading indicator models), structural econometric models (e.g., Bayesian Vector AutoRegression (VAR) and Dynamic Stochastic General Equilibrium (DSGE) models), survey-based methods, and market-based methods (e.g., inflation-linked securities). Despite their widespread use, these models often struggle with forecasting accuracy in their original formulations. This paper explores two key strands of literature aimed at improving inflation predictability.

The first strand focuses on enhancing econometric sophistication. Approaches include time-varying coefficient (TVC) models, model combinations, threshold models, and Markov-switching models. These techniques are better equipped to capture time variation and state dependency in forecasts. Specifically, this paper employs TVC models and forecast combination techniques.

TVC models have predominantly been applied within the contexts of Phillips curve and VAR models (see, e.g., Stock and Watson, 2007, Koop and Korobilis, 2012, D’Agostino, Gambetti and Giannone, 2013, Clark and Doh, 2014, and Clark and Ravazzolo, 2015). While generally effective, they can exhibit instabilities over time. In this paper, we utilize TVC models in simple bivariate regression frameworks to generate baseline individual forecasts.

Forecast combination models have gained significant traction in inflation forecasting (see the surveys of Timmermann, 2006, Aiolfi, Capistran and Timmermann, 2011, and Wang, Hyndman, Li and Kang, 2023). These models capitalize on the strengths of diverse approaches, reduce forecast errors, and effectively address model uncertainty. Applications to inflation forecasting include Stock and Watson (2004), Ang, Bekaert and Wei (2007), Bjørnland, Gerdrup, Jore, Smith and Thorsrud (2012), Hubrich and Skudelny (2017), and Fulton and Hubrich (2021).¹ The prevailing consensus is that forecast combinations generally outperform individual methods. This paper adopts this approach, combining individual

¹ Beyond inflation, combination methods have also been used for forecasting output and industrial production (Stock and Watson, 2003), output growth (Stock and Watson, 2004), equity premiums (Rapach, Strauss and Zhou, 2010), and multiple macroeconomic variables (Pirschel and Wolters, 2018).

forecast models to produce the final inflation forecasts.

The second strand leverages frequency-domain methods, such as Fourier and wavelet transforms, which analyze the cyclical components of time series data instead of aggregate data. These methods identify and utilize specific frequency bands to ultimately enhance forecasting accuracy. This paper employs wavelet transforms, which are particularly adept at capturing transient phenomena like sudden inflation spikes or shifts. By distinguishing short- and long-term fluctuations, wavelet methods complement and improve upon traditional time-domain approaches.²

Compared to the literature using time series models, this literature is still on its infancy. For out-of-sample inflation forecasting, Rua (2017) and Martins and Verona (2024) are the primary studies, applying wavelet methods within principal component and Phillips curve frameworks, respectively. This paper evaluates the effectiveness of such models in improving inflation forecasts through more granular frequency-domain insights.³

An alternative to traditional methods is the use of nonlinear econometric techniques like machine learning (ML) and artificial intelligence (AI). Recent studies, such as Medeiros, Vasconcelos, Veiga and Zilberman (2021) and Naghi, O'Neill and Danielova Zaharieva (2024), demonstrate the superior performance of ML methods, including LASSO and random forests, over conventional approaches. However, this paper focuses solely on linear models to rigorously assess the added value of frequency-domain information. It also excludes theoretical models like agent-based and DSGE models due to their mixed forecasting performance (e.g., Poledna, Miess, Hommes and Rabitsch, 2023 and del Negro, Dogra, Gleich, Gundam, Lee, Nallamotu and Pacula, 2024).

² Previous studies using frequency-domain methods include Martins and Verona (2023), Giri (2022), and Andreani and Giri (2023), which analyze inflation dynamics and of its sub-components, and Rua (2012), which explores the relationship between inflation and money growth.

³ An alternative time-series Phillips-curve based forecasting model that uses frequency-domain method is the one developed by Ashley and Verbrugge (2023), which applies a frequency-decomposition (band-pass) of the unemployment gap. Other out-of-sample forecast applications using wavelets include Rua (2011), who forecast GDP growth using a factor-augmented wavelets approach; Zhang, Gençay and Yazgan (2017), Faria and Verona (2018, 2020, 2021) and Stein (2024) who focus on forecasting stock market returns; Caraiani (2017), who forecasts exchange rates; Kilponen and Verona (2022), who use different proxies for Tobin's Q and cash flow to forecast aggregate investment rate; and Faria and Verona (2025), who forecast bond (and equity) returns.

Finally, predictors commonly used in inflation forecasting span a wide array of macroeconomic and financial variables. Financial variables, in particular, are advantageous due to their real-time availability and low measurement error. They also serve as leading indicators of business cycles, as evidenced by Estrella and Mishkin (1998) and Stock and Watson (2003). Moreover, credit conditions are a critical driver of business cycle fluctuations (Philippon, 2009 and Gilchrist and Zakrajšek, 2012). This paper incorporates several financial variables within simple econometric models to evaluate their contribution to inflation forecasting.

3 Data

We use quarterly time series from 1978:Q1 until 2023:Q4. Let P_t be the CPI or the PCE price index in quarter t . Our out-of-sample (OOS) forecasting exercise targets the annualized h -period average inflation rate, computed as $\pi_t^h = \frac{400}{h} \ln(P_t/P_{t-h})$. We focus on the 1-quarter, 4-quarter, and 8-quarter ($h=1, 4$, and 8) average inflation rates as they are the most relevant for monetary policymakers.

While PCE inflation is particularly significant from the perspective of monetary policy, because the longer-run inflation objective of the Federal Open Markets Committee is stated in terms of PCE inflation, CPI inflation is also important as it provides a more straightforward signal about direct consumer price changes, given that it represents what households actually pay out of pocket. Panel A of table 2 reports the sample statistics for these different measures of inflation. PCE inflation is, on average, lower, slightly more persistent, and less volatile than CPI inflation. This is expected, as the latter measure weights housing, energy, and food prices more heavily, which makes it then more susceptible to short-term fluctuations. These inflation rate measures are also highly correlated between themselves. Their correlation coefficients are 0.96, 0.98, and 0.99 for $h=1$, $h=4$, and $h=8$, respectively.

As regards the predictors, we start from a large set of variables taken from the McCracken and Ng (2016) FRED-QD dataset. We noticed that many of them did not add any value, neither as individual predictors in bivariate regressions nor in multiple regression forecasts or in the final combination exercise. Hence,

in our baseline forecasting exercise, we ultimately use ten macroeconomic / financial variables, which are reported in the second column of table 1 and have been widely used in the literature on inflation forecast (see e.g., Stock and Watson, 2003). For the sake of brevity, we include only a short description of the predictors here, and refer the reader to the respective data source (reported in the third column in table 1) for a more extensive discussion of the data. The ten predictors are:

1. Dividend-price (DP) ratio: difference between the log of dividends (12-month moving sums of dividends paid on the S&P 500) and the log of prices (the S&P 500 index).
2. Treasury bill rate (TBL): the secondary market rate of three-month US treasury bills.
3. Long-term US government bond return (LTR).
4. Term spread (TMS): difference between the long term yield on government bonds and the Treasury-bill.
5. Default return spread (DFR): difference between returns on long-term corporate bonds and long-term government bonds returns.
6. Shadow rate (SHR): the shadow federal funds rate.
7. M2 growth rate: real M2 money stock, deflated by CPI.
8. Inflation expectations (MSC): Michigan survey of consumers.
9. Unemployment (U) rate: quarterly average of the civilian unemployment rate.
10. CPI/PCE energy inflation: annualized quarterly rate of growth of the respective price index.

The dividend-price ratio (predictor 1) is a measure of stock market valuation which is often used as a predictor of future inflation, especially over longer horizons (see e.g., Ang et al., 2007). When stock prices are high relative to dividends (a low dividend-price ratio), it might indicate that investors expect

strong future growth and low inflation, as higher inflation would typically depress stock prices. Short-term interest rates, and particularly the policy rate set by the central bank (predictors 2 and 6) – influence inflation through various channels (e.g., borrowing costs and investment). The returns on various type of asset – such as predictors 3 and 5 – are often used to hedge against inflation (see e.g., Fama and Schwert, 1977). The slope of the yield curve (predictor 4) is a reliable leading indicator of the business cycle and, potentially, of inflation (see e.g., Estrella and Hardouvelis, 1991 and Faria and Verona, 2020). Changes in the money supply (predictor 7) is often used as predictors of inflation based on the quantity theory of money (see e.g., Rua, 2012 and Mankiw, 2024). Finally, predictors 8 to 10 are the key variables in the new Keynesian Phillips curve framework (see e.g., Coibion and Gorodnichenko, 2015 and Martins and Verona, 2024).

Figure 2 displays the time series of the predictors (black lines) along with their long-run trends (blue lines), which, as discussed in the next section, are used as predictors in the frequency-domain forecasting models. Panel B of table 2 summarizes the sample statistics for these predictors. They exhibit diverse time series properties, particularly in terms of higher-order moments and persistence, making them valuable for forecasting various inflation measures across different horizons.

4 Forecasting models and methodology

In this section, we describe the models and methodology used to forecast inflation. Broadly speaking, we consider linear models and divide them in two categories. In the first one, we include standard time series models such as bivariate models (with constant and time-varying coefficients), multivariate models, factor model, Phillips curve model, and survey expectations. In the second one, we consider similar models but predictors are the low-frequency time series components of the original predictors, as well as forecast combination in the frequency domain.

In creating the model suite, we cast our net relatively wide. While the above set of models is a fairly comprehensive list of the sort of models that have appeared in the literature, it is of course far from being

exhaustive (recall the list of models mentioned in section 2). For instance, we do not include ARIMA models and (Bayesian) VAR models, as they are usually not better than simpler time-series models (see e.g., Faust and Wright, 2013). We also leave out the Stock and Watson (2007) unobserved components stochastic volatility (UCSV) model, as it does not consistently outperform simpler univariate models (see e.g., Jarocinski and Lenza, 2018 and Banbura, Lenza and Paredes, 2024) and its forecasts are close to simple random walk forecasts (Verbrugge, 2024).

Our out-of-sample (OOS) forecasts are direct forecasts produced with a sequence of expanding windows. We start by obtaining the first OOS forecasts with the sample 1978:Q1–1999:Q4. The sample is then increased by one observation and a new set of OOS forecasts is produced. This procedure is repeated until the end of the sample. We focus on forecasting the annualized h -quarter average inflation, with each average inflation rate indicated by superscript h in π_t^h . In turn, $\hat{\pi}_{t+h}^h$ denotes a forecast of inflation (1-quarter, 4-quarter, or 8-quarter, as indicated by superscript h) obtained in period t for the corresponding inflation horizon (subscript $t+h$).

In section 4.1 we describe the individual forecasting models – the benchmark random walk model and our model suite, which consists of 54 forecasting models. Table 3 contains a full nomenclature. In section 4.2 we describe our methodology to combine the individual model forecasts.

4.1 Individual forecasting models

4.1.1 The benchmark model

The most widely used model as benchmark in the literature on inflation forecasting is the random walk model of Atkeson and Ohanian (2001) (denoted AO). According to this model, the h -period-ahead forecast is given by $\hat{\pi}_{t+h}^h = \frac{1}{4} \sum_{\tau=0}^3 \pi_{t-\tau}^h$.

4.1.2 The model suite

Forecasting models in the Time Domain (TD)

We first consider ten bivariate models of the form

$$\pi_t^h = c^{h,p} + \beta^{h,p} x_{p,t-1} + \varepsilon_t^{h,p} ,$$

where $p = 1, \dots, 10$ (the number refers to the predictor used, as reported in the first column in table 1).

The h -period-ahead forecasts are given by $\hat{\pi}_{p,t+h}^h = \hat{c}^{h,p} + \hat{\beta}^{h,p} x_{p,t}$. These models are denoted as TS-1 to TS-10.⁴

Following Goyal and Welch (2008), we consider a “kitchen sink” model (denoted KS-TS) that incorporates all ten predictors into a multiple predictive regression model:

$$\pi_t^h = c^{h,KS} + \sum_{p=1}^{10} \beta^{h,p,KS} x_{p,t-1} + \varepsilon_t^{h,p,KS} ,$$

where the forecasts are given by

$$\hat{\pi}_{KS,t+h}^h = \hat{c}^{h,KS} + \sum_{p=1}^{10} \hat{\beta}^{h,p,KS} x_{p,t} .$$

This model fits the data in-sample quite well, but its OOS performance is quite often not good. Hence, in the spirit of Pesaran and Timmermann (1995), we consider a model (denoted TS-SIC) that select the forecasting model using the SIC criteria, from among the 2^p possible specifications for the $p = 10$ potential predictors, based on data available at the time of forecast formation (i.e. there is no look-ahead bias). The idea is to use the SIC to guard against in-sample overfitting, since the SIC penalizes models

⁴ Following Rapach et al. (2010), we also evaluate the performance of the forecast resulting from the combination of individual model forecasts (TS-1 to TS-10). Some of the forecasts were acceptable, but it turned out that they did not add any value (i.e. they are never selected) in a forecast combination exercise, so we excluded them from the suite of models.

with more parameters.⁵

As individual predictor in a bivariate model, we also use the first principal component extracted from the original set of predictors (model denoted TS-PCA).

We then run the forecast with a new Keynesian Phillips curve in the spirit of Coibion and Gorodnichenko (2015) (denoted TS-PC). As predictors, we use inflation expectations (π^e), unemployment rate (un), and energy inflation (en) (predictors 8 to 10). In particular, the TS-PC model is given by

$$\pi_t^h = c^{h,PC} + \alpha_1^h \pi_{t-1}^e + \alpha_2^h un_{t-1} + \alpha_3^h en_{t-1} + \varepsilon_t^{h,PC}, \quad (1)$$

and the forecasts are computed as

$$\hat{\pi}_{TS-PC,t+h}^h = \hat{c}^{h,PC} + \hat{\alpha}_1^h \pi_t^e + \hat{\alpha}_2^h un_t + \hat{\alpha}_3^h en_t. \quad (2)$$

We then consider ten bivariate models with time-varying coefficients (TVC), which are best suited to address the issue of parameter instability due to changes in economic structure or in macroeconomic interrelations. We follow Dangl and Halling (2012) and specify the following predictive regression model for each individual predictor p , $p = 1, \dots, 10$:

$$\pi_t^h = c_t^{h,p} + \beta_t^{h,p} x_{p,t-1} + \varepsilon_t^{h,p} \quad (3)$$

$$\begin{pmatrix} c_t^{h,p} \\ \beta_t^{h,p} \end{pmatrix} = \begin{pmatrix} c_{t-1}^{h,p} \\ \beta_{t-1}^{h,p} \end{pmatrix} + \begin{pmatrix} w_{1,t}^p \\ w_{2,t}^p \end{pmatrix} \quad (4)$$

⁵ In this case, we consider $p = 5$ to limit the computational time. Similar results were obtained using the AIC criteria.

where

$$\varepsilon_t^{h,p} \sim N(0, \sigma_p^2) \quad (5)$$

$$w_t^p \sim N(0, W_t^p) \quad (6)$$

and $w_t^p = (w_{1,t}^p, w_{2,t}^p)'$. The h-period-ahead forecast based on this TVC model is given by

$$\hat{\pi}_{p,t+h}^h = \hat{c}_{t,t}^{h,p} + \hat{\beta}_{t,t}^{h,p} x_{p,t} ,$$

where $\hat{c}_{t,t}^{h,p}$ and $\hat{\beta}_{t,t}^{h,p}$ are estimates of $c_t^{h,p}$ and $\beta_t^{h,p}$, respectively, in equation (3) based on data available through quarter t . This methodology allows for gradual changes of the intercept and the slope coefficients so that the model forecast can respond to e.g. changes in policy, technology, and institutions. To estimate the TVC model (3)-(6), we follow Dangl and Halling (2012) and employ Bayesian model averaging to average across models with different assumptions of the degree of time-variation of the coefficients. These models are denoted TS-TVC-1 to TS-TVC-10.⁶ We note that the univariate models with constant coefficients (TS-1 to TS-10), when estimated with an extending (or rolling) window, mimic time-varying coefficients in an ad-hoc way. The Dangl and Halling (2012) methodology accounts for time-varying coefficients in a systematic and statistically consistent way.

Besides simple univariate time series models, it has become increasingly standard in the forecasting literature to consider the expectations of inflation stated in surveys (e.g., Ang et al., 2007 and Berge, 2018). Our NKPC already includes inflation expectations from a survey of households, namely the MSC. The MSC-based survey-based forecasts are given by $\hat{\pi}_{TS-MS C,t+h}^h = \pi_{t+1}^e$, where π_{t+1}^e is the MSC median expected change in prices during the next 12 months. This model is denoted TS-MS C. Similarly, we run the forecasts using the year-ahead CPI forecast from the Survey of Professional Forecasters (SPF). This model is denoted TS-SPF. Since neither survey elicits an explicit 1-quarter and 8-quarter-ahead forecast,

⁶ Following Dangl and Halling (2012), we set the scaling factor that determines the confidence assigned to the null-hypothesis of no-predictability (g) to 50, and a grid of values (0.96, 0.97, 0.98, 0.99, and 1) for the discount factor δ .

we follow Berge (2018) and use the 4-quarter-ahead expectation to forecast inflation at all horizons.

Forecasting models in the Frequency Domain (FD)

In the incipient but growing literature on forecasting with wavelets, a common result is that the low-frequency (LF) components of the predictors are the ones that carry most of the relevant information for forecasting purposes. For instance, Faria and Verona (2020) show that the lowest frequency component of the term spread is a good predictor of the equity premium, whereas the term spread itself and its other frequency components perform much worse in forecasting.

Following this literature, we extract the LF components from the original set of predictors by band-passing each time series of the predictors with the Haar filter, which is commonly used in macroeconomic and financial applications.⁷ In this paper, we follow Martins and Verona (2024) and consider as LF fluctuations those with a period longer than 16 years.

We then consider ten bivariate models of the form

$$\pi_t^h = c^{h,p,LF} + \beta^{h,p,LF} x_{p,t-1}^{LF} + \epsilon_t^{h,p,LF} , \quad (7)$$

where $p = 1, \dots, 10$ (the number refers to the predictor used, as reported in the first column in table 1) and x_p^{LF} is the LF component of predictor p . The h -period-ahead forecasts are given by $\hat{\pi}_{p,LF,t+h}^h = \hat{c}^{h,p,LF} + \hat{\beta}^{h,p,LF} x_{p,t}^{LF}$. These models are denoted as WAV-1 to WAV-10.

As in the case of the time domain, we consider KS and SIC models which use the ten low-frequency components of the individual predictors (models denoted WAV-KS and WAV-SIC, respectively). Like-

⁷ See e.g., Faria and Verona (2018, 2025), Bandi, Perron, Tamoni and Tebaldi (2019), Kilponen and Verona (2022), Martins and Verona (2024), Canova (2024), and Stein (2024). In this paper we use a two-sided version of the Haar filter. To ensure that the method does not have a look-ahead bias, we recompute the frequency components recursively at each iteration of the OOS forecasting process using data from the start of the sample through the quarter at which the forecasts are made. Forecasts are thus made only with current and past information. We use reflecting boundary conditions, whereas each time series beyond its boundaries is a symmetric reflection of itself, to lessen the impact of circular filtering (Gallegati, Gallegati, Ramsey and Semmler, 2011).

wise, as individual predictor in a bivariate model, we use the first principal component extracted from the low frequencies of the predictors (model denoted WAV-PCA).

Next, we run the forecast with a new Keynesian Phillips curve in the frequency domain (denoted WAV-PC). Following Martins and Verona (2024), the WAV-PC model is

$$\pi_t^h = \pi_t^{h,LF} = c^{h,LF} + \alpha_1^{h,LF} \pi_{t-1}^{e,LF} + \alpha_2^{h,LF} un_t^{LF} + \alpha_3^{h,LF} en_t^{LF} + \varepsilon_t^{h,LF} .$$

Essentially, this model forecasts the low-frequency component of inflation using the corresponding frequency components of the predictors.⁸ Martins and Verona (2024) show that this model outperforms several others (including the benchmark AO model) as it allows to track well the trend of inflation. The forecasts with the WAV-PC model are given by

$$\hat{\pi}_{WAV-PC,t+h}^h = \hat{\pi}_{t+h}^{h,LF} = \hat{c}^{h,LF} + \hat{\alpha}_1^{h,LF} \pi_t^{e,LF} + \hat{\alpha}_2^{h,LF} un_t^{LF} + \hat{\alpha}_3^{h,LF} en_t^{LF} .$$

As in the time domain case, we estimate the ten bivariate models (equation (7)) with time-varying coefficients (models denoted WAV-TVC-1 to WAV-TVC-10).

The next model we consider is based on Faria and Verona (2023) and run the forecast of inflation in time-frequency domain. This method goes as follows. First, we use the Haar filter to decompose both inflation and its predictors into f time series frequency components (called D_1 to D_4).⁹ We then estimate, separately, each frequency component D_f of inflation using the corresponding frequency component of predictor x_p :

$$\pi_t^{h,p,f} = c^{h,p,f} + \beta^{h,p,f} x_{p,t-1}^f + \varepsilon_t^{h,p,f} . \quad (8)$$

⁸ This regression is akin to the band spectrum regression discussed by Engle (1974), and has been increasingly used in economics with wavelet-based frequency decomposition (see e.g., Gallegati et al., 2011, Gallegati and Ramsey, 2013, Ortu, Tamoni and Tebaldi, 2013, and Faria and Verona, 2018, 2021).

⁹ The first component (D_1) captures fluctuations of the original variable with a period between 2 and 4 quarters, while components D_2 and D_3 capture fluctuations with a period of 1-2 and 2-4 years, respectively. Finally, component D_4 captures fluctuations with a period longer than 4 years. We note that the sum of these four time series frequency components gives exactly the time series of the original variable.

We use the estimation results in (8) to produce the one-step ahead OOS forecast of the corresponding frequency component of inflation:

$$\hat{\pi}_{t+h}^{h,p,f} = \hat{c}^{h,p,f} + \hat{\beta}^{h,p,f} x_{p,t}^f ,$$

where $\hat{c}^{h,p,f}$ and $\hat{\beta}^{h,p,f}$ are the OLS estimates of $c^{h,p,f}$ and $\beta^{h,p,f}$, respectively, using data from the beginning of the sample until quarter t .

We then compute the forecasts of each frequency components D_f of inflation as the mean forecast combination for that frequency f :

$$\hat{\pi}_{c,t+h}^{h,f} = \frac{1}{10} \sum_{i=1}^{10} \hat{\pi}_{i,t+h}^{h,p,f} .$$

The overall forecast of inflation made at time t for $t+l$ in the frequency domain is obtained by summing the forecasts of the f individual frequencies of inflation:

$$\hat{\pi}_{WAV-FC,t+h}^h = \sum_{f=1}^4 \hat{\pi}_{c,t+h}^{h,f} . \quad (9)$$

In practice, we consider two forecasts using this method: the first one is obtained by summing all frequency components of inflation (model denoted WAV-FC-1), whereas the second one only consider only the low-frequency forecasts (model denoted WAV-FC-2).

Finally, we run the forecasts directly using the low-frequency components of the surveys. These models are denoted as WAV-MSF and WAV-SPF.

4.2 Forecast combination models

A (almost) pervasive result in the literature is that combining different forecasting models produces better results than individual models. Following this literature, we compute the final forecast of inflation as the combination of the forecasts coming from the individual models described in section 4.1.2.

Forecast combination can be implemented in many different ways. Following Stock and Watson (2004) and Rapach et al. (2010), we consider several combinations of the models' forecasts, which are given by

$$\hat{\pi}_{c,t+h}^h = \sum_{m=1}^{m_{max}} \omega_{m,t} \hat{\pi}_{m,t+h}^h, \quad (10)$$

where $\{\omega_{m,t}\}_{m=1}^{m_{max}}$ are the ex-ante combining weights formed at time t , and m_{max} is the maximum number of forecasts used. The combining methods we consider differ in how the weights are determined and can be organized into two classes.

The first choice of weights is simply to equally weight all models that enter the combination. That is, we construct a simple mean of all the forecasts, which sets $\omega_{m,t} = 1/m_{max}$ for $m = 1, \dots, m_{max}$ in equation (10). This model is denoted Mean.¹⁰

Stock and Watson (2004) find that simple averaging often matches or exceeds more complex methods such as time-varying weights combination, a result they named “forecast combination puzzle”.¹¹ However, in a more recent study, Dellas, Gibson, Hall and Tavlas (2018) show that it is possible to improve results even further by having time-varying weights, as combinations of forecasts themselves are likely to be subject to e.g. structural breaks as well. In fact, TVC forecasts produce superior forecasts than combinations derived using a linear framework as TVC can accommodate structural change, both in the actual inflation process and the forecasting process (that is, forecasters may change the way they forecast). Moreover, Timmermann (2006) has noted that equal weights will be appropriate when models have equal forecast error variance. Hence, in the second class of combining methods, the combining weights formed at time t are functions of the historical forecasting performance of the individual models over the holdout out-of-sample period. Their discount mean square prediction error (DMSPE) combining method employs the following weights:

$$\omega_{m,t} = \frac{\phi_{m,t}^{-1}}{\sum_{m=1}^{m_{max}} \phi_{m,t}^{-1}}, \quad (11)$$

¹⁰ Similar results have been obtained using median and trimmed mean combination methods.

¹¹ Recent studies addressing this puzzle are Chan and Pauwels (2018) and Liu, Hao and Wang (2024).

where

$$\phi_{m,t} = \sum_{s=n}^{t-1} \theta^{t-1-s} \left(\pi_{t+h}^h - \hat{\pi}_{m,t+h}^h \right)^2 .$$

Here, n denotes the last observation before the holdout out-of-sample period that is used to determine the weights and θ is a discount factor. The DMSPE method assigns greater weights to individual predictive regression forecasts that have lower forecasting errors (better forecasting performance) over the holdout out-of-sample period. When $\theta = 1$, there is no discounting, and equation (11) produces the optimal combination forecast derived by Bates and Granger (1969) for the case where the individual forecasts are uncorrelated. When $\theta < 1$, forecast accuracy in the more distant past is discounted relative to recent performance, with smaller values of θ indicating greater discounting and, hence, more volatile weights. We consider three different values of the discount factor: 0.33, 0.67, and 1.¹² These models are denoted DMSPE_1, DMSPE_2, and DMSPE_3, respectively. As initial holdout period, we use the period 1995:Q1–1999:Q4.

5 Empirical results

5.1 Forecast accuracy

Forecast accuracy is evaluated using the root mean squared error (RMSE), calculated for each model and compared to the RMSE of the benchmark AO model. The statistical significance of RMSE differences is assessed using the Diebold and Mariano (1995) and West (1996) test statistics, with Newey-West standard errors.¹³ To complement this statistical analysis, graphical evidence is provided to illustrate the economic significance of forecast differences and to track the performance of the models over time.

¹² For the discount factor θ , Stock and Watson (2004) consider 0.90, 0.95, and 1, Rapach and Zhou (2013) use 0.75, and Denk and Löffler (2024) also consider a lower value of 0.50.

¹³ This study focuses on *point* inflation forecast evaluations, while inflation *density* forecast evaluations can be found in related literature, such as Giordani and Söderlind (2003), Clark (2011), and Groen, Paap and Ravazzolo (2013).

5.1.1 Individual forecasting models

We first evaluate each forecasting model independently. Tables 4 and 5 report the RMSEs for the AO benchmark model (panel A) and the RMSEs of individual forecast models (panel B) relative to the AO model's RMSEs for the models in the time domain and in the frequency domain, respectively. Asterisks indicate statistical significance of relative predictive accuracy at the 10 % (*), 5 % (**), and 1 % (***) levels, and bold underlined entries indicate the best-performing model for each inflation measure and forecasting horizon.

The AO model performs better when forecasting PCE inflation compared to CPI inflation, making it a more challenging benchmark to outperform for the former inflation measure. This result aligns with previous findings that PCE inflation is more predictable, as it better captures underlying economic trends by filtering out the more volatile components of inflation. For instance, during the Global Financial Crisis, CPI inflation experienced a sharp decline from 6.2 % to -9.2 % between 2008Q3 and 2008Q4, while PCE inflation showed a more moderated decline from 4.3 % to -6.4 %.

Regarding the individual forecasting models, we highlight four results that apply to both inflation measure being forecasted.

First, forecasting inflation at shorter horizons ($h=1$) is significantly more challenging than at longer horizons ($h=4$ and 8). This is due to higher forecast errors, particularly during volatile periods like the Global Financial Crisis, and to the RMSE as evaluation criteria. Only a few models outperform the AO benchmark for CPI inflation at $h=1$, and none beat it for PCE inflation.

Second, among constant-coefficient models (TS-1 to TS-10 and WAV-1 to WAV-10), only one – TS-8 – outperforms the AO model (and only for CPI inflation at $h=1$). However, models with time-varying coefficients frequently deliver statistically significant improvements in predictive accuracy, making them a promising approach for enhancing inflation forecasting.

Third, survey-based models show varying levels of predictability. The SPF model performs well at longer horizons ($h=4$ and $h=8$), while the MSC model fails to outperform the AO model, even for CPI inflation,

which it is specifically designed to forecast.

Fourth, models using multiple predictors generally exhibit weak performance, although the WAV-PC model demonstrates strong results for CPI inflation at $h=4$ and $h=8$, which are comparable to those of the best individual models.

Among the individual models, TS-TVC-1 and TS-SPF stand out as the best-performing TS models for both CPI and PCE inflation, while WAV-SPF consistently outperforms other WAV models. Nevertheless, the performance of many other models is similar to these top performers.

Graphical analysis provides further insights into these results. For CPI inflation, forecasts generated by selected individual models at three forecasting horizons are shown in the left-hand graphs of figure 3. Realized inflation is plotted with black lines, AO model forecasts with red lines, and forecasts from the best TS and WAV models with green and blue lines, respectively. The AO model frequently lags behind realized inflation, especially at turning points, which negatively affects its performance during these periods. By contrast, the best individual models tend to produce more stable forecasts. For instance, the best WAV model, which incorporates the low-frequency component of the SPF, performs particularly well. However, even these models struggle to capture sharp inflation surges, such as the one observed during 2021-2022.

To better visualize the relative performance of the best TS and WAV models over time, the right-hand graphs in figure 3 plot the cumulative differences in squared forecast errors (SFE) between these models and the AO model. When the lines in these graphs increase, it indicates that the best TS or WAV model is outperforming the AO benchmark. Overall, the WAV models consistently deliver consistently stronger performance, a result that can be attributed to the low-frequency characteristics of their forecasts.¹⁴

The results presented in tables 4 and 5 are, overall, not particularly encouraging. Only a few predictors and models outperform the benchmark AO model, raising questions about the appropriateness of the current suite of models. To address this issue, we conduct an experiment similar to the one performed

¹⁴ Similar conclusions can be reached looking at PCE inflation forecasts. Figures are available upon request.

by Ang et al. (2007). Specifically, at each point of the out-of-sample (OOS) period, we identify the best-performing individual model and record its forecast for that period. Evaluating the forecasting accuracy of this approach reveals substantial improvements in the relative RMSE, which improves to 0.50 for CPI inflation and 0.48 for PCE inflation at $h=1$, 0.26 for CPI inflation and 0.24 for PCE inflation at $h=4$, and 0.14 for CPI inflation and 0.13 for PCE inflation at $h=8$. These results suggest that the current suite of models is thus theoretically capable of accurately tracking inflation.

Figure 4 highlights the best-performing individual forecasting models for CPI inflation ($h=4$) at each point of the OOS period. Each blue dot represents the selected model (y-axis) for a specific time period (x-axis). The figure reveals substantial variability in the best-performing model. Rarely does a single model maintain its position as the best performer for more than one consecutive quarter. A notable exception is the WAV-4 model (model 30), which remains the best model for five consecutive quarters during the recent inflation surge.¹⁵

This temporal instability in the best predictor or model reinforces the importance of adopting a model combination approach, which is explored in the next section.

5.1.2 Combining individual model forecasts

The next step in the analysis involves evaluating combinations of individual model forecasts. For comparison, panel A of table 6 reports the relative RMSEs of the best individual models compared to the AO benchmark. Panel B presents the relative RMSEs of the combination forecast models.

In the first four lines in panel B we report the combination forecast using all the 54 models' forecasts ("Mean all" and "DMSPE all" combinations), that is, we set $m_{max} = 54$ in equation (10). Overall, combining the forecasts of all 54 models often results in improved forecasts relative to the AO benchmark. However, these combinations often underperform the best individual models, highlighting the limited value of simple averaging in this context.

¹⁵ Similar variability is observed across different forecasting horizons and for PCE inflation. These additional results are available upon request.

Inspired by the findings of Aiolfi and Timmermann (2006), we explore whether trimming the model space to a smaller subset enhances performance. We do so by searching for the combination of individual model forecasts that gives the lowest relative RMSE. For computational reasons, the maximum number of models in the combination is set to four ($m_{max} = 4$ in equation (10)). Their RMSEs relative to the AO model’s RMSEs are reported in the fifth to eighth lines in panel B, along with the individual models used (reported in squared brackets).

The results reveal that limiting the forecast combination to four models significantly improves accuracy, particularly for short forecasting horizons ($h=1$). Time-varying combination methods, such as the “DM-SPE_1” model, perform well at short horizons due to their capacity to use only the most recent forecasts. For longer horizons, however, simpler approaches, such as the “Mean best” model, outperform, reflecting the tendency for longer-term forecasts to benefit less from time variation in model weights.

Among the individual models included in successful combinations, the WAV-4 model stands out. It is the bivariate model with constant coefficients that forecasts inflation using the low-frequency component of the term spread. This model appears in 20 of the 24 forecast combinations. This finding underscores the term spread’s importance as an indicator of future inflation.¹⁶ Other models, such as TS-TVC-1, perform well at short horizons by capturing well high-frequency fluctuations, while constant coefficient models are more useful at longer horizons, especially the WAV models. Multivariate models are rarely included in the optimal combinations.

Finally, individual models with time-varying coefficients tend to excel individually but offer limited additional value when combined. Conversely, constant-coefficient models, though less effective individually, are frequently included in successful combinations. This suggests that forecast combination methods can effectively account for time variation in the data, reducing the need for TVC models in these exercises.

Graphical analyses in figure 5 compare the forecasts of the best combination models to those of the best individual models across different forecasting horizons. The left-hand graphs plot realized inflation

¹⁶ Faria and Verona (2020) show that the trend of the term spread is also a remarkably good equity premium predictor.

(black lines), the best combination forecasts (blue lines), and the best individual forecasts (red lines). The right-hand graphs depict the cumulative differences in squared forecast errors (SFE) between these models. For the one-quarter and one-year average inflation (graphs in the first and second rows), the outperformance of the best combination model occurs in three distinct periods: during the GFC, during year 2015, and in the period following the Covid recession. For the two-year average inflation (graph in the bottom), both models display similar performances across the entire sample period, with two exceptions. The first is in the years after the GFC, in which the best individual model performs better than the best combination model, as the latter is not able to capture the inflation drop during that period. The second exception is in the last two years of the sample period, in which the best combination model clearly outperforms the best individual model as it captures the inflation surge of the 2020s more effectively. These results emphasize the utility of combination models, particularly during periods of heightened and persistent inflation.

5.2 The usefulness of frequency-domain information

Previous research has demonstrated that incorporating frequency-domain (FD) information can improve forecast accuracy compared to models relying solely on time-domain (TD) data.¹⁷ Motivated by these findings, we run our forecast combination using two subsets of models: one comprising only TS models (models 1-26) and the other including only WAV models (models 27-54). Panel C of table 6 presents the relative RMSEs for these subsets.

The first two rows report the results when combining all the individual models forecasts in the respective subset. Combining all models within each subset produces similar results, though forecasts from the “Mean all WAV” combination tend to show greater statistical significance. The last two rows report the same results when we trim the model space and limit the combination forecast to have (at most) 4

¹⁷ For inflation, see Martins and Verona (2024); for stock market returns, see Faria and Verona (2018, 2020, 2021, 2025); for investment, see Kilponen and Verona (2022). Furthermore, Faria and Verona (2025) show that those better forecasts would also translate in more profitable trading opportunities.

individual models forecasts.

In this case, FD models demonstrate a clear advantage at forecasting at longer horizons ($h=4$ and 8). For instance, the best-performing model to forecast at $h=8$ relies exclusively on FD models, while the models at $h=4$ perform equally well with or without TD information. At shorter horizons ($h=1$), combining both TD and FD forecasts provides the greatest accuracy, emphasizing the complementary nature of these datasets and models.

Overall, these results confirm the value of extracting and leveraging frequency-domain information in forecasting, especially at longer horizons.

5.3 Sensitivity analyses

5.3.1 On the assumptions about FD models

We test the robustness of our findings by considering alternative assumptions about FD models. First, using cycles longer than 8 years (instead of 16) slightly reduces predictive accuracy, confirming that very low-frequency data carry the most forecasting power. Second, applying different wavelet filters, such as Daubechies filters of length 4 and 8,¹⁸ produces results similar to those obtained with the Haar filter, further supporting the robustness of the baseline findings. Third, similar findings are observed when the Hodrick and Prescott (1997) filter is used to extract low-frequency components of predictors.¹⁹

5.3.2 On the predictors used

Inflation forecasts in this study are based on ten commonly used predictors. We have checked that including additional variables yielded limited gains in accuracy.

¹⁸ These filters are also widely used in the literature (see e.g., Gallegati et al., 2011, Rua, 2017, and Crowley and Hudgins, 2021, 2023).

¹⁹ As standard with quarterly data, to extract the cycle with this filter we set the smoothness parameter of the filter to 1600.

An alternative common method for efficiently incorporating information from multiple predictors involves estimating predictive regressions based on principal components, which capture the key comovements across predictors while filtering out much of the noise in individual variables. We implement this method using the McCracken and Ng (2016) FRED-QD dataset. Starting with the full dataset, we exclude variables with outliers, those with missing observations at the start of the sample period, and all variables in *Group 6: Prices*. This leaves us with 129 potential predictors of inflation. From this subset, we extract the first ten principal components (standardizing the predictors beforehand, as is customary) and use them as inputs in models TS-1 to TS-10, TS-KS, TS-SIC, and TS-TVC-1 to TS-TVC-10. For the corresponding WAV models, we use the low-frequency components of these factors. In the final model combination exercise, we exclude the TS-PCA and WAV-PCA models (which correspond to TS-1 and WAV-1, respectively) and include forecasts from the TS-PC, TS-MSC, TS-SPF models and their WAV counterparts. These models are taken from the original set of forecasts.

Overall, we find comparable results to those obtained with the ten original predictors, albeit somewhat less pronounced.

6 Concluding remarks

Inflation concerns all economic agents, making accurate forecasts essential for informed decisions. Although inflation forecasting has a rich and extensive literature, no single method consistently outperforms others across all time horizons. Even after decades of research, the simple random walk model remains a challenging benchmark to beat.

In this paper, we contribute to the field by introducing an enhanced approach to inflation forecasting using a thick modeling framework. Our key innovation lies in incorporating frequency-domain models into an otherwise standard forecast combination framework. By integrating models from both the time and frequency domains, we demonstrate that combining forecasts improves inflation predictions, especially

during periods of rising inflation. The inclusion of frequency-domain information is central to achieving these forecasting gains.

Overall, pooling forecasts from different models provides a hedge against instability in individual forecast performance. Future research could investigate the advantages of integrating frequency-domain information with advanced forecasting approaches. Promising techniques include the three-pass regression filter of Kelly and Pruitt (2015), the scaled principal component analysis developed by Huang, Jiang, Li, Tong and Zhou (2022), and various machine learning models as applied by Naghi et al. (2024). Additionally, innovative combination techniques like the approximate Bayesian model averaging employed by Garratt and Petrella (2022) offer promising avenues for further enhancement.

References

- Aiolfi, Marco and Allan Timmermann**, “Persistence in forecasting performance and conditional combination strategies,” *Journal of Econometrics*, 2006, 135 (1-2), 31–53.
- , **Carlos Capistran, and Allan Timmermann**, “Forecast Combinations,” in Michael P. Clements and David F. Hendry, eds., *The Oxford Handbook of Economic Forecasting*, Oxford University Press, 2011, chapter 12, pp. 355–388.
- Andreani, Michele and Federico Giri**, “Not a short-run noise! The low-frequency volatility of energy inflation,” *Finance Research Letters*, 2023, 51 (C).
- Ang, Andrew, Geert Bekaert, and Min Wei**, “Do macro variables, asset markets, or surveys forecast inflation better?,” *Journal of Monetary Economics*, 2007, 54 (4), 1163–1212.
- Ashley, Richard and Randal Verbrugge**, “The Intermittent Phillips Curve: Finding a Stable (But Persistence-Dependent) Phillips Curve Model Specification,” Working Papers 201909R2, Federal Reserve Bank of Cleveland 2023.

- Atkeson, Andrew and Lee E. Ohanian**, “Are Phillips curves useful for forecasting inflation?,” *Federal Reserve Bank of Minneapolis Quarterly Review*, 2001, 25 (2), 2–11.
- Banbura, Marta and Elena Bobeica**, “Does the Phillips curve help to forecast euro area inflation?,” *International Journal of Forecasting*, 2023, 39 (1), 364–390.
- , **Michele Lenza, and Joan Paredes**, “Forecasting inflation in the US and in the euro area,” *Handbook on Macroeconomic Forecasting*, 2024, *forthcoming*.
- Bandi, Federico, Bernard Perron, Andrea Tamoni, and Claudio Tebaldi**, “The Scale of Predictability,” *Journal of Econometrics*, 2019, 208 (1), 120–140.
- Bates, J. M. and C. W. J. Granger**, “The Combination of Forecasts,” *Operational Research Quarterly*, 1969, 20 (4), 451–468.
- Berge, Travis J.**, “Understanding survey-based inflation expectations,” *International Journal of Forecasting*, 2018, 34 (4), 788–801.
- Bjørnland, Hilde C., Karsten Gerdrup, Anne Sofie Jore, Christie Smith, and Leif Anders Thorsrud**, “Does Forecast Combination Improve Norges Bank Inflation Forecasts?,” *Oxford Bulletin of Economics and Statistics*, 2012, 74 (2), 163–179.
- Canova, Fabio**, “FAQ: How do I estimate the output gap?,” *Economic Journal*, 2024, *forthcoming*.
- Caraiani, Petre**, “Evaluating exchange rate forecasts along time and frequency,” *International Review of Economics & Finance*, 2017, 51 (C), 60–81.
- Chan, Felix and Laurent L. Pauwels**, “Some theoretical results on forecast combinations,” *International Journal of Forecasting*, 2018, 34 (1), 64–74.
- Clark, Todd**, “Real-Time Density Forecasts From Bayesian Vector Autoregressions With Stochastic Volatility,” *Journal of Business & Economic Statistics*, 2011, 29 (3), 327–341.

- **and Francesco Ravazzolo**, “Macroeconomic Forecasting Performance under Alternative Specifications of Time-Varying Volatility,” *Journal of Applied Econometrics*, 2015, 30 (4), 551–575.
- Clark, Todd E. and Taeyoung Doh**, “Evaluating alternative models of trend inflation,” *International Journal of Forecasting*, 2014, 30 (3), 426–448.
- Coibion, Olivier and Yuriy Gorodnichenko**, “Is the Phillips Curve Alive and Well after All? Inflation Expectations and the Missing Disinflation,” *American Economic Journal: Macroeconomics*, 2015, 7 (1), 197–232.
- Crowley, Patrick M. and David Hudgins**, “Okun’s law revisited in the time-frequency domain: introducing unemployment into a wavelet-based control model,” *Empirical Economics*, 2021, 61 (5), 2635–2662.
- **and —**, “Resilient Control for Macroeconomic Models,” *Computational Economics*, 2023, 61 (4), 1403–1431.
- D’Agostino, Antonello, Luca Gambetti, and Domenico Giannone**, “Macroeconomic forecasting and structural change,” *Journal of Applied Econometrics*, 2013, 28 (1), 82–101.
- Dangl, Thomas and Michael Halling**, “Predictive regressions with time-varying coefficients,” *Journal of Financial Economics*, 2012, 106 (1), 157–181.
- del Negro, Marco and Frank Schorfheide**, “DSGE Model-Based Forecasting,” in G. Elliott, C. Granger, and A. Timmermann, eds., *Handbook of Economic Forecasting*, Vol. 2 of *Handbook of Economic Forecasting*, Elsevier, 2013, chapter 2, pp. 57–140.
- **, Keshav Dogra, Aidan Gleich, Pranay Gundam, Donggyu Lee, Ramya Nallamotu, and Brian Pacula**, “The NY Fed DSGE Model: A Post-COVID Assessment,” *AEA Papers and Proceedings*, 2024, 114, 95–100.

- Dellas, Harris, Heather D. Gibson, Stephen G. Hall, and George S. Tavlas**, “The macroeconomic and fiscal implications of inflation forecast errors,” *Journal of Economic Dynamics and Control*, 2018, 93 (C), 203–217.
- Denk, Sebastian and Gunter Löffler**, “Predicting the Equity Premium with Combination Forecasts: A Reappraisal,” *Review of Asset Pricing Studies*, 2024, 14 (4), 545–577.
- Diebold, Francis X. and Roberto S. Mariano**, “Comparing Predictive Accuracy,” *Journal of Business & Economic Statistics*, 1995, 13 (3), 253–263.
- Dur, Ayşe and Enrique Martínez García**, “Mind the gap! – A monetarist view of the open-economy Phillips curve,” *Journal of Economic Dynamics and Control*, 2020, 117, 103959.
- Engle, Robert F**, “Band spectrum regression,” *International Economic Review*, 1974, 15, 1–11.
- Estrella, Arturo and Frederic Mishkin**, “Predicting U.S. Recessions: Financial Variables As Leading Indicators,” *Review of Economics and Statistics*, 1998, 80 (1), 45–61.
- **and Gikas A. Hardouvelis**, “The Term Structure as a Predictor of Real Economic Activity,” *Journal of Finance*, 1991, 46 (2), 555–576.
- Eugster, Patrick and Matthias W. Uhl**, “Forecasting inflation using sentiment,” *Economics Letters*, 2024, 236, 111575.
- Fama, Eugene F. and G. William Schwert**, “Asset returns and inflation,” *Journal of Financial Economics*, 1977, 5 (2), 115–146.
- Faria, Gonçalo and Fabio Verona**, “Forecasting stock market returns by summing the frequency-decomposed parts,” *Journal of Empirical Finance*, 2018, 45, 228 – 242.
- **and —**, “The yield curve and the stock market: Mind the long run,” *Journal of Financial Markets*, 2020, 50 (C).

- **and** — , “Out-of-sample time-frequency predictability of the equity risk premium,” *Quantitative Finance*, 2021, 21 (12), 2119–2135.
- **and** — , “Forecast combination in the frequency domain,” Bank of Finland Research Discussion Papers 1/2023 2023.
- **and** — , “The economic value of frequency-domain information,” *Journal of Portfolio Management*, 2025, *forthcoming*.
- Faust, Jon and Jonathan H. Wright**, “Forecasting Inflation,” in G. Elliott, C. Granger, and A. Timmermann, eds., *Handbook of Economic Forecasting*, Vol. 2 of *Handbook of Economic Forecasting*, Elsevier, 2013, chapter 1, pp. 2–56.
- Fisher, Irving**, *The purchasing power of money*, Macmillan company, 1911.
- Fulton, Chad and Kirstin Hubrich**, “Forecasting US Inflation in Real Time,” *Econometrics*, 2021, 9 (4), 1–20.
- Gallegati, Marco and James B. Ramsey**, “Bond vs stock market’s Q: Testing for stability across frequencies and over time,” *Journal of Empirical Finance*, 2013, 24 (C), 138–150.
- , **Mauro Gallegati, James B. Ramsey, and Willi Semmler**, “The US Wage Phillips Curve across Frequencies and over Time,” *Oxford Bulletin of Economics and Statistics*, 2011, 73 (4), 489–508.
- Garratt, Anthony and Ivan Petrella**, “Commodity prices and inflation risk,” *Journal of Applied Econometrics*, 2022, 37 (2), 392–414.
- Gilchrist, Simon and Egon Zakrajšek**, “Credit Spreads and Business Cycle Fluctuations,” *American Economic Review*, 2012, 102 (4), 1692–1720.
- Giordani, Paolo and Paul Söderlind**, “Inflation forecast uncertainty,” *European Economic Review*, 2003, 47 (6), 1037–1059.

- Giri, Federico**, “The relationship between headline, core, and energy inflation: A wavelet investigation,” *Economics Letters*, 2022, 210 (C).
- Gordon, Robert**, “The Theory of Domestic Inflation,” *American Economic Review*, 1977, 67 (1), 128–34.
- Goyal, Amit and Ivo Welch**, “A Comprehensive Look at The Empirical Performance of Equity Premium Prediction,” *Review of Financial Studies*, 2008, 21 (4), 1455–1508.
- , —, and **Athanasse Zafirov**, “A Comprehensive 2022 Look at the Empirical Performance of Equity Premium Prediction,” *Review of Financial Studies*, 2024, 37 (11), 3490–3557.
- Granger, Clive W.J and Yongil Jeon**, “Thick modeling,” *Economic Modelling*, 2004, 21 (2), 323–343.
- Groen, Jan J.J., Richard Paap, and Francesco Ravazzolo**, “Real-Time Inflation Forecasting in a Changing World,” *Journal of Business & Economic Statistics*, 2013, 31 (1), 29–44.
- Hodrick, Robert J. and Edward C. Prescott**, “Postwar U.S. Business Cycles: An Empirical Investigation,” *Journal of Money, Credit and Banking*, 1997, 29 (1), 1–16.
- Huang, Dashan, Fuwei Jiang, Kunpeng Li, Guoshi Tong, and Guofu Zhou**, “Scaled PCA: A New Approach to Dimension Reduction,” *Management Science*, 2022, 68 (3), 1678–1695.
- Huber, Florian, Luca Onorante, and Michael Pfarrhofer**, “Forecasting euro area inflation using a huge panel of survey expectations,” *International Journal of Forecasting*, 2024, 40 (3), 1042–1054.
- Hubrich, Kirstin and Frauke Skudelny**, “Forecast Combination for Euro Area Inflation: A Cure in Times of Crisis?,” *Journal of Forecasting*, 2017, 36 (5), 515–540.
- Jarocinski, Marek and Michele Lenza**, “An Inflation-Predicting Measure of the Output Gap in the Euro Area,” *Journal of Money, Credit and Banking*, 2018, 50 (6), 1189–1224.

- Kelly, Bryan and Seth Pruitt**, “The three-pass regression filter: A new approach to forecasting using many predictors,” *Journal of Econometrics*, 2015, 186 (2), 294–316.
- Kilponen, Juha and Fabio Verona**, “Investment dynamics and forecast: Mind the frequency,” *Finance Research Letters*, 2022, 49 (C).
- Koop, Gary and Dimitris Korobilis**, “Forecasting inflation using dynamic model averaging,” *International Economic Review*, 2012, 53 (3), 867–886.
- Liu, Li, Xianfeng Hao, and Yudong Wang**, “Solving the Forecast Combination Puzzle Using Double Shrinkages,” *Oxford Bulletin of Economics and Statistics*, 2024, 86 (3), 714–741.
- Mankiw, N. Gregory**, “Six beliefs I have about inflation: Remarks prepared for NBER conference on “Inflation in the Covid era and beyond”,” *Journal of Monetary Economics*, 2024, p. 103631.
- Martins, Manuel M.F. and Fabio Verona**, “Inflation dynamics in the frequency domain,” *Economics Letters*, 2023, 231, 111304.
- and —, “Forecasting inflation with the new Keynesian Phillips curve: frequencies matter,” *Oxford Bulletin of Economics and Statistics*, 2024, 86 (4), 811–832.
- McCracken, Michael W. and Serena Ng**, “FRED-MD: A Monthly Database for Macroeconomic Research,” *Journal of Business & Economic Statistics*, 2016, 34 (4), 574–589.
- Medeiros, Marcelo C., Gabriel F. R. Vasconcelos, Alvaro Veiga, and Eduardo Zilberman**, “Forecasting Inflation in a Data-Rich Environment: The Benefits of Machine Learning Methods,” *Journal of Business & Economic Statistics*, 2021, 39 (1), 98–119.
- Naghi, Andrea A., Eoghan O’Neill, and Martina Danielova Zaharieva**, “The benefits of forecasting inflation with machine learning: New evidence,” *Journal of Applied Econometrics*, 2024, n/a (n/a).
- Ortu, Fulvio, Andrea Tamoni, and Claudio Tebaldi**, “Long-Run Risk and the Persistence of Consumption Shocks,” *Review of Financial Studies*, 2013, 26 (11), 2876.

- Pesaran, M Hashem and Allan Timmermann**, “Predictability of Stock Returns: Robustness and Economic Significance,” *Journal of Finance*, 1995, 50 (4), 1201–1228.
- Philippon, Thomas**, “The Bond Market’s q,” *Quarterly Journal of Economics*, 2009, 124 (3), 1011–1056.
- Pirschel, Inske and Maik H. Wolters**, “Forecasting with large datasets: compressing information before, during or after the estimation?,” *Empirical Economics*, September 2018, 55 (2), 573–596.
- Poledna, Sebastian, Michael Gregor Miess, Cars Hommes, and Katrin Rabitsch**, “Economic forecasting with an agent-based model,” *European Economic Review*, 2023, 151, 104306.
- Rapach, David E. and Guofu Zhou**, “Forecasting Stock Returns,” in G. Elliott, C. Granger, and A. Timmermann, eds., *Handbook of Economic Forecasting*, Vol. 2 of *Handbook of Economic Forecasting* 2013, chapter 6, pp. 328–383.
- , **Jack K. Strauss, and Guofu Zhou**, “Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy,” *Review of Financial Studies*, 2010, 23 (2), 821–862.
- Rua, Antonio**, “A wavelet approach for factor-augmented forecasting,” *Journal of Forecasting*, 2011, 30 (7), 666–678.
- , “Money Growth and Inflation in the Euro Area: A Time-Frequency View,” *Oxford Bulletin of Economics and Statistics*, 2012, 74 (6), 875–885.
- , “A wavelet-based multivariate multiscale approach for forecasting,” *International Journal of Forecasting*, 2017, 33 (3), 581–590.
- Sims, Christopher A.**, “Macroeconomics and Reality,” *Econometrica*, 1980, 48 (1), 1–48.
- Stein, Tobias**, “Forecasting the equity premium with frequency-decomposed technical indicators,” *International Journal of Forecasting*, 2024, 40 (1), 6–28.

- Stock, James H. and Mark W. Watson**, “Forecasting inflation,” *Journal of Monetary Economics*, 1999, 44 (2), 293–335.
- **and** — , “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, 2003, 41 (3), 788–829.
- **and** — , “Combination forecasts of output growth in a seven-country data set,” *Journal of Forecasting*, 2004, 23 (6), 405–430.
- **and** — , “Why Has U.S. Inflation Become Harder to Forecast?,” *Journal of Money, Credit and Banking*, 2007, 39 (s1), 3–33.
- Timmermann, Allan**, “Forecast Combinations,” in G. Elliott, C. Granger, and A. Timmermann, eds., *Handbook of Economic Forecasting*, Vol. 1 of *Handbook of Economic Forecasting*, Elsevier, 2006, chapter 4, pp. 135–196.
- Verbrugge, Randal J.**, “Inflation’s Last Half Mile: Higher for Longer?,” *Economic Commentary*, 2024, (2024-09), 1–8.
- Wang, Xiaoqian, Rob J. Hyndman, Feng Li, and Yanfei Kang**, “Forecast combinations: An over 50-year review,” *International Journal of Forecasting*, 2023, 39 (4), 1518–1547.
- West, Kenneth D.**, “Asymptotic Inference about Predictive Ability,” *Econometrica*, 1996, 64 (5), 1067–1084.
- Wu, Jing Cynthia and Fan Dora Xia**, “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound,” *Journal of Money, Credit and Banking*, 2016, 48 (2-3), 253–291.
- Zhang, Keyi, Ramazan Gençay, and M. Ege Yazgan**, “Application of wavelet decomposition in time-series forecasting,” *Economics Letters*, 2017, 158, 41–46.

(Predictor number) / acronym	Predictor name	Data source
(1) / DP	Dividend-price ratio	Goyal, Welch and Zafirov (2024)
(2) / TBL	Treasury bill rate	Goyal et al. (2024)
(3) / LTR	Long-term bond return	Goyal et al. (2024)
(4) / TMS	Term spread	Goyal et al. (2024)
(5) / DFR	Default return spread	Goyal et al. (2024)
(6) / SHR	Shadow rate	Wu and Xia (2016)
(7) / M2	M2 growth rate	McCracken and Ng (2016)
(8) / MSC	Inflation expectations	Martins and Verona (2024)
(9) / U	Unemployment	Martins and Verona (2024)
(10) / CPI energy	CPI / PCE energy inflation	Martins and Verona (2024)

Table 1: Predictors of inflation

	mean	median	1st perc.	99th perc.	std. dev.	skew.	kurt.	AR(1)
Panel A) Target variables								
CPI inflation (h=1)	3.51	3.07	-3.43	13.3	3.09	0.83	6.63	0.70
CPI inflation (h=4)	3.48	2.86	-0.67	13.2	2.64	1.83	6.69	0.96
CPI inflation (h=8)	3.40	2.75	0.43	12.0	2.39	2.13	7.72	0.98
PCE inflation (h=1)	3.00	2.56	-2.39	10.8	2.46	0.88	5.81	0.78
PCE inflation (h=4)	2.97	2.43	-0.63	10.3	2.19	1.62	5.84	0.97
PCE inflation (h=8)	2.90	2.30	0.46	9.85	2.01	1.88	6.56	0.99
Panel B) Predictors								
DP	-3.74	-3.87	-4.48	-2.83	0.43	0.47	2.24	0.98
TBL	0.04	0.04	0.00	0.15	0.04	0.81	3.38	0.96
LTR	0.02	0.01	-0.11	0.21	0.06	0.75	4.52	-0.06
TMS	0.02	0.02	-0.03	0.04	0.02	-0.60	3.28	0.83
DFR	0.00	0.00	-0.11	0.06	0.03	-0.44	12.8	-0.11
SHR	0.04	0.05	-0.03	0.18	0.04	0.73	3.62	0.96
M2	0.01	0.01	-0.02	0.05	0.01	3.57	30.8	0.47
MSC	3.59	3.07	2.08	9.80	1.61	2.51	9.05	0.95
U	6.10	5.72	3.54	10.6	1.76	0.85	3.60	0.89
CPI energy	4.28	4.36	-53.1	45.4	19.0	-0.95	7.35	0.27

Table 2: Summary statistics, U.S. data, 1978:Q1-2023:Q4

This table reports summary statistics for different inflation measures (panel A) and their predictors (panel B).

Panel A) Models in the time domain	
TS-1 to TS-10	1-10
TS-KS	11
TS-SIC	12
TS-PCA	13
TS-PC	14
TS-TVC-1 to TS-TVC-10	15-24
TS-MSC	25
TS-SPF	26
Panel B) Models in the frequency domain	
WAV-1 to WAV-10	27-36
WAV-KS	37
WAV-SIC	38
WAV-PCA	39
WAV-PC	40
WAV-TVC-1 to WAV-TVC-10	41-50
WAV-FC-1	51
WAV-FC-2	52
WAV-MSC	53
WAV-SPF	54

Table 3: The model suite

Inflation measure	CPI			PCE		
Forecasting horizon	h=1	h=4	h=8	h=1	h=4	h=8
Panel A) Benchmark						
AO	2.57	2.03	1.66	1.88	1.61	1.39
Panel B) Individual forecast model – TD						
TS-1	1.13	1.12	1.15	1.24	1.19	1.19
TS-2	1.05	1.06	1.18	1.11	1.14	1.25
TS-3	1.11	1.13	1.24	1.18	1.18	1.24
TS-4	1.17	1.15	1.25	1.24	1.21	1.26
TS-5	1.13	1.15	1.24	1.21	1.20	1.24
TS-6	1.06	1.08	1.19	1.13	1.16	1.25
TS-7	1.18	1.49	1.52	1.26	1.52	1.49
TS-8	0.94*	0.93	1.06	0.98	0.97	1.06
TS-9	1.12	1.10	1.21	1.22	1.16	1.25
TS-10	1.16	1.34	1.38	1.24	1.38	1.37
TS-KS	1.01	1.04	1.02	1.04	1.03	1.04
TS-SIC	0.97	1.01	1.03	1.01	1.04	1.03
TS-PCA	1.04	1.06	1.12	1.09	1.11	1.15
TS-PC	0.97	0.93	1.05	1.00	0.95	1.07
TS-TVC-1	<u>0.91**</u>	<u>0.84**</u>	0.94*	<u>0.94</u>	0.87**	0.96
TS-TVC-2	0.98	0.93	0.99	1.03	1.00	1.03
TS-TVC-3	0.93	0.89*	0.94*	0.96	0.92	0.94*
TS-TVC-4	0.99	0.90*	0.92**	1.01	0.93	0.93**
TS-TVC-5	1.05	0.94	0.95*	1.08	0.97	0.95*
TS-TVC-6	0.97	0.93	0.97	1.03	0.98	1.01
TS-TVC-7	0.98	1.06	1.03	1.03	1.12	1.05
TS-TVC-8	0.94**	0.96	1.02	0.96	0.98	1.01
TS-TVC-9	0.99	0.94	0.96	1.03	0.97	0.95
TS-TVC-10	0.97	0.89*	0.93**	1.00	0.91*	0.93**
TS-MSC	0.95	0.90	0.97	1.08	1.07	1.15
TS-SPF	0.95	0.85**	<u>0.88***</u>	0.98	<u>0.87*</u>	<u>0.88*</u>

Table 4: Out-of-sample root mean squared forecast errors, time domain individual models

Panel A): Root mean squared errors (RMSEs) at different forecasting horizons (h=1, h=4, and h=8) for the AO model. Panel B): RMSEs relative to those of the AO model ($RMSE_j / RMSE_{AO}$ for model j). Asterisks indicate statistical significance of the Diebold-Mariano-West test of comparative predictive accuracy at the 10 % (*), 5 % (**), and 1 % (***) levels, relative to the AO model. The out-of-sample period is 2000:Q1-2023:Q4 for h=1, 2000:Q4-2023:Q4 for h=4, and 2001:Q4-2023:Q4 for h=8. Bold underlined entries denote the best model for that horizon and inflation measure.

Inflation measure	CPI			PCE		
Forecasting horizon	h=1	h=4	h=8	h=1	h=4	h=8
Panel A) Benchmark						
AO	2.57	2.03	1.66	1.88	1.61	1.39
Panel B) Individual forecast model – FD						
WAV-1	1.06	1.00	1.02	1.15	1.09	1.09
WAV-2	1.06	1.03	1.08	1.16	1.13	1.15
WAV-3	1.27	1.36	1.45	1.35	1.37	1.36
WAV-4	1.15	1.15	1.28	1.25	1.20	1.26
WAV-5	1.17	1.12	1.25	1.32	1.26	1.39
WAV-6	1.06	1.03	1.07	1.16	1.12	1.14
WAV-7	1.17	1.21	1.22	1.25	1.26	1.22
WAV-8	1.01	0.95	1.03	1.06	0.99	1.05
WAV-9	1.21	1.28	1.47	1.38	1.45	1.62
WAV-10	1.24	1.40	1.65	1.35	1.46	1.64
WAV-KS	1.01	1.00	1.04	1.01	1.00	1.03
WAV-SIC	0.99	0.95	1.02	1.02	0.99	1.04
WAV-PCA	1.08	1.06	1.13	1.16	1.13	1.18
WAV-PC	0.97	0.88**	0.88**	1.03	0.94	0.93
WAV-TVC-1	0.97	0.91	0.96	1.01	0.95	0.99
WAV-TVC-2	0.99	0.96	1.00	1.05	1.04	1.05
WAV-TVC-3	1.03	0.91	0.99	1.02	0.93	0.95
WAV-TVC-4	0.96	0.89**	0.95*	0.99	0.91*	0.95*
WAV-TVC-5	0.98	1.21	1.05	1.02	1.09	1.07
WAV-TVC-6	1.01	0.90	0.94*	1.16	0.94	0.99
WAV-TVC-7	1.16	1.09	1.27	1.15	1.06	1.24
WAV-TVC-8	1.00	0.96	1.00	1.05	0.98	1.03
WAV-TVC-9	0.95	0.88*	0.91***	1.15	0.95	0.95*
WAV-TVC-10	1.24	0.91*	0.98	1.34	0.93	0.98
WAV-FC-1	0.96	0.91*	0.98	0.99	0.93	0.97
WAV-FC-2	0.98	0.90*	0.94	1.02	0.92	0.94
WAV-MS	1.00	0.92	0.97	1.13	1.07	1.12
WAV-SPF	0.97	0.86*	0.86***	1.01	0.89*	0.86*

Table 5: Out-of-sample root mean squared forecast errors, frequency domain individual models
Panel A): Root mean squared errors (RMSEs) at different forecasting horizons (h=1, h=4, and h=8) for the AO model. Panel B): RMSEs relative to those of the AO model ($RMSE_j / RMSE_{AO}$ for model j). Asterisks indicate statistical significance of the Diebold-Mariano-West test of comparative predictive accuracy at the 10 % (*), 5 % (**), and 1 % (***) levels, relative to the AO model. The out-of-sample period is 2000:Q1-2023:Q4 for h=1, 2000:Q4-2023:Q4 for h=4, and 2001:Q4-2023:Q4 for h=8. Bold underlined entries denote the best model for that horizon and inflation measure.

Inflation measure	CPI			PCE		
Forecasting horizon	h=1	h=4	h=8	h=1	h=4	h=8
Panel A) Best individual models						
Best individual models	0.91**	0.84**	0.86***	0.94	0.87*	0.86*
[model used]	[TS-TVC-1]	[TS-TVC-1]	[WAV-SPF]	[TS-TVC-1]	[TS-SPF]	[WAV-SPF]
Panel B) Combination forecast models						
Mean all	0.94	0.87**	0.91**	0.98	0.90*	0.92**
DMSPE_1 all	0.94*	0.91**	0.96*	0.94	0.92**	0.97*
DMSPE_2 all	0.93*	0.89**	0.95**	0.95	0.91**	0.95**
DMSPE_3 all	0.94	0.89**	0.94**	0.98	0.92*	0.95*
Mean best	0.89**	0.77***	0.76*	0.92*	0.77**	0.75*
[models used]	[12 15 20 30]	[2 15 30 31]	[30 31 47]	[12 15 17 30]	[15 30 31 32]	[30 31 32]
DMSPE_1 best	0.83***	0.82***	0.78	0.84***	0.83***	0.76
[models used]	[2 17 30]	[4 15 54]	[4 9 30]	[17 20 30]	[4 15 45]	[4 9 30]
DMSPE_2 best	0.86***	0.82***	0.81	0.87***	0.84***	0.77
[models used]	[2 3 15 30]	[4 15 54]	[4 9 30]	[10 17 20 30]	[4 10 15 46]	[9 30]
DMSPE_3 best	0.89**	0.78***	0.79**	0.91*	0.79**	0.79**
[models used]	[10 15 20 30]	[10 30 31 32]	[4 30 31 54]	[10 15 17 30]	[10 30 31 42]	[6 9 30 31]
Panel C) Combination forecast models – TD vs FD						
Mean all TS only	0.94	0.88**	0.92*	0.97	0.91*	0.92
Mean all WAV only	0.95	0.88**	0.92***	0.99	0.90*	0.92**
Mean best TS only	0.90**	0.83**	0.85***	0.93*	0.85**	0.84**
[models used]	[15 17 22]	[4 15 24 26]	[6 9 26]	[15 17 22]	[15 26]	[6 9 26]
Mean best WAV only	0.92*	0.77**	0.76*	0.93	0.77**	0.75*
[models used]	[30 31 37 46]	[30 31 32]	[30 31 47]	[30 31 37 46]	[30 31 32]	[30 31 32]

Table 6: Out-of-sample root mean squared forecast errors, combinations of models

Panel A): RMSEs at different forecasting horizons (h=1, h=4, and h=8) of individual forecasting models relative to those of the AO model. Panels B) and C): RMSEs of combinations of models relative to those of the AO model. Asterisks indicate statistical significance of the Diebold-Mariano-West test of comparative predictive accuracy at the 10 % (*), 5 % (**), and 1 % (***) levels, relative to the AO model. The out-of-sample period is 2000:Q1-2023:Q4 for h=1, 2000:Q4-2023:Q4 for h=4, and 2001:Q4-2023:Q4 for h=8. Bold underlined entries denote the best model for that horizon and inflation measure.

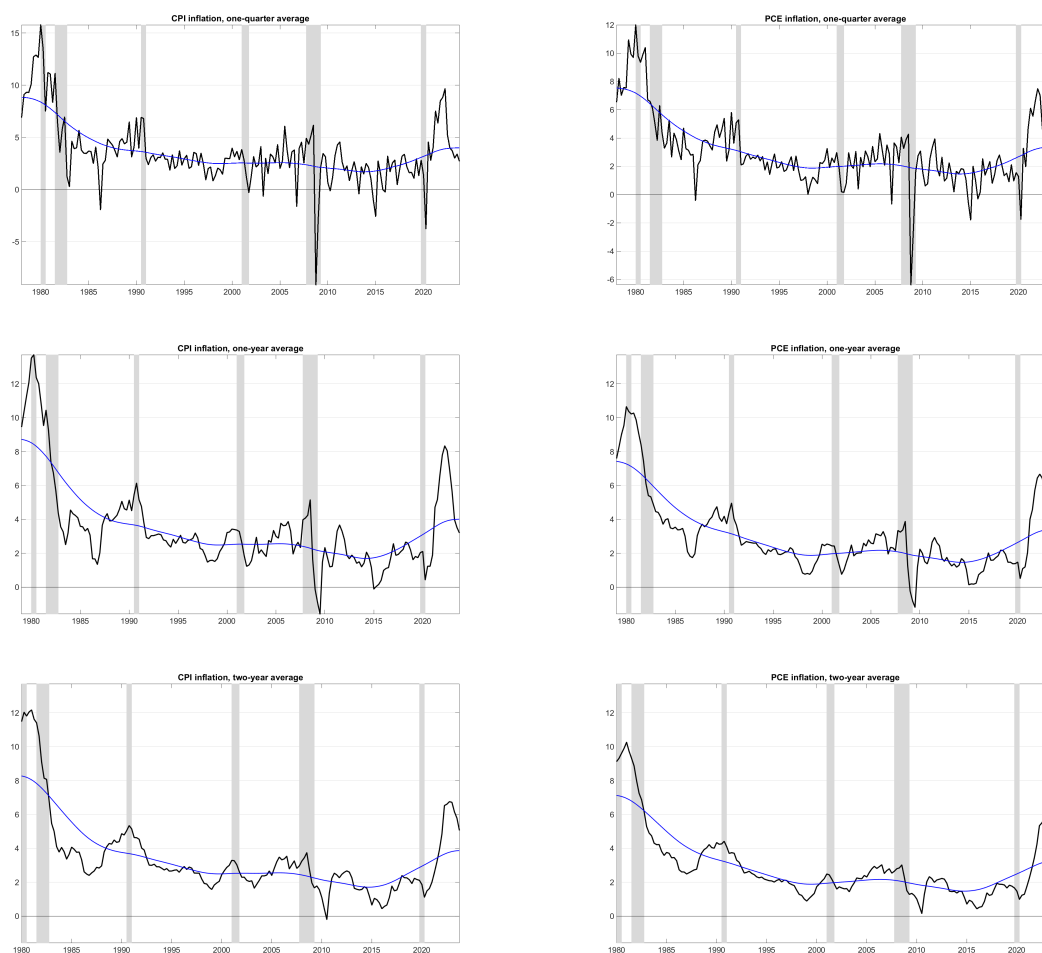


Figure 1: Annualized inflation rates (percent)

This figure plots the quarterly U.S. one-quarter, one-year, and two-year average inflation rates corresponding to various price indexes (black lines) along with their long-run trends (blue lines), which have been computed using the Haar filter and capture fluctuations longer than 16 years. Sample period: 1978-2023. Shading indicates periods of NBER-dated recessions.

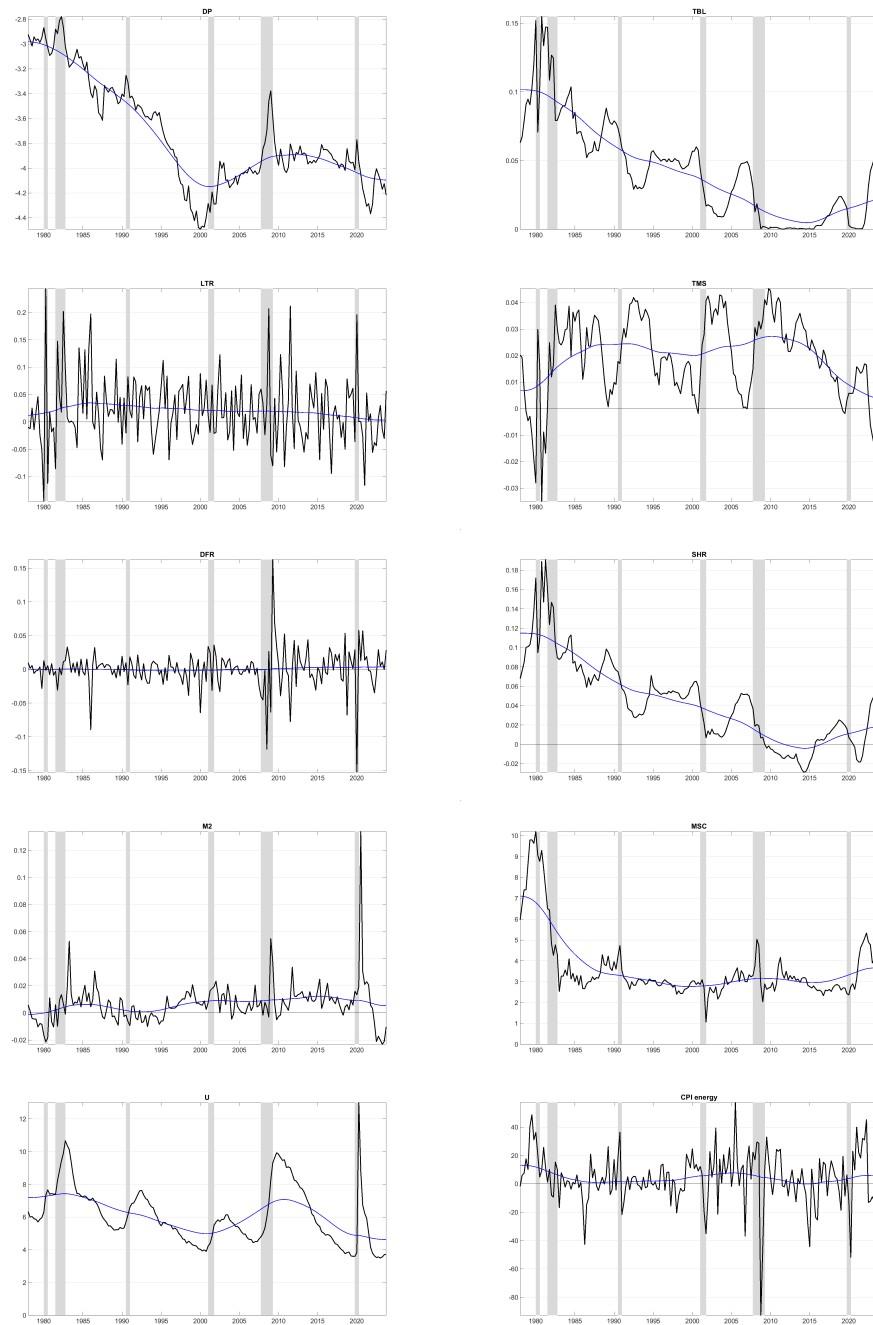


Figure 2: Predictors of inflation

This figure plots the predictors of inflation (black lines) along with their long-run trends (blue lines), which have been computed using the Haar filter and capture fluctuations longer than 16 years. Sample period: 1978-2023. Shading indicates periods of NBER-dated recessions.

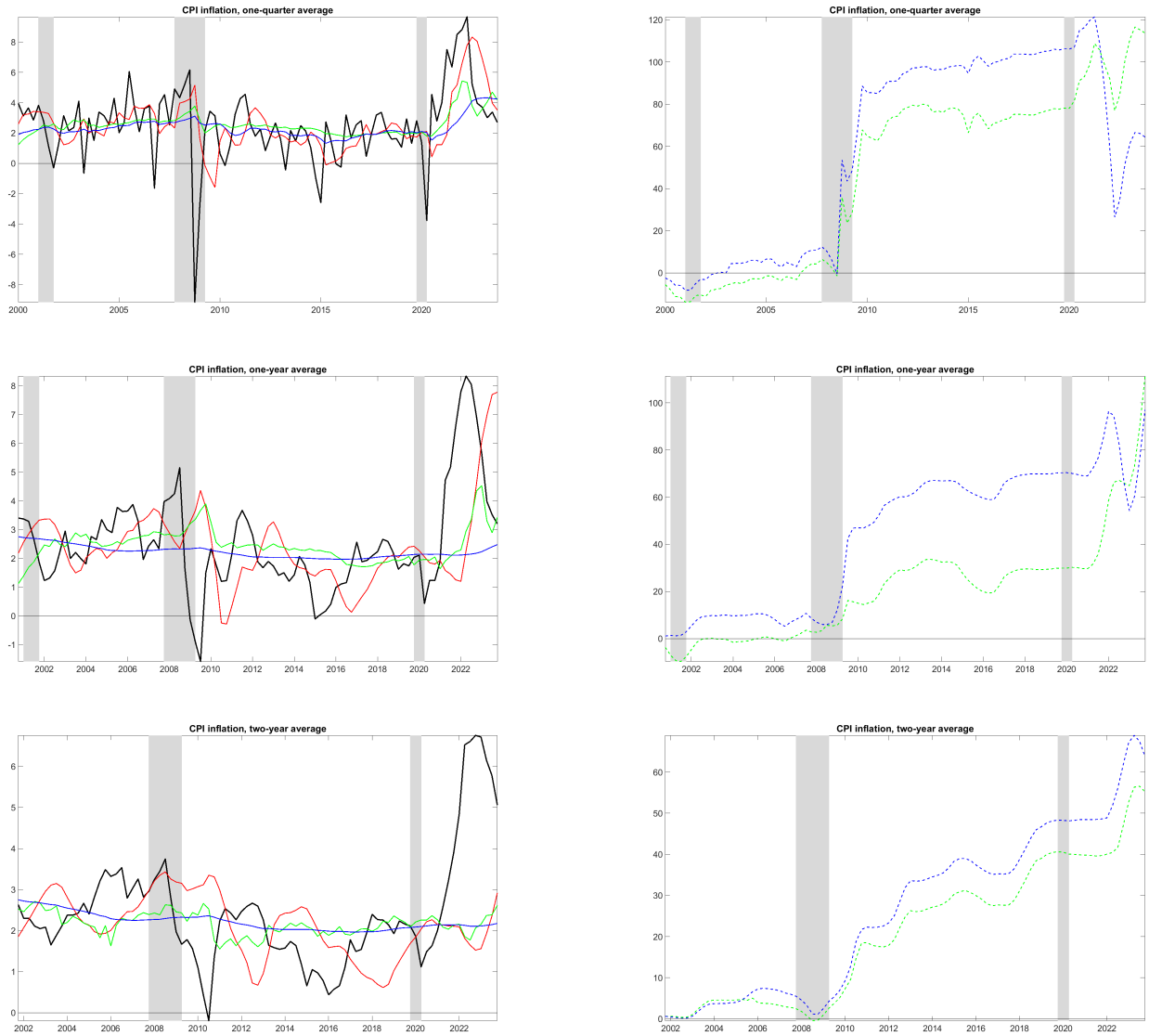


Figure 3: CPI inflation forecasts and cumulative squared forecast error differences: best individual models vs AO benchmark

The graphs on the left report realized inflation (black lines) and its forecasts made with the AO model (red lines), with the best individual TS model (green lines), and with the best individual WAV model (blue lines). The graphs on the right report the cumulative differences between the squared forecast errors of the best individual TS/WAV model and those of the AO model (green/blue dashed lines). First row: CPI inflation, $h=1$. Second row: CPI inflation, $h=4$. Third row: CPI inflation, $h=8$.

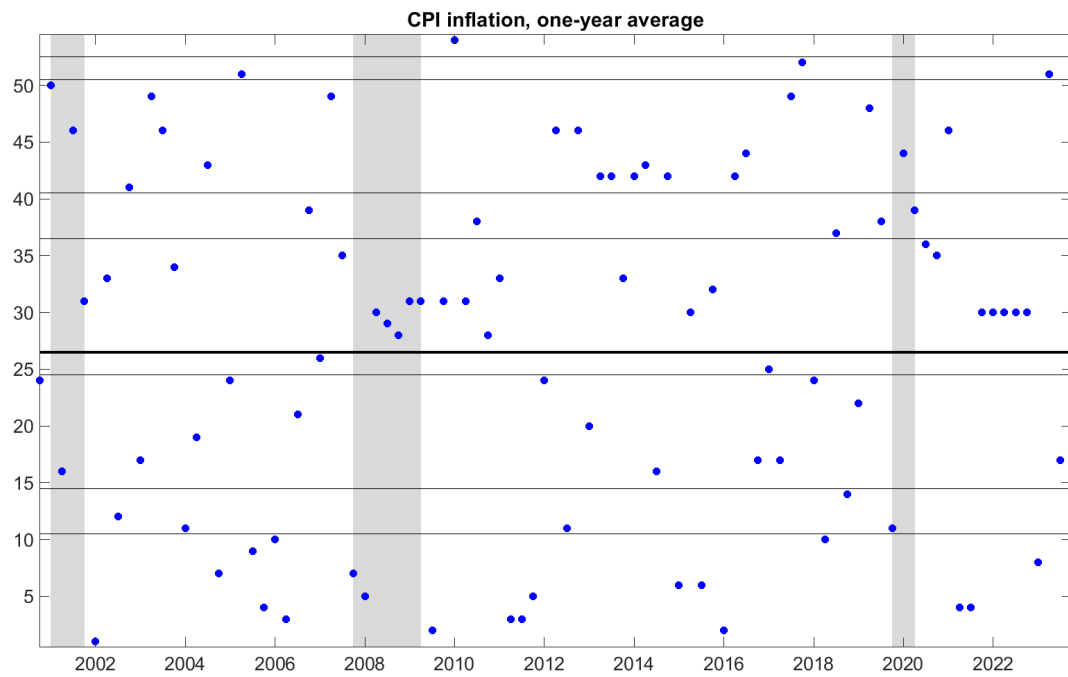


Figure 4: Best individual forecasting models over time

This figure plots the best-performing individual forecasting models for CPI inflation ($h=4$) at each point of the out-of-sample period.

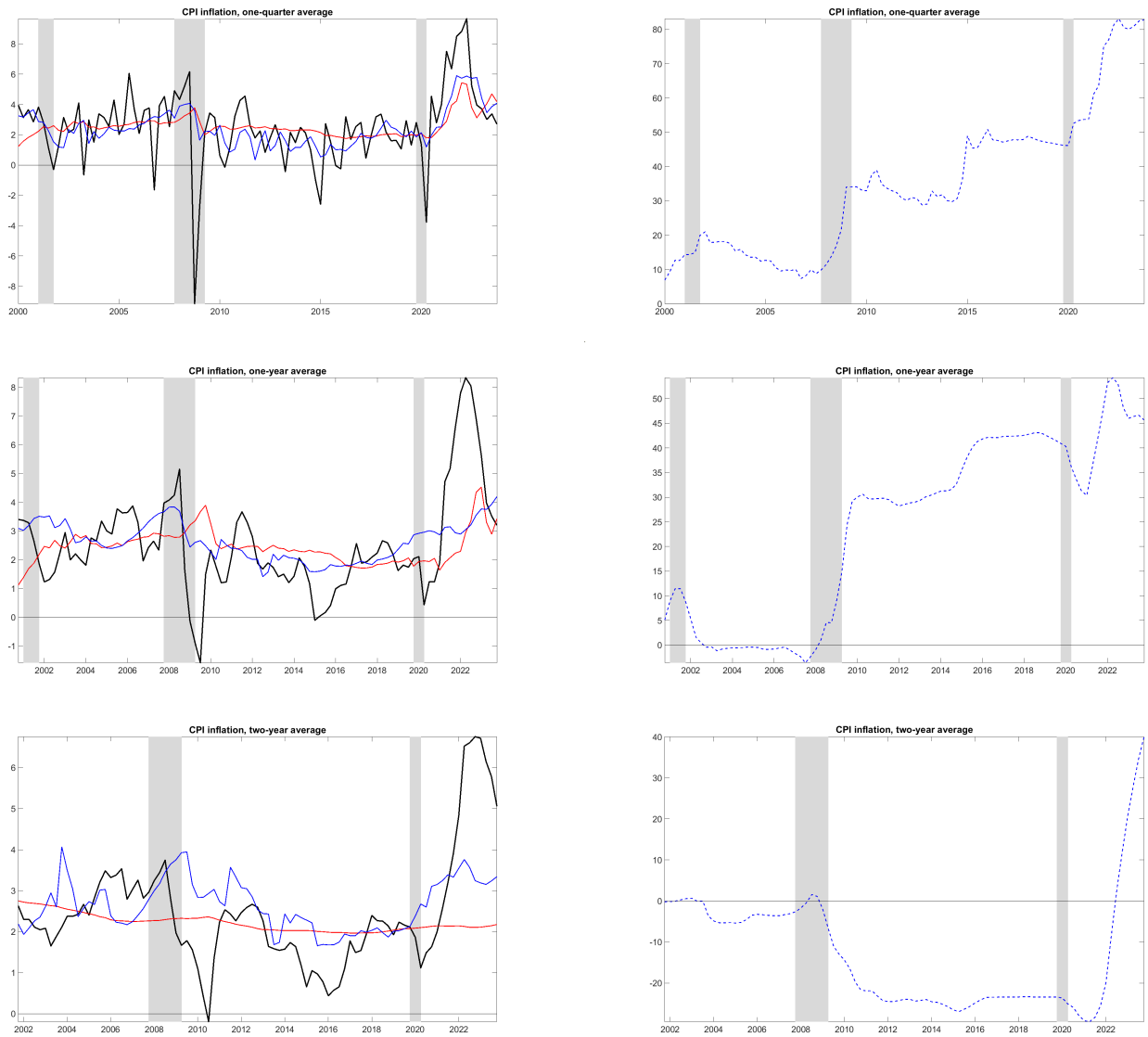


Figure 5: CPI inflation forecasts and cumulative squared forecast error differences: best combination model vs best individual model

The graphs on the left report realized inflation (black lines) and its forecasts made with the the best individual model (red lines) and with the best combination model (blue lines). The graphs on the right report the cumulative differences between the squared forecast errors of the best combination model and those of the best individual model (blue dashed lines). First row: CPI inflation, $h=1$. Second row: CPI inflation, $h=4$. Third row: CPI inflation, $h=8$.

Bank of Finland Research Discussion Papers 2025

ISSN 1456-6184, online

1/2025 Fabio Verona

From waves to rates: enhancing inflation forecasts through combinations of frequency-domain models