Selling price expectations and headline inflation – Developing Predictive Models for HICP Inflation Using EU Business Survey Data on Selling Price Expectations

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European Commission[1]

Abstract

The study's primary objective is to explore the ability of selling price expectations from the EU harmonised business surveys to forecast inflation, as measured by the Harmonised Index of Consumer Prices (HICP). By leveraging the extensive dataset of sectoral selling price expectations, this study aims to identify the selling price expectations indicators that contain the most information, leading to the most accurate out-of-sample inflation forecasts. To mitigate model uncertainty, two alternative approaches are used to extract information from our large datasets: variable selection and factor models.

Keywords: Inflation expectations, Forecasting

JEL Classification: E31, E37, D84

[1] This paper should not be reported as representing the views of the European Commission (EC). The views expressed are those of the authors and do not necessarily reflect those of the EC.

1. Introduction

Inflation forecasting is crucial for economic policy and planning, yet the complexity and variability of inflation drivers across sectors pose significant challenges. As firms are key players in consumer price formation, this study investigates the extent to which selling price expectations (SPE) from the EU harmonised business surveys can improve forecasts of the Harmonised Index of Consumer Prices (HICP) inflation. Recent studies evidence that business surveys from the EU harmonised programme offer valuable leading information that can enhance the accuracy of inflation forecasts. For example,using recent advances in computationa statistics Huber, Onorante and Pfarrhofer (2024) show that that including a wide range of business and consumer surveys improves price forecasts and assessments of tail risks to inflation.[2] The European Central Bank (ECB 2024) focues on the information content of selling price expectations in services sectors, showing their usefulness in predicting turning points in inflation and improving three-month-ahead inflation forecasts, particularly during the recent inflation surge. The ECB also provides evidence for the high non-linearity of the predictive relationship[3]

This study aims to develop a framework for assessing the predictive power of managers' expectations of selling prices over different time horizons and to identify the sectors that have a major influence on the future evolution of consumer prices. Its goal is to exploit the key information contained in managers' expectations of selling prices to provide a clearer picture of future inflation trends.

As a first step in evaluating the performance of SPE-driven forecast models in a more comprehensive setting, this study makes a formal comparison with random walk models for annual inflation. Furthermore, in the absence of official monthly inflation forecasts, quarterly forecasts by the European Commission can be used to assess the plausibility of the inflation forecasts across the five-months horizon window set in the empirical analysis.

2. Data

The independent variables used to model HICP inflation are business selling price expectations from the Harmonised Business Surveys for the euro area. National institutes in each of the 19

[2] More precisely, the analysis suggests that including a wide range of firms' and consumers' opinions about future economic developments offers useful information to forecast prices and assess tail risks to inflation. These predictive improvements arise from surveys related to expected inflation and other questions related to the general economic environment. Moreover, firms' expectations about the future seem to have more predictive content than consumer expectations.

[3] Using the selling price expectations of the euro area services sector compiled by the European Commission, which comprises selling price expectations of firms in both business-to-consumer and business-to business domains, the authors found that selling price expectations for services do hold some predictive power for HICP services, which is more visible around turning points and when inflation is high.

participating countries[4] conduct the surveys. The harmonised questionnaire contains questions in all business surveys (i.e., manufacturing industry, services, retail trade and construction) on the selling prices managers are expected to set. The relevant survey question reads as follows:

"How do you expect your selling prices to change over the next 3 months? They will: (1) increase, (2) remain unchanged, (3) decrease."

The dataset is comprehensive and contains more than 20 years of monthly data on managers' selling price expectations, from January 2004 to June 2024 across 69 economic activities (2-digit NACE divisions) in manufacturing, services, retail and construction for 19 euro-area countries. The data series chosen for this analysis are both non-seasonally and seasonally adjusted.

The dependent variable of interest is the euro-area annual headline inflation, i.e., year-on-year percentage changes of the euro-area overall HICP. Several approaches pursued in the note include analysing the headline inflation index directly as well as forecasting individual components separately (food, non-energy industrial goods, energy, and services) and aggregating these forecasts to obtain the forecast of the headline index. Regarding the transformation of the dependent variable used, both the year-on-year growth rate and the 3-month-on-3-month change price momentum were analysed and compared.

The focus of the analysis is the euro area since the advance flash inflation estimate is published by Eurostat for the euro area at the end of the reference month. By contrast, the EU aggregate is only available 2-3 weeks after the euro-area flash. Moreover, the euro-area inflation rate receives more attention as it is the key ECB policy target variable. The inflation rate for the EU remains a heterogenous aggregate where intra-EU exchange rate movements play a role in price formation. Finally, "official" seasonally adjusted HICP series, which are used in the 3-month-on-3-month percentage change (momentum) calculations, are published by the ECB[5] only for the euro-area aggregates.

2.1 Relevance of selling price expectations

BCS selling price expectations are particularly valuable for several reasons:

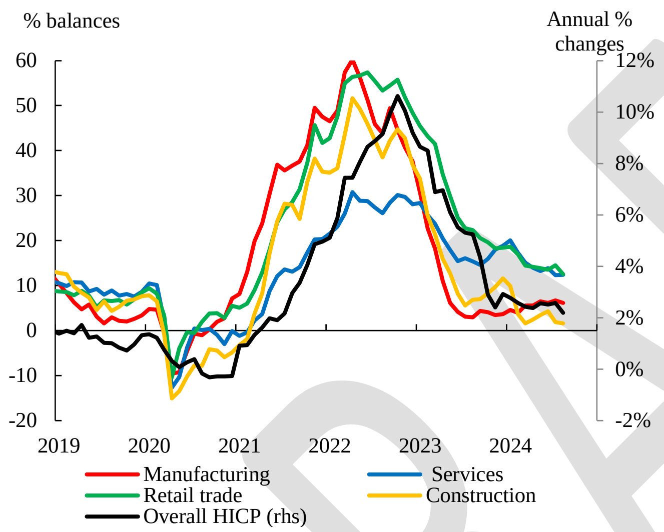
1. Forward-looking Information: Unlike historical price data, which reflect past economic conditions, selling price expectations offer insights into future pricing behaviours of firms. This forward-looking aspect can potentially provide an early warning signal for inflationary pressures.

[4] Ireland is not included in the eurozone countries because the Bank of Ireland, which had been conducting the survey since 2016, ceased to do so in February 2023. Since July 2024, a new institute (IPSOS) has conducted the surveys. However, these data will only be included once enough data points are available to check the consistency with previous data.

[5] See ECB Data Portal

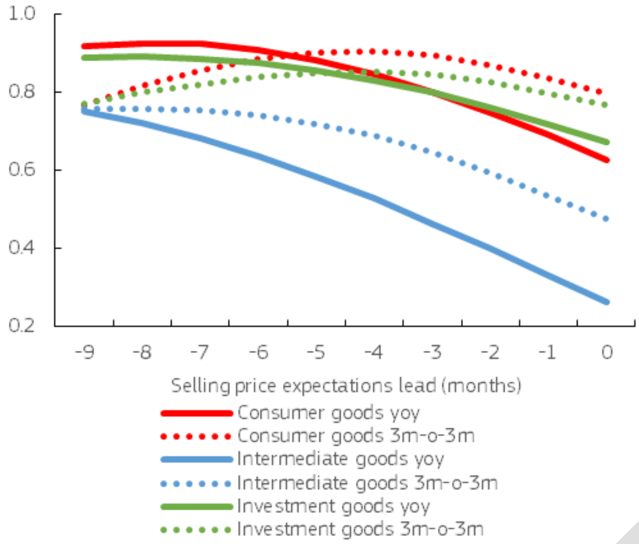
2. Sectoral Insights: The surveys cover various sectors, including manufacturing, services, retail, and construction. This granularity allows for a more nuanced understanding of inflation dynamics across different parts of the economy. Naturally, only a small subset of goods produced, and services provided by firms covered by the BCS SPE survey (i.e. NACE-2 divisions of manufacturing C, services H-S and retail G) enter directly into the *consumer* price basket. Conversely, there are goods and services in the HICP *consumer* basket that are not accounted for by the divisions for which SPE are available (e.g. most energy). The match between the SPE and HICP is, therefore, not perfect, but appears sufficiently good to explore the SPE dataset with the goal of shedding light of consumer price pressures.

Graph 1 – Selling price expectations and overall HICP inflation.



A first visual inspection of SPE and headline HICP reveals a significant contemporaneous correlation between year-on-year HICP inflation and the seasonally adjusted selling price expectations (see European Commission 2023 Q1 EBCI Special Topic). More recently, however, this correlation has weakened as major inflation shocks stroke (COVID-19 pandemic, supply-side bottlenecks, energy and food commodity price shocks) increasing volatility and pushing consumer price inflation to historical highs. As these shocks wore off and inflation started moderating in late 2022, outsized base effects began distorting the profile of annual inflation, again increasing volatility unrelated to current price developments. For this reason, the European Commission EBCI special topic of 2024-Q1 examined the predictive power of the surveys against the momentum of price changes, measured as the 3-month-on-3-month percentage change of the HICP series rather than annual HICP inflation. The analysis highlighted that the correlation changed over time and that some subsectors have a higher correlation with the corresponding HICP than other subsectors. For example, within industry, SPE from the main industrial grouping (MIG) producing consumer goods have a higher correlation with non-energy industrial goods and processed food HICP momentum than with the other MIGs. This is the case also when looking at year-on-year changes when selling price expectations are leading by at least 3 months.

Graph 2: correlation between HICP NEIG and processed food and SPE (Jan 2002 - May 2024)



Moreover, the analysis pointed out that higher correlations are reached with some months of lead in some subsectors such as services, while in other cases – such as retail trade - the coincident correlation is stronger.

Given the complexity of the selling price expectations-inflation relationship, it has become clear that a simple weighted average would not be the best composite indicator to now-/forecast the HICP. With the aim of identifying one or several models with the highest predictive power for HICP inflation, the analysis takes a look at the full dataset of BCS selling price expectations:

- It includes all 64 subsectors for which SPE are available in the explanatory variable dataset, thus allowing for potential impacts on prices coming from various parts of manufacturing, services, retail trade and construction.
- It includes variables as well as 12 lags of each of the 64 SPE series to allow for various sectors to impact prices at different horizons. Preliminary correlation analysis indeed confirms the intuitive sequence of pipeline pressure for consumer prices, with manufacturing SPE impacting prices first (with longest lags), followed by services and retail.
- The analysis tries to address the instability of the relationship by looking at various moving windows of different lengths within the available dataset: January 2010 – June 2024.

Finally, to maximise the predictive power of SPE with respect to consumer price inflation in the euro area, several approaches to expressing the latter were explored:

- Annual rates of inflation - annual rate of change of the price series (neither seasonally nor calendar adjusted)

- Momentum in price change: 3m-o-3m change in the seasonally and calendar-adjusted series for which simple correlation analysis revealed higher values of correlation coefficient than for the annual inflation rates when selling price expectations are leading by up to three months (see Graph 2).

- The dependent variable was both expressed as a headline index (aggregate HICP) as well as separately, for each of the 4 major components (food, industrial goods, energy, and services) that were later aggregated up to the headline HICP using standard weights.

3. Econometric analysis

Our econometric analysis aims to determine the optimal combination of inflation predictors from the rich set of SPE indicators. We formulate multiple alternative models, each with a distinct combination of predictors and compare their out-of-sample performance in forecasting inflation. Following the literature on forecasting with large sets of predictors[6], we adopt two approaches to formulating these models: either selecting specific variables from the set of predictors or estimating factors, which are specific combinations of predictors that extract the most relevant information from the set.

All models are estimated using elastic net regression[7], a popular approach to mitigating the impact of high correlation among predictors and implicitly selecting the most relevant ones. In essence, our models comprise linear regression models with regularized coefficients, optimized for out-of-sample performance[8]. Recognising the observed problem of instability of the postulated relationship this performance is evaluated using rolling window cross-validation[9], which generates out-of-sample performance metrics that enable model comparisons. Additionally, pairwise forecast accuracy comparisons are performed to further assess model performance.

In our first approach (variable selection) we employ two widely used variable selection techniques: forward unidirectional and forward stepwise methods. Each technique utilises a distinct algorithm to identify a subset of indicators that are most strongly correlated with the target variable over the

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[6] Z. Wang, Z. Zhu and C Yu, 'Variable Selection in Macroeconomic Forecasting with Many Predictors', Econometrics and Statistics, 2023, https://doi.org/10.1016/j.ecosta.2023.01.003, J. H. Stock, M W. Watson, Forecasting with Many Predictors, Editor(s): G. Elliott, C.W.J. Granger, A. Timmermann, Handbook of Economic Forecasting, Elsevier, https://doi.org/10.1016/S1574-0706(05)01010-4.

[7] H. Zou, T. Hastie, 'Regularization and variable selection via the elastic net' Journal of the Royal Statistical Society. Series B (Statistical Methodology), 67 (2) (2005), pp. 301-320

[8] The model specification takes the form: y(t+h) = c0 + c1*f1(SPE(t,t-1,..)) + …+ ck*fk(SPE(t,t-1,..)) + ε(t+h), where, y(t+h) represents the target variable at time t+h, SPE(t,t-1,..) denotes the information set comprising SPE indicators up to time t, f1(.),..fk(.) represents appropriate transformations of this information, which may include current values, past lags, squared terms, and extracted factors (i.e. principal components), c0, c1, …, ck are the regularized coefficients, and ε(t+h) is the error term at time t+h.

[9] The process is built in the econometric software Eviews 13 used for the current analysis.

total sample.[10] To minimise the risk of omitting important predictors, we apply both selection methods in a complementary manner and experiment with different initial variable sets for selection. For each selected subset, we perform elastic net regression to optimise the contribution of each selected indicator based on out-of-sample forecast accuracy, as evaluated through cross-validation.

In our second approach (factor extraction) we employ two closely related techniques: Scaled Principal Component Analysis (SPCA)[11] and Partial Least Squares (PLS) regression[12]. The former, a recent modification of traditional PCA, extracts factors from a set of predictors while accounting for their correlation with the target variable. Similarly, Partial Least Squares is a traditional method that extracts factors by maximizing their correlation with the target variable. We apply both methods to the entire sample, using alternative initial sets as well. Subsequently, we perform elastic net regression on the computed factors, optimizing the contribution of each factor based on the model's out-of-sample performance.

4. Results

Results[13] can be organized as answers to specific research questions:

How much information is contained in historic SPE data? How far back should one go when using past SPE data for forecasting inflation?"

Assuming all available *SPE* indicators at time *t* can be collected in the information set Ω_t, we explore three distinct information sets to forecast inflation at period *t + h*, namely h months ahead: SPE data (1) from the latest month, i.e. Ω_t (information set 1), (2) from the four latest months, i.e. $\{\Omega_t, \Omega_{t-1}, \Omega_{t-2}, \Omega_{t-3}\}$ (information set 2), and (3) from all twelve past months, i.e. $\{\Omega_t, \Omega_{t-1}, \ldots, \Omega_{t-12}\}$ (information set 3). Information set 2 is designed to capture the three-months ahead expectation horizon inherent in the SPE survey data, while information set 3 incorporates all previous monthly lags over the past year, examining potential benchmarking behavior in updating expectations by the survey respondents. This includes, for example, the possibility that respondents form or update their expectations based on seasonal patterns emerging every three, six or twelve months.[14]

[10] Both methods are built in the econometric software Eviews 13 used for the current analysis, see online manual: https://www.eviews.com/help/helpintro.html#page/content%2FVarsel-Background.html%23ww277151

[11] D. Huang, F. Jiang , K. Li, G. Tong, G. Zhou, 'Scaled PCA: A New Approach to Dimension Reduction', Management Science, 2021, https://doi.org/10.1287/mnsc.2021.4020

[12] For a tutorial see P. Geladi and B, Kowalski, 'Partial Least Squares: A tutorial', Analytica Chimica Acta, 1986, https://doi.org/10.1016/0003-2670(86)80028-9. For a relevant application of PLS in nowcasting quarterly GDP by the European Commission, see: European Business Cycle Indicators, 2018, European Economy, Technical Paper 025, European Commission, http://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en

[13] The implementation of the above analysis is carried out using the econometric software EViews 13. To facilitate result reproduction and regular updates (following new data releases), a set of programs has been developed, enabling efficient and timely execution.

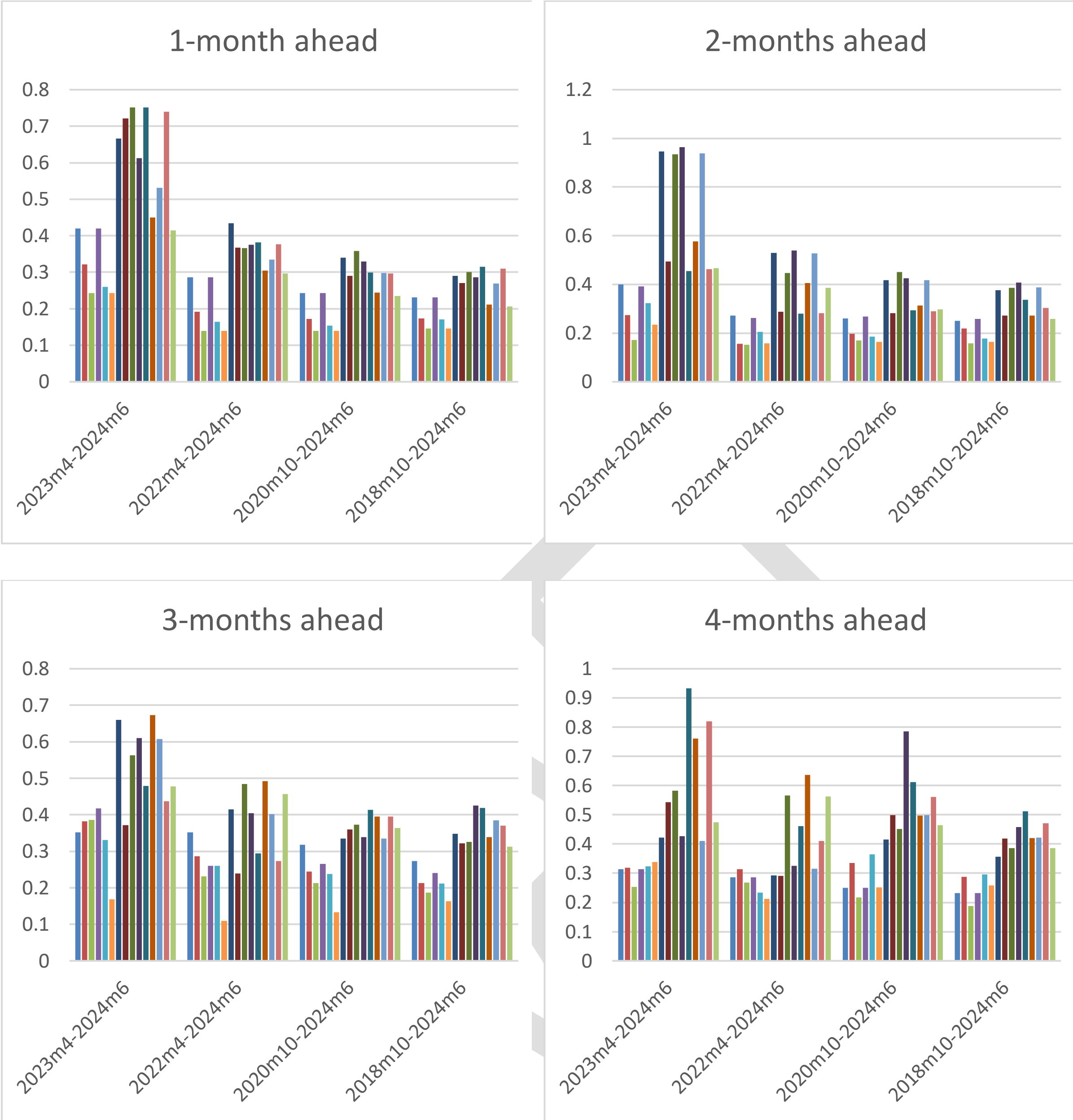
[14] Richer information sets, including square terms and interactions across the SPE indicators, as well as other macroeconomic indicators could be possibly added in the future.

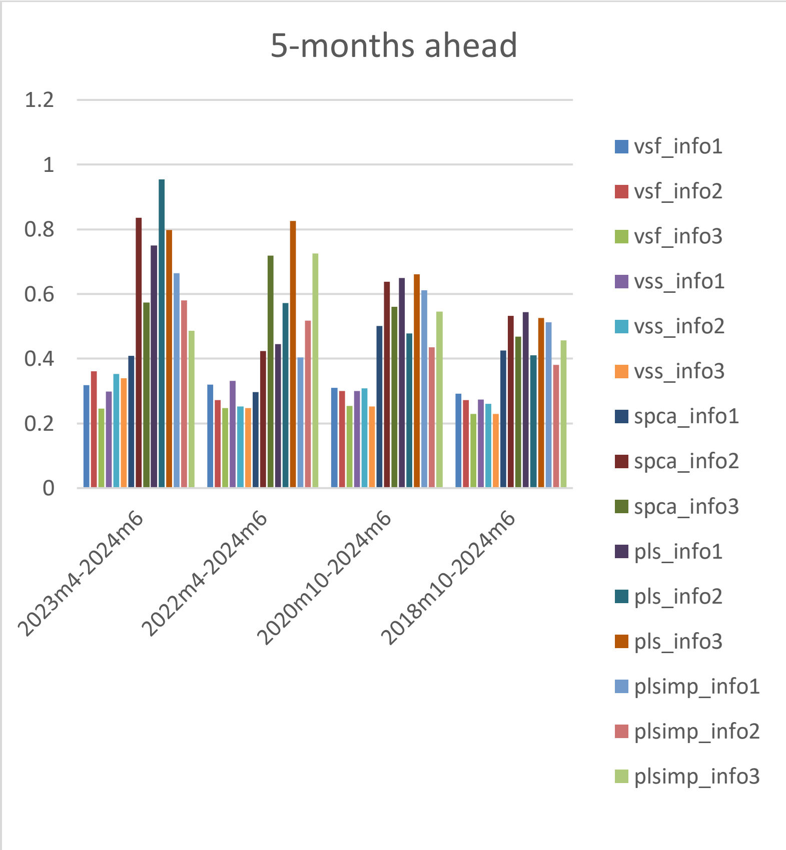
In terms of forecasting accuracy, as measured by the root mean square forecast error relative to the standard deviation of the target variable (annual inflation rates), Figure X1 below reveals that variable selection models generally outperform specific linear combinations of SPE indicators, which form distinct factors (as extracted by the Scaled Principal Component Analysis (SPCA) and Partial Least Squares (PLS) models[15]). Moreover, among variable selection models, which were found to be the most accurate, information set 3 yields the most accurate forecasts, suggesting that expectations older than four months contain valuable information for future inflation. This may be attributed to the information content of revisions to previous expectations.

Recognising the potential effect of the sample start/length on the strength of the SPE-HICP relationship, we look at four distinct periods, each with a unique turning point in the inflation trajectory, and each with a different starting observation and a common (latest available) end observation: (a) the period covering the recent disinflationary period (2023m4-2024m6), spanning 15 months; (b) the period starting shortly before the recent peak in inflation (2022m4-2024m6), covering 27 months; (c) the period starting shortly before the recent inflation increase (2020m10-2024m6), encompassing 45 months; and (d) a longer period that includes the less volatile pre-crisis era (2018m10-2024m6), covering 69 months. Notably, the latest (shortest) period exhibits higher relative forecast errors, partly due to the lower variance of the target variable (a denominator effect). Across the other periods, relative forecast accuracy remains broadly stable, especially for variable selection models, despite the fluctuations in inflation throughout the recent shock. Factor models remain less accurate, showing a greater instability in their performance.

Figure X1: Relative Root Mean Square Error (in proportion to the standard deviation of the target variable) across models, horizons, information sets and forecast (test) samples.

[15] We also present results from a modified PLS implementation (PLSIMP) that leverages the entire sample of explanatory variables when calculating factor loadings, incorporating the most recent values of these variables rather than omitting them due to lagged effects. This is achieved by simply extending the sample to encompass the forecast period, and imputing zero values to the target variable for the forecast period, thereby maintaining a consistent sample size throughout.


1-month ahead
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2023m4-2024m6
2022m4-2024m6
2020m10-2024m6
2018m10-2024m6
2-months ahead
1.2
1
0.8
0.6
0.4
0.2
0
3-months ahead
4-months ahead
0.9

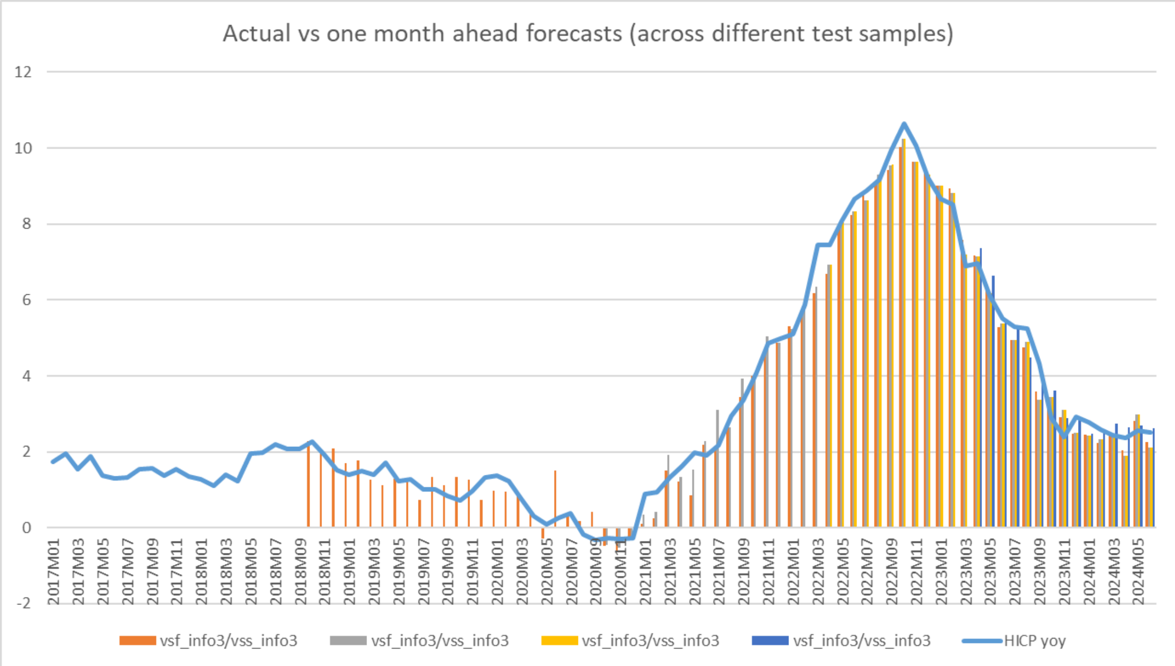


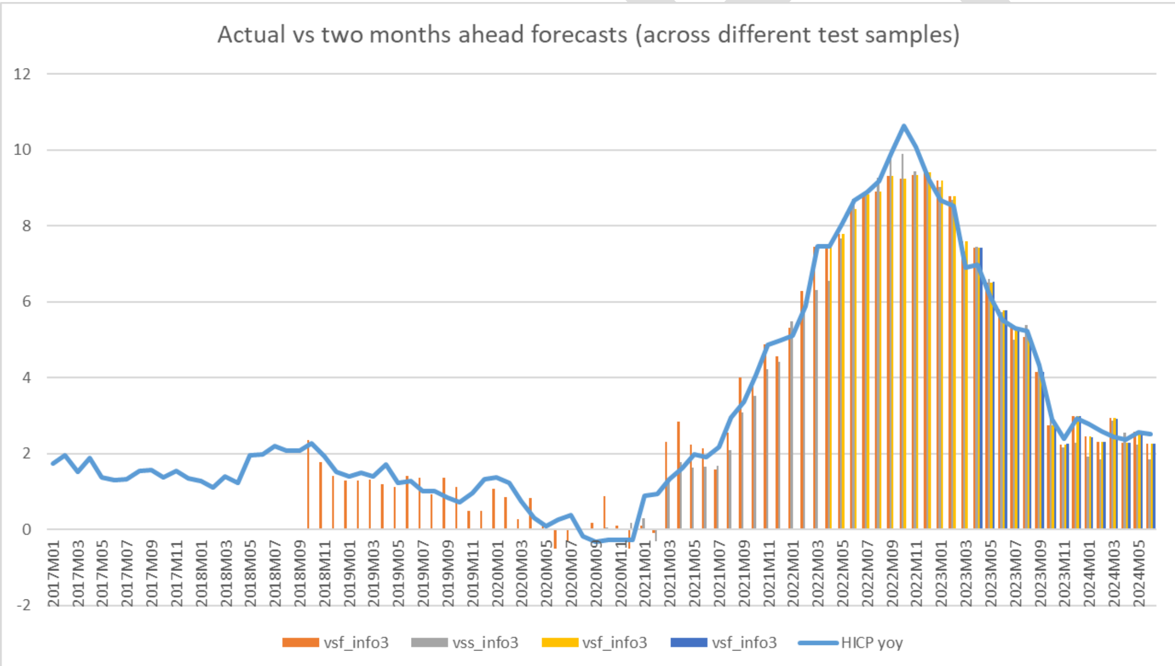
Note: Horizontal groups depict four different forecast periods, starting from the most recent (2023m4-2024m6) and backwards expanding to 2018m10-2024m6. In each period, forecast errors are calculated from rolling window forecasts. In each rolling window, we forecast the last (most recent) observation using the remaining observations to estimate the model (out of sample forecasts), given the model's regularization parameter (lambda). Each model is then regularized based on its accuracy over the specific period. To avoid overfitting, models are estimated using the previous n months, where n equals 24 plus the number of parameters of each model. This preserves the same degrees of freedom for estimation across models, but leads to different estimation sample sizes in general. For each model and forecast horizon, however, the estimation sample size remains constant across the four forecast periods.

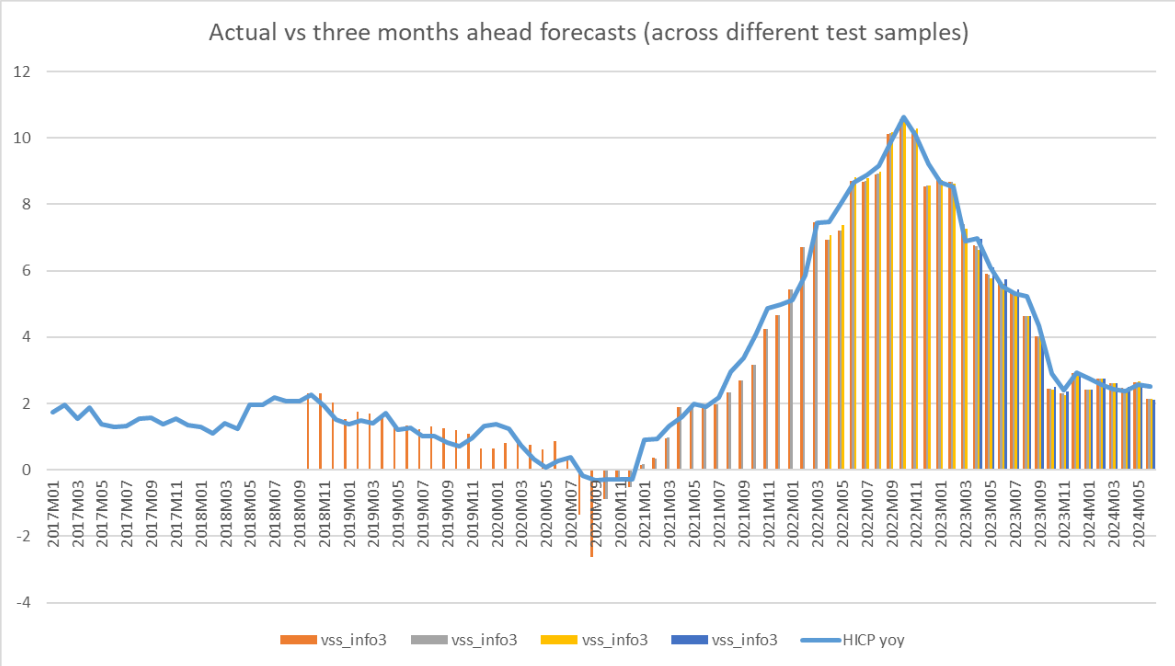
Figure X1a shows the specific forecasts[16] from the most accurate models, for each horizon and from the four distinct forecast test periods.

Figure X1a: Forecasts from the minimum Relative RMSE models across horizons and forecast (test) samples (periods)

[16] We produce rolling-window forecasts. In each window, the last (most recent) observation is forecasted using the remaining observations in that window. In that sense the forecasts are out of sample. The models are then evaluated or cross-validated or regularised, based on their performance over a set of such rolling windows. The forecasts of the best such models are depicted in the graph X1a. Since the choice of the forecast for month x depends on the cross-validation sample, which also takes account of the month x+1, the forecast is not pure out of sample. However, this occurs only via a single regularisation/penalty parameter, which commonly penalises the coefficients in the model. Therefore, the effect on underestimation of forecast uncertainty may be limited. Furthermore, using out of sample forecasts from in-sample regularised models controls for common shifts in the magnitude of coefficients, leaving the individual contribution of specific predictors unaffected.


Actual vs one month ahead forecasts (across different test samples)
vsf_info3/vss_info3
vsf_info3/vss_info3
vsf_info3/vss_info3
vsf_info3/vss_info3
HICP yoy


Actual vs two months ahead forecasts (across different test samples)
vsf_info3
vss_info3
vsf_info3
vsf_info3
HICP yoy


Actual vs three months ahead forecasts (across different test samples)
vss_info3
vss_info3
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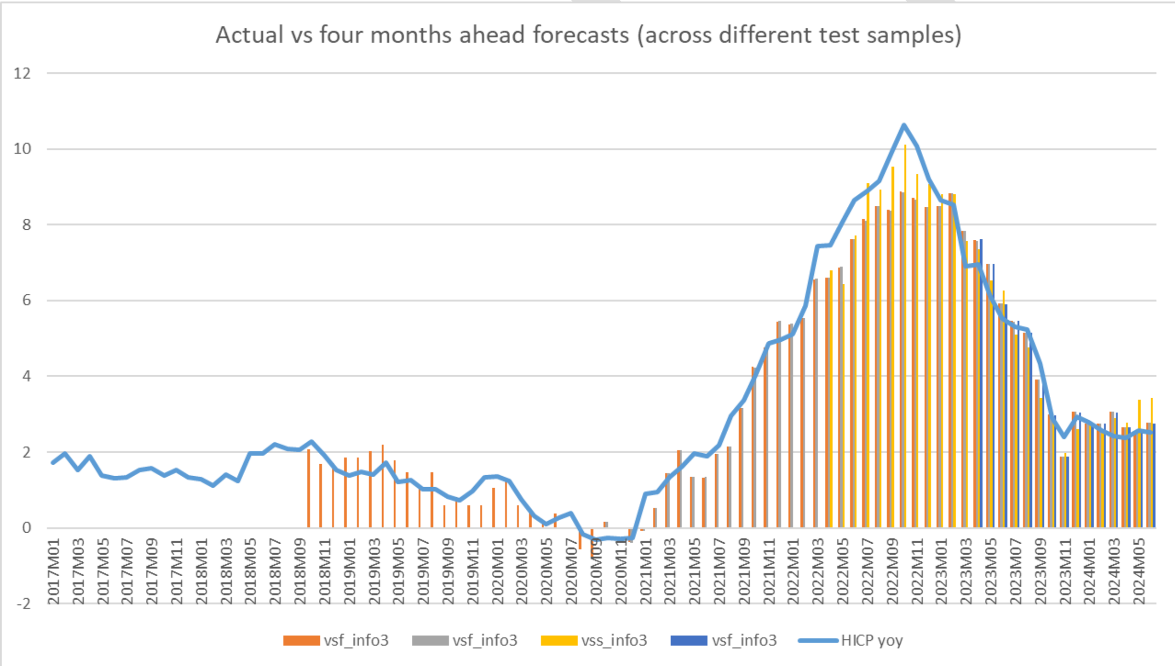
vss_info3
HICP yoy


Actual vs four months ahead forecasts (across different test samples)
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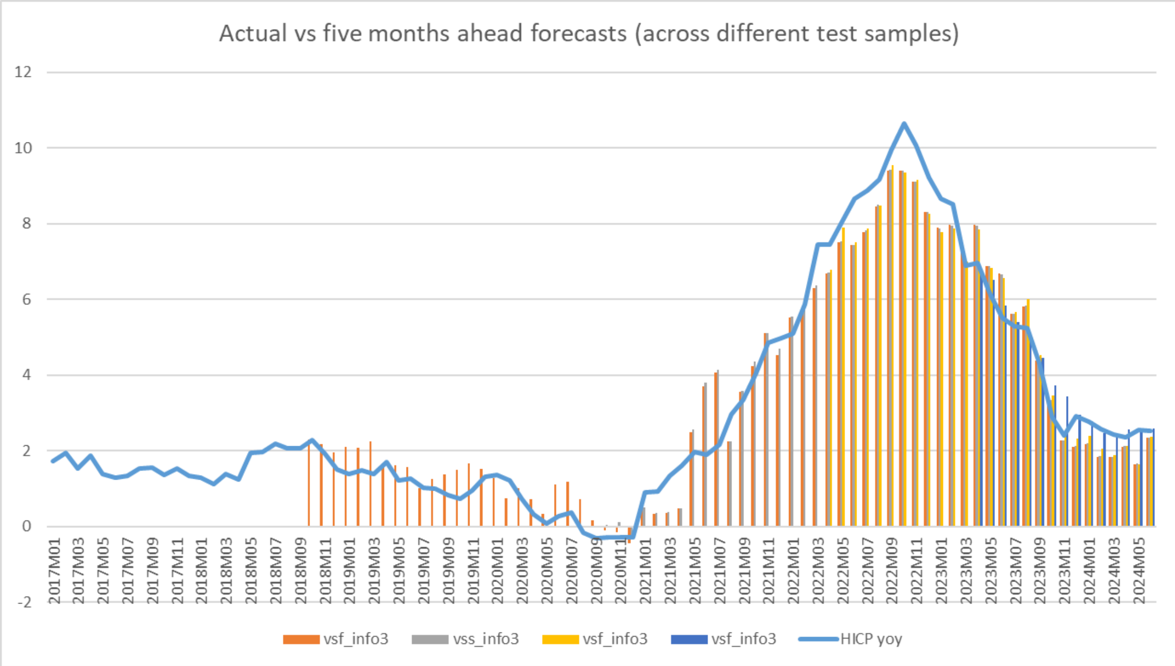
vsf_info3
vss_info3
vsf_info3
HICP yoy

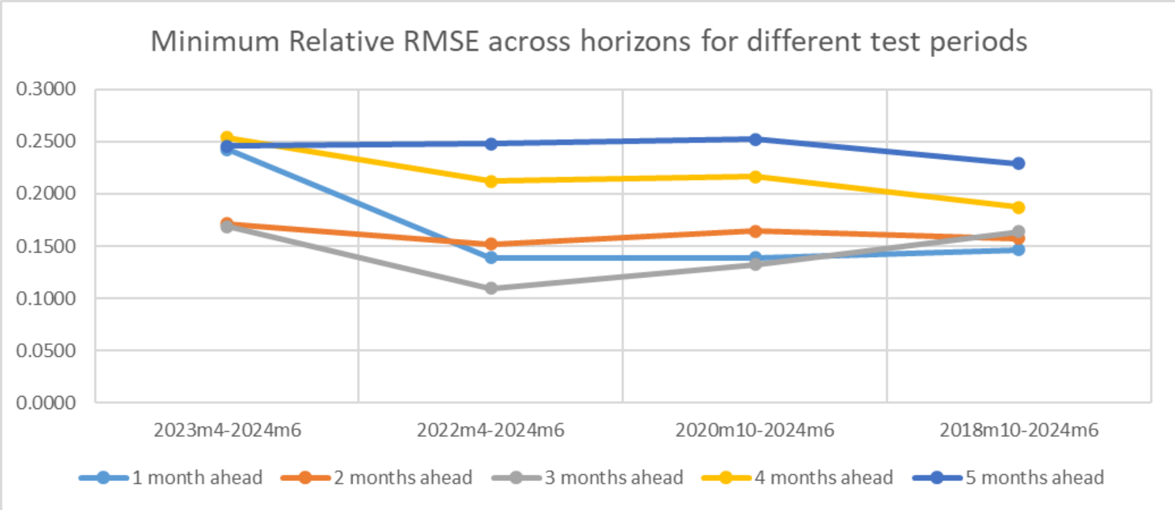


Note: Coloured bars depict rolling window forecasts from the most accurate models (for which the name appears in the legend in each sub-plot) at four different forecast periods, depicted at the Figure X1, starting from the most recent (2023m4-2024m6) and backwards expanding to 2018m10-2024m6. In each rolling window, we forecast the last (most recent) observation using the remaining observations to estimate the model (out of sample forecasts), given the model's regularization parameter (lambda). Each model is then regularized based on its accuracy over the specific period. To avoid overfitting, models are estimated using the previous n months, where n equals 24 plus the number of parameters of each model. This preserves the same degrees of freedom for estimation across models, but leads to different estimation sample sizes in general. For each model and forecast horizon, however, the estimation sample size remains constant across the four forecast periods.

At what forecast horizons do SPE data exhibit the greatest predictive power?

Figure X1b presents the minimum relative RMSEs for each horizon and forecast test period across our implemented models. Over the longer period, relative forecast accuracy seems to follow the forecast horizon, with one period ahead forecasts being the most accurate and five period ahead the least. Looking at more recent periods, however, the three-period ahead forecasts gain accuracy and outperform the one-period ahead ones. This may partly reflect the fact that the formulation of the SPE questions is in terms of three-months ahead expectations. This may also signal that the insights of the respondents for the future trajectory of inflation improved during the last inflation shock.

Figure X1b: Minimum Relative Root Mean Square Error (in proportion to the standard deviation of the target variable) across horizons and forecast test samples.

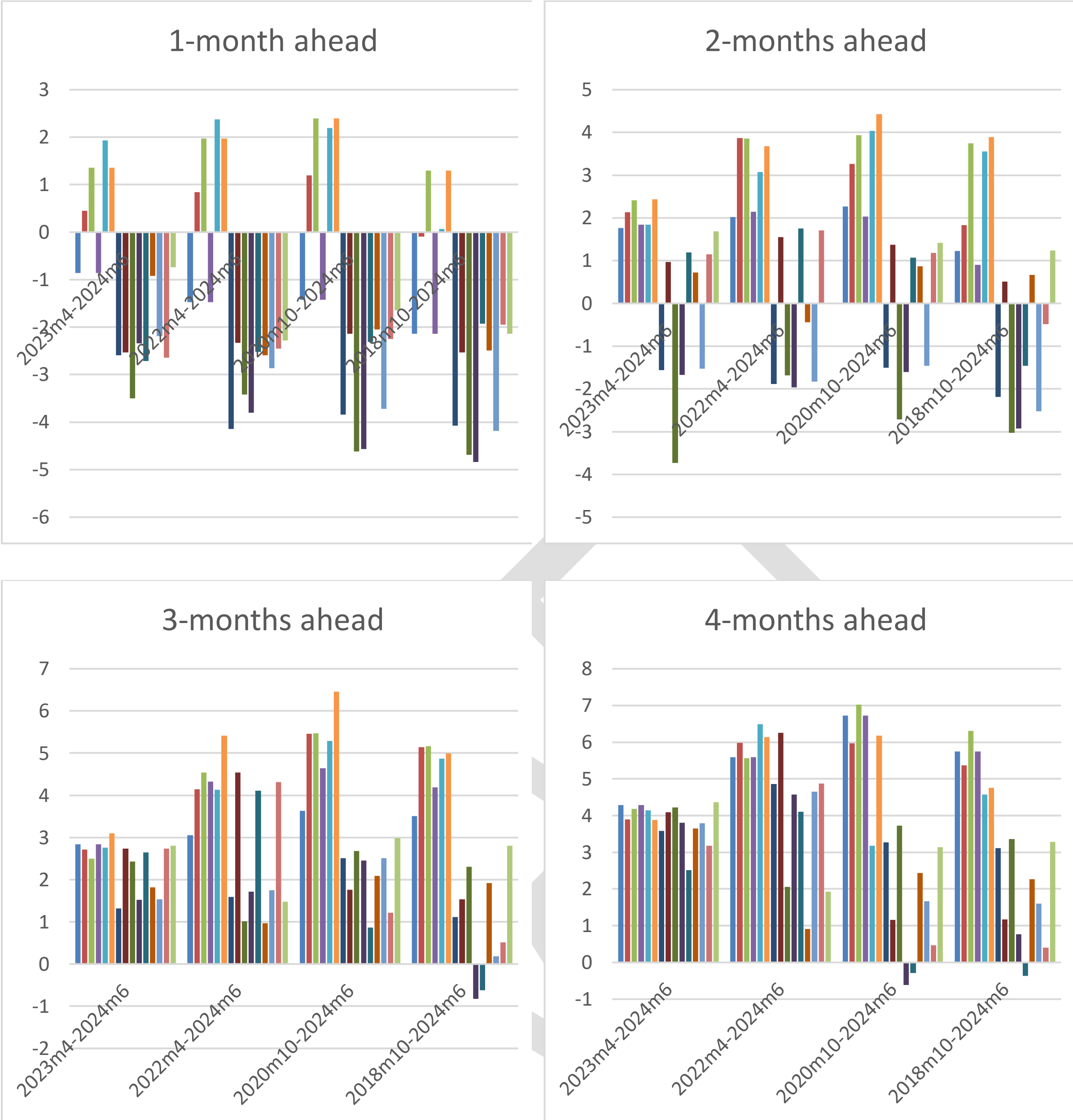


What is the relative performance of SPE data-based forecasts versus a naive benchmark?

In terms of performance relative to a random walk inflation model, which assumes that the best prediction of future inflation is its current value, variable selection models once again demonstrate their superior performance compared to factor extraction models. They consistently outperform random walk models across all forecast horizons, from one to five periods ahead, particularly when utilizing richer information sets (information sets 2 and 3). Moreover, for longer forecast horizons, the informativeness of SPE data appears to gain significance, especially during the inflation crisis period, as the majority of models (both variable selection and factor extraction) tend to outperform the random walk model.

Figure X2: Diebold-Mariano (1995)[17] test of forecast accuracy outperformance compared to random walk inflation model, across models, horizons, information sets and forecast (test) samples.

[17] Diebold, F.X. and Mariano, R.S. (1995) Comparing predictive accuracy. *Journal of Business and Economic Statistics*, **13**, 253-263.


1-month ahead
3
2
1
0
-1
-2
-3
-4
-5
-6
2023m4-2024m6
2022m4-2024m6
2020m10-2024m6
2018m10-2024m6
2-months ahead
5
4
3
2
1
0
-1
-2
-3
-4
-5
2023m4-2024m6
2022m4-2024m6
2020m10-2024m6
2018m10-2024m6
3-months ahead
7
6
5
4
3
2
1
0
-1
-2
2023m4-2024m6
2022m4-2024m6
2020m10-2024m6
2018m10-2024m6
4-months ahead
8
7
6
5
4
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1
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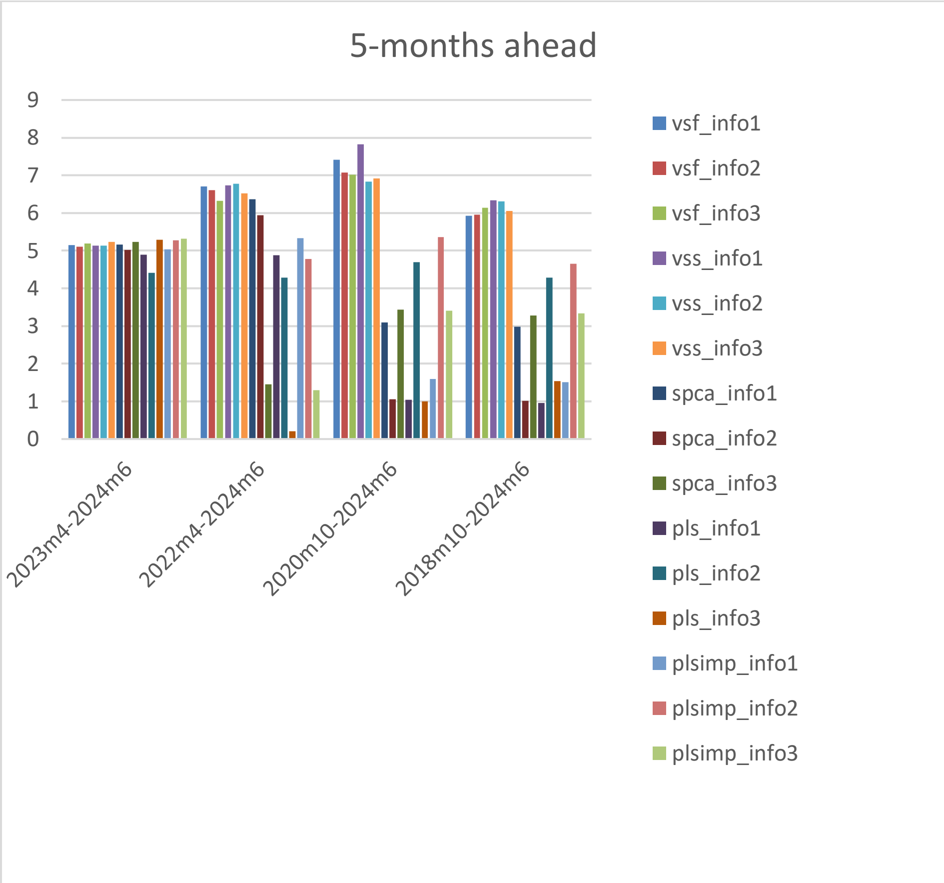
-1
2023m4-2024m6
2022m4-2024m6
2020m10-2024m6
2018m10-2024m6



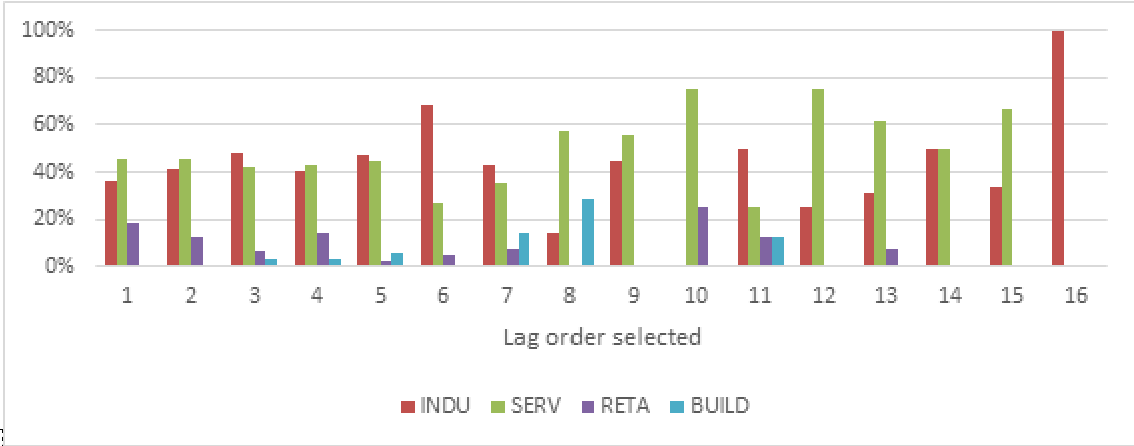
Note: A positive value indicates overperformance of a model relative to the random walk inflation model. A value around or above two indicates statistically significant overperformance. Horizontal groups depict four different forecast periods, starting from the most recent (2023m4-2024m6) and backwards expanding to 2018m10-2024m6. Models are estimated using the previous n months, where n equals 24 plus the number of parameters of each model.

SPE in which economic sectors appear to be most relevant in forecasting inflation? Are there differences in terms of the lag structure?

Looking at the variables selected in the VSS approach (which gives the most accurate forecasts), it appears that SPE indicators for branches in industry and service are most frequently selected for forecasting inflation in model specifications that permit up to 5-month lags (Figure X3a). Furthermore, in models using only information set 1 (no lagged variables, Figure X3b), indicators for branches in industry seem to be more relevant in forecasting 2 and 3 months ahead, while services in forecasting 1 and 5 months ahead. In a further attempt to detect potentially significant impact of specific indicators at specific lags, Figure X3c shows the total number of times a specific lag order of a specific SPE indicator has been selected, summing across all horizons.

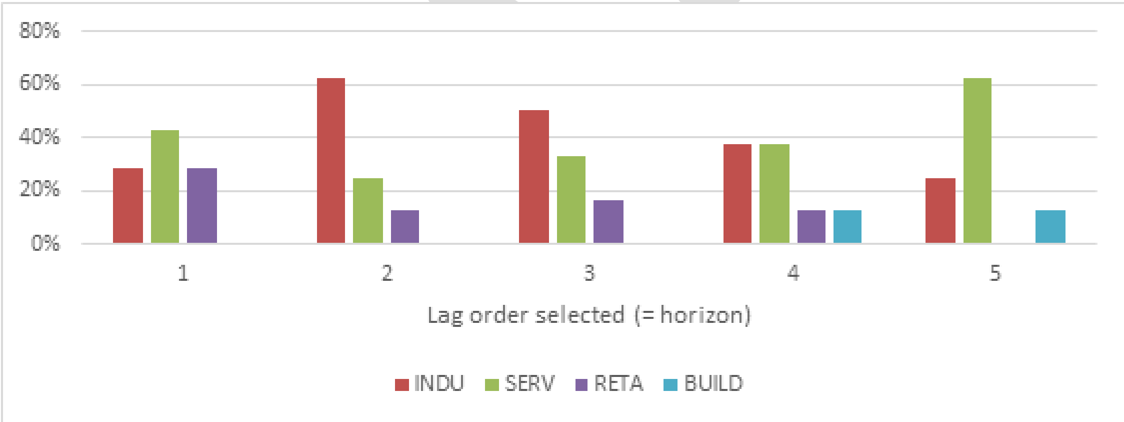
Figure X3: Percentage of variables selected in the VSS models, by type of sector

(a) All information sets



Note: The 16 lags result from the fact that we have maximum 12 lags for each forecast horizon (according to our largest information set 3) from which we forecast up to 5 months ahead (t+5). This creates a maximum gap between the earliest predictor and current inflation of about 12 (for one period ahead) + 4 (remaining horizons up to 5).

(b) Information set 1



(c) Information set 3: Variables selected (sum across horizons)

	Industry																					
lags	v1	v2	v4	v5	v6	v7	v9	v11	v12	v15	v16	v17	v19	v20	v21	v22	v23	v24	v26	v27	v30	v31
1																						
2					1		1		1													
3				3					2								1					
4					1												2					
5			1					2				2				1	1	2				
6			4														1			1		2
7			1					1		1				1								1
8								1														
9	1					1												1	1			
10																						
11		2															2					
12											1						1					
13	1	1											1					1				
14		3																				
15																					1	
16															1							

	Services																	Retail				Building	
lags	v34	v36	v37	v41	v42	v43	v44	v45	v46	v49	v50	v51	v52	v53	v55	v56	v58	v60	v61	v64	v65	v67	v68
1																1							
2				1						1						2	2	2					
3																2	2	1					
4									1	1	1					2		1					
5		1	2				2									2	1				1		
6		1							1							2							
7		1				2					1												1
8	3							1															2
9					1			2			1	1											
10							1	1			1								1				
11								2												1		1	
12					2			3		1													
13			1							1		1	2	1	2						1		
14									1	1			1										
15	1													1									
16																							

We further test what is the additional forecasting ability of SPEs related to services and retail trade compared to the industry and construction. We use Diebold and Mariano test and compare the accuracy of forecasts with the full set of SPE indicators and information set 3, with forecasts obtained using only subset of SPE indicators related with industry and construction. As Figure X3b shows, two and three months ahead forecasts are particularly benefitted by the input of SPEs on services and retail trade. Factor models, and particularly the SPCA model, was found to perform better with the smaller subset of only industry- and construction-related variables, reflecting the potential gains from extracting more informative signals and less noise from fewer variables.

Figure X3b: Diebold-Mariano (1995)[18] test of equal forecast accuracy between models estimated using the full set of SPE indicators vs a subset of SPE indicators related with industry and construction (all forecasts use information set 3).

[18] Diebold, F.X. and Mariano, R.S. (1995) Comparing predictive accuracy. *Journal of Business and Economic Statistics*, **13**, 253-263.

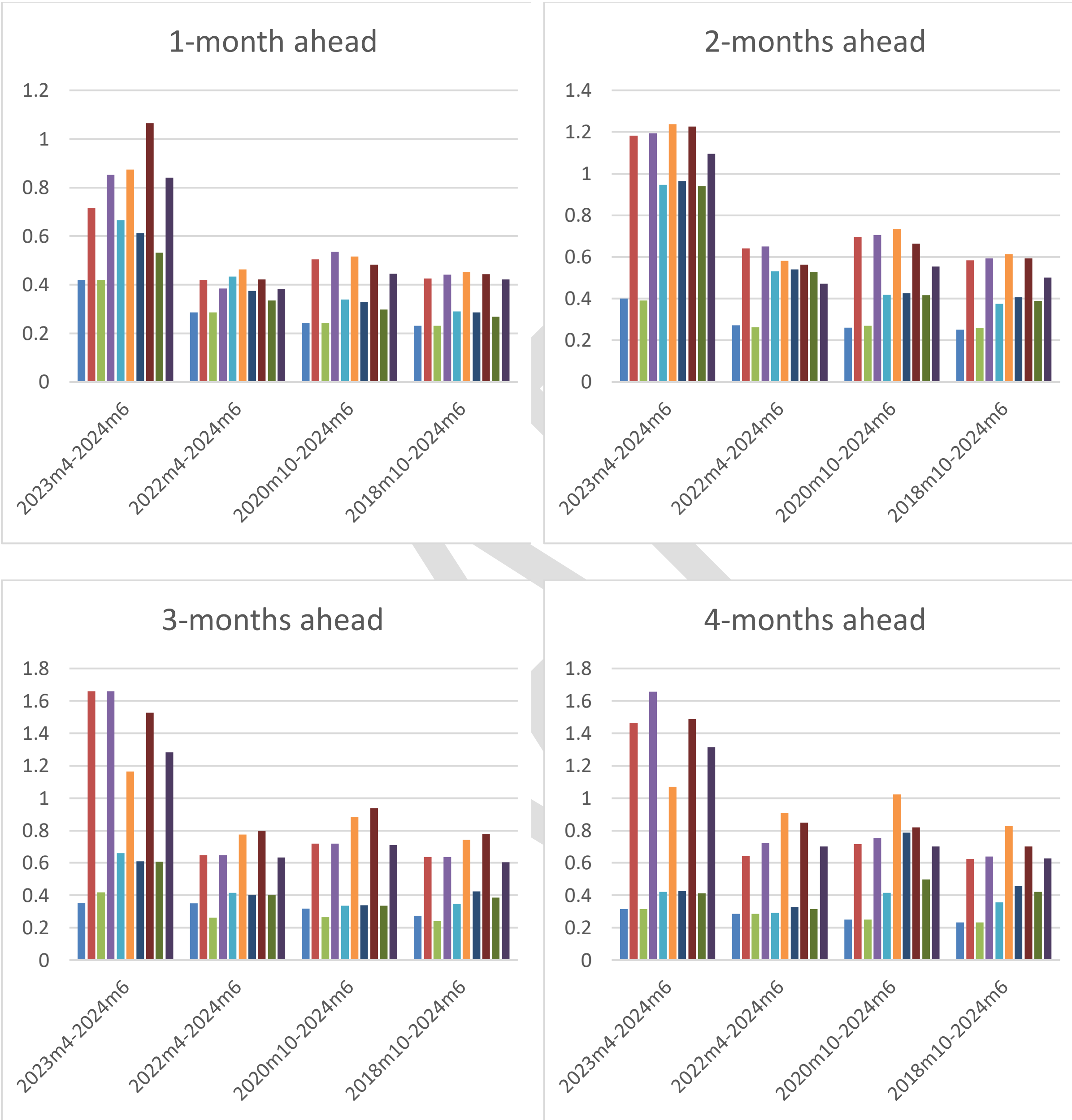
Note: Positive values indicate that the full set of SPEs produces less accurate forecasts, negative values that the set of industry- and construction-related SPEs produce less accurate forecasts, or equivalently that services- and retail-related SPEs improve forecasting accuracy. Statistically significant indicators hover around values above two in absolute terms.

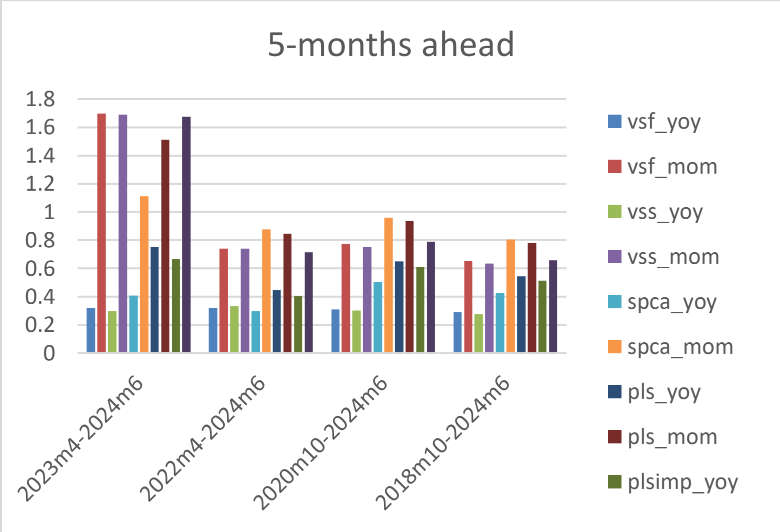
Is information in SPE data more relevant to forecast inflation momentum or annual inflation?

Inflation momentum exhibits a more complex autocorrelation structure than annual inflation, suggesting that it may be more predictable based on past information. However, respondents in the SPE survey may not fully anticipate how inflation momentum or short-term trends are formed, which could reduce their relative predictive power compared to annual inflation. On the other hand it may be possible that respondents have an annual comparison in mind, even though asked about next three months.

A comparison of relative RMSE reveals that SPE data yield more accurate forecasts for annual inflation than for momentum inflation, consistently across all horizons, using the basic information set 1, see Figure X4 below:

Figure X4: Relative Root Mean Square Error (in proportion to the standard deviation of the target variable) across models, horizons, information sets and forecast (test) samples, when target variable is annual (yoy) and momentum (mom) inflation.





Note: see Figure X1

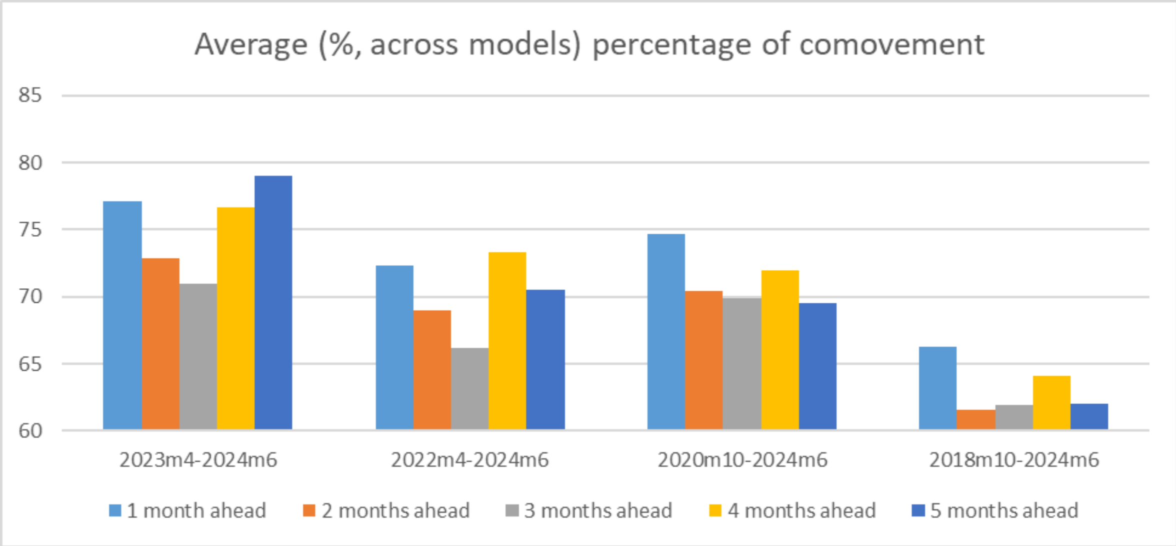
Has the anticipation of forthcoming inflation by SPE respondents improved over time?

Figure X1 reveals a notable deterioration in the forecasting performance of SPE data over the recent period, which has been marked by a surge in inflation (as from end-2020), a subsequent decline (from late-2022), and a recent stabilisation (from late-2023). Notably, these findings are robust across alternative modelling approaches, including variable selection and factor component methods.

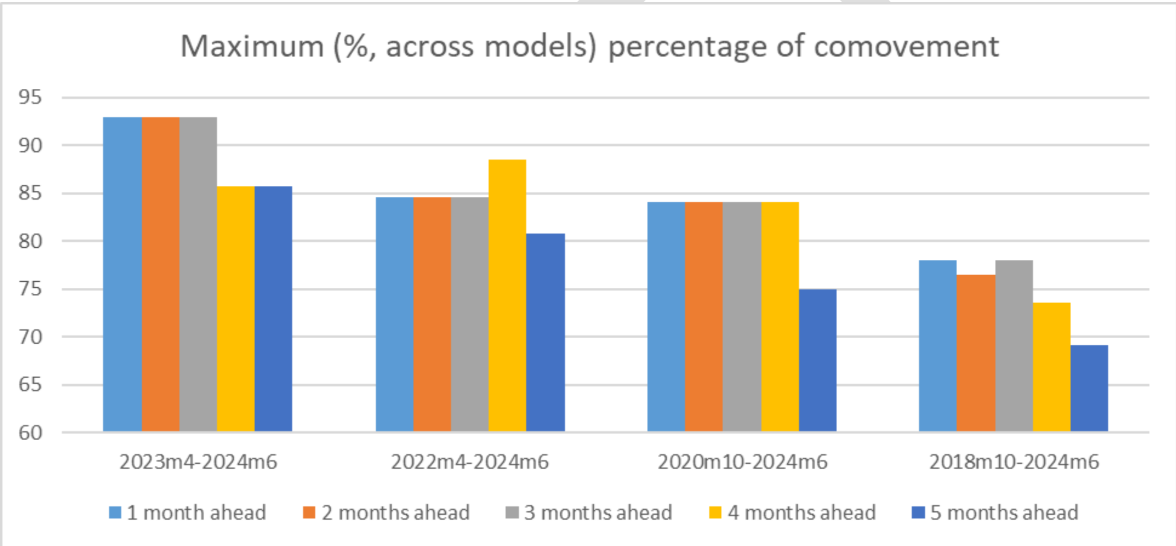
As previously noted, however, for the increase in the relative RMSE there is also a denominator effect at play especially in the most recent forecast period (2023m4-2024m6) where inflation (target variable) stabilised. Indeed, as Figure X5 shows, the percentage of contemporaneous monthly changes of SPE-based forecasts and inflation going in the same direction shows a marginal increase during the inflation crisis periods compared to the larger sample. This is evidence that SPE data at least maintain their information content in forecasting inflation during the inflation crisis.

Figure X5: Percentage of contemporaneous monthly changes in the same direction between forecast and target variable, across models, horizons, information sets and forecast (test) samples. Average and maximum values across models

(a) Average



(b) Maximum



Are there differences in the forecasting ability of SPE data across the various components of HICP inflation?

A comparison of relative RMSE across models (figure X6) utilising information set 1 (which includes only the latest available SPE observation) for forecasting headline, services, non-energy intensive goods (NEIG), food and energy inflation reveals that services and energy inflation are less predictable (exhibiting higher relative RMSE) than headline and NEIG inflation.

Figure X6: Relative Root Mean Square Error (in proportion to the standard deviation of the target variable) across models, horizons, information sets and forecast (test) samples, for various inflation target variables: annual HICP (yoy), food, non-energy industrial goods (neig), services (serv) and energy (ener).: Averages across models

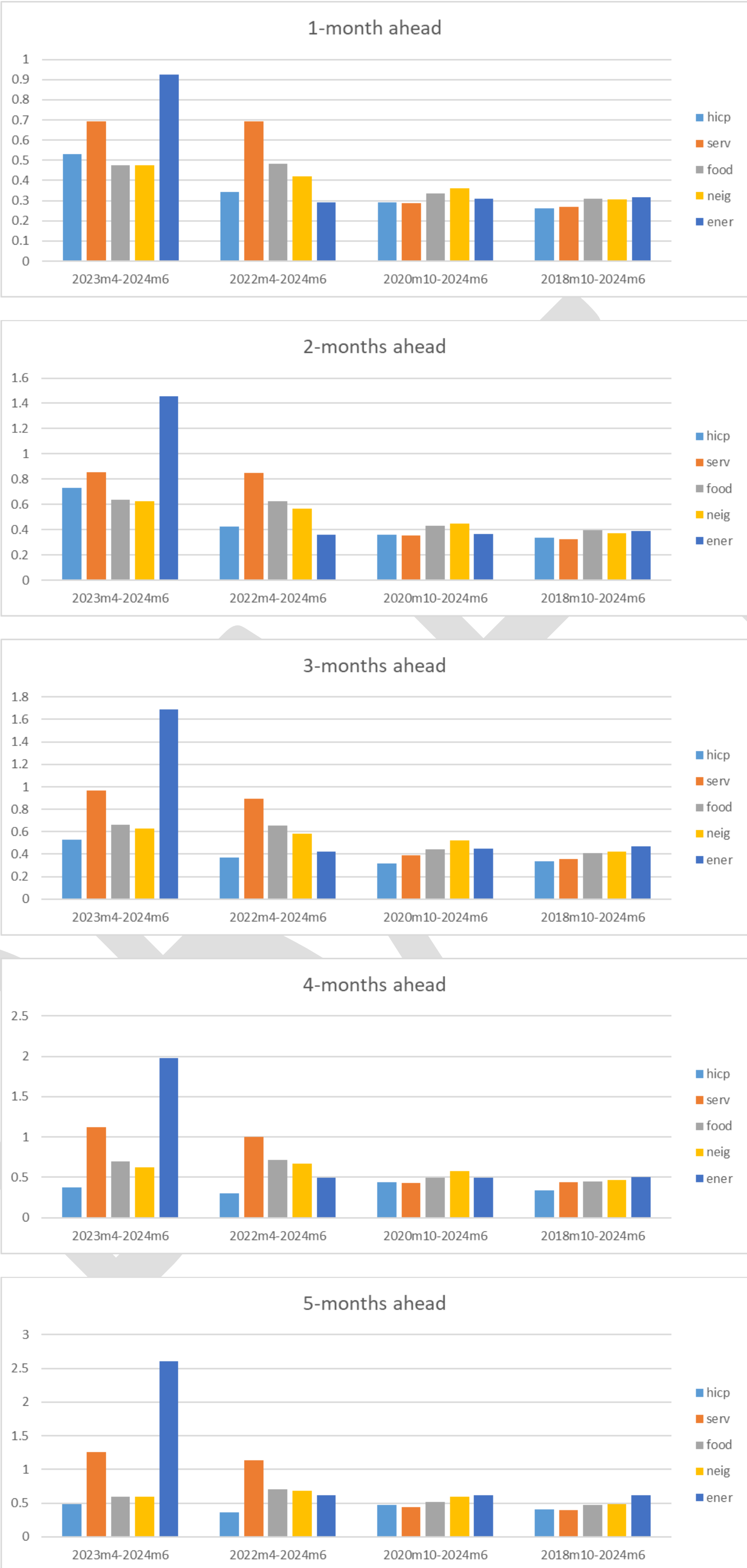
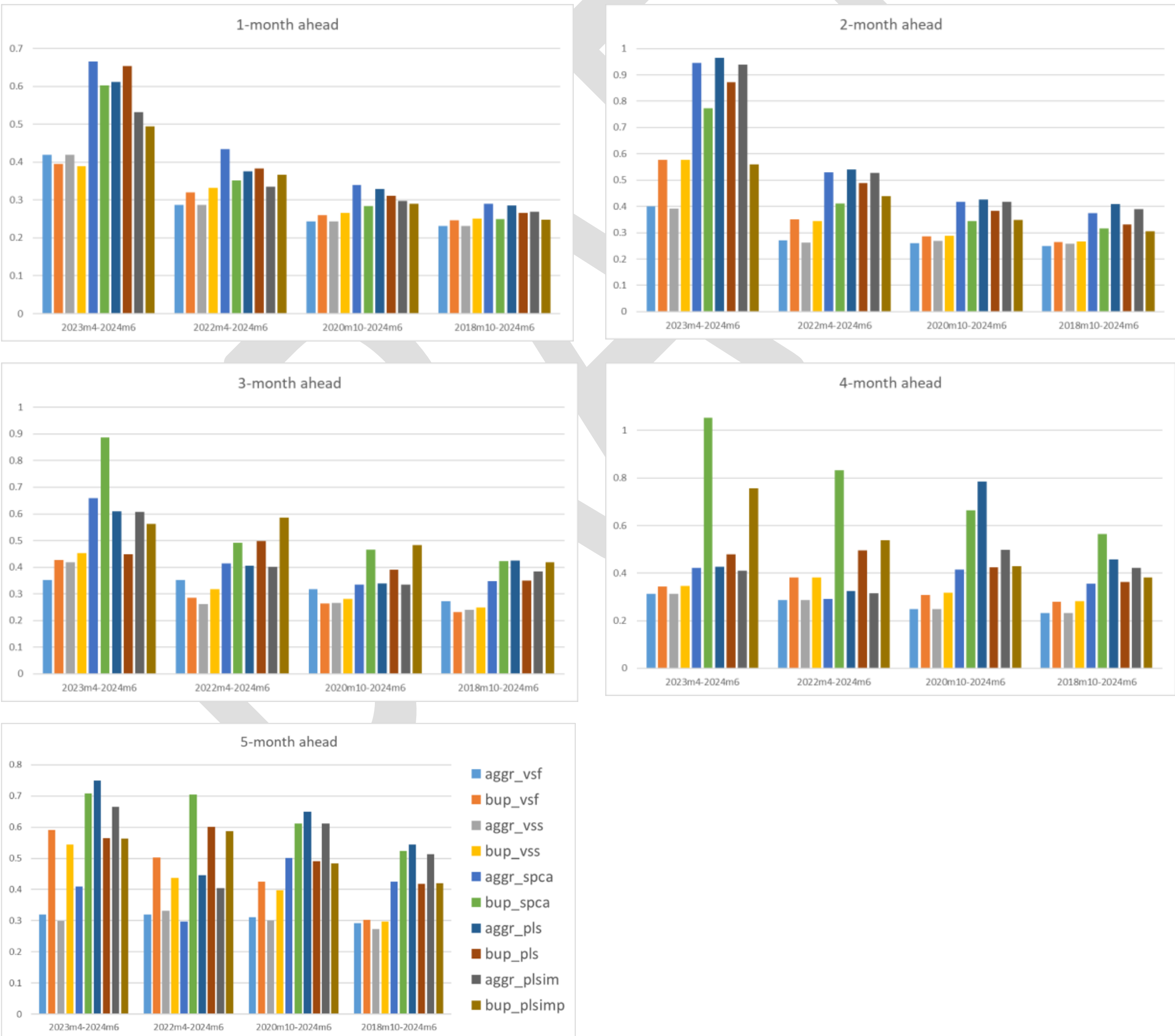


Figure X6b compares the relative RMSEs of models forecasting the aggregate (headline) inflation measure and bottom-up forecasts based on the four inflation components. For each implemented model, the figure juxtaposes the aggregate forecast ('aggr' in the Figure) with the bottom-up ('bup' in the Figure), The bottom-up approach seems slightly less accurate than the direct in general, for most forecast horizons. Some HICP components that were previously (see Figure above) found to be forecasted less accurately than direct inflation, may have injected their higher inaccuracy to the bottom-up forecast, since the latter is a weighted average of individual component forecasts. However, it seems that the accuracy of the bottom-up forecasts is not much lower than the direct forecast, suggesting some offsetting counteraction by individual component forecast errors at play.

Figure X6b: Relative Root Mean Square Error (in proportion to the standard deviation of the target variable) across horizons, information sets and forecast (test) samples for the aggregate (aggr) and the bottom-up (bup) inflation forecast



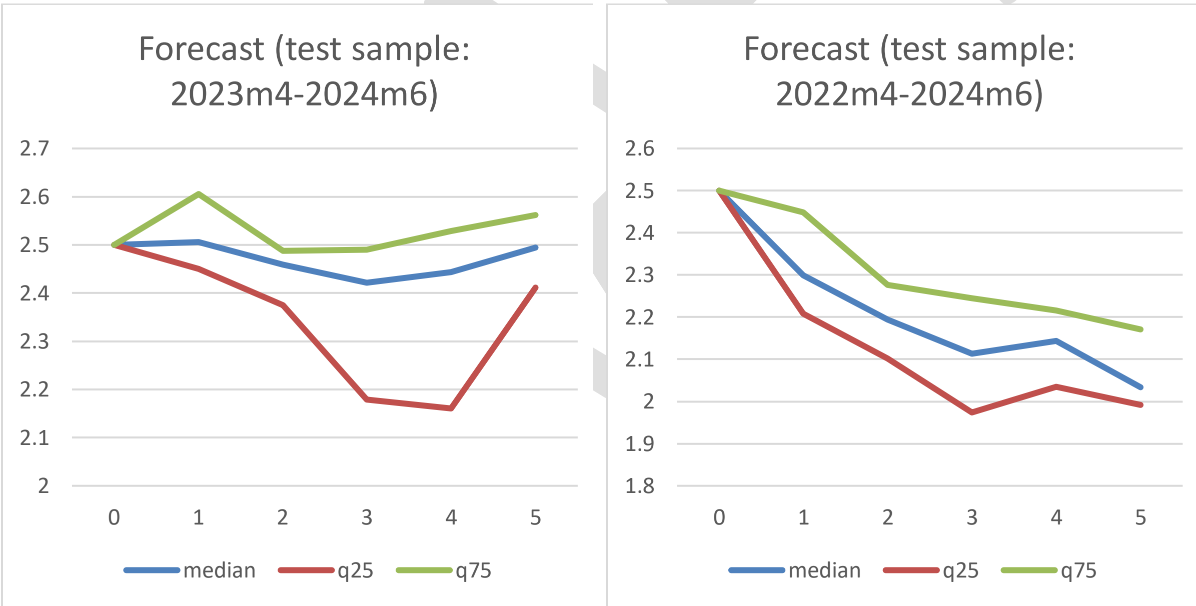
What is the best model to forecast inflation using SPE data?

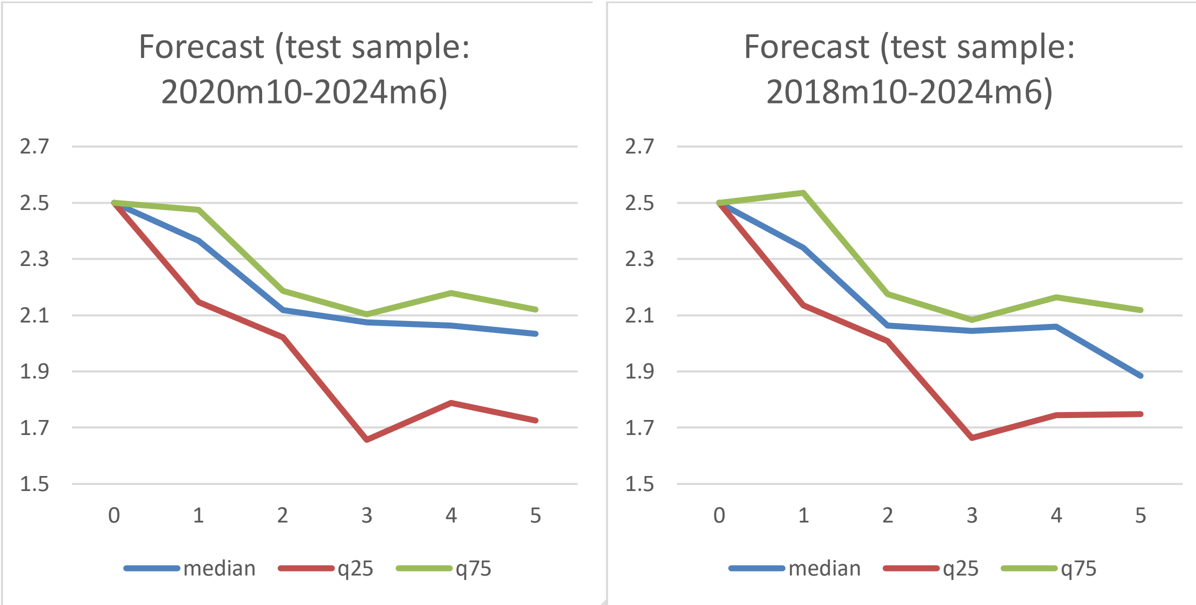
Overall, from the previous forecast performance metrics, variable selection models excel in distilling valuable insights from the SPE dataset, whereas factor models (PLS, SPCA) tend to incorporate less pertinent information, leading to inferior inflation forecasts.

What are the forecasts for headline inflation for the second half of 2024?

Direct forecasts for HICP inflation show some sensitivity to the sample used to train/test the models (see Figure X7 below); when the most recent period of inflation stabilisation is used to test and regularise the model (upper left subplot), forecasts for the next five months (i.e. July to November 2024) point to some persistence of inflation quite above the target level of 2% for horizons up to five months ahead. When test samples are extended backwards, models forecast a return to around 2% within the five months forecast period.

Figure X7: Median and 25th and 75th percentiles of point forecast distribution for HICP inflation across all models and information sets, for horizons 1 to 5 months ahead (i.e., for the period July to November 2024).





Note: Each subplot presents forecasts for the common forecast horizon that spans five months ahead. Subplots differ in the test samples used to regularise the models.

Alternatively, Figure X8 depicts the bottom-up forecasts calculated by the weighted average of the individual HICP components of services, food, non-energy industrial goods and energy. They seem to point to slower disinflation process than the direct/aggregate forecasts, with the median forecast remaining above 2% until the end of the forecast horizon, consistently across all four test periods/samples. According to unreported results for the individual HICP components, the hump-shaped recovery of inflation observed at horizons three and four months ahead, seems to come from the food and energy components, while services forecast exhibit and downward trajectory.

Figure X8: Median and 25th and 75th percentiles of point forecast distribution for HICP inflation across all models and information sets, for horizons 1 to 5 months ahead. Bottom-up approach.

Note: Each subplot presents forecasts for the common forecast horizon that spans five months ahead. Subplots differ in the test samples used to regularize the models.

5. Concluding remarks

In conclusion, this study highlights some properties of selling price expectations with the potential to enhance the accuracy of inflation forecasts. The empirical analysis demonstrates that our exhibit fairly small forecast errors given that they are solely based on SPE data, with a minimum size of about 10% of the historical variability in inflation data (about 0.3 pps in some subsamples), and consistently outperform random walk benchmarks, particularly at the three-months-ahead horizon, where respondents' insights appear to be most aligned with actual inflation trends, in accordance with the three months ahead formulation of the survey question. Moreover, despite challenges such as inflationary shocks and resulting parameter instability over time, SPE-based models show an increasing comovement with actual inflation throughout the recent inflation shock, underscoring their robustness in volatile economic environments. Furthermore, visual inspection of the best forecasts across different regularization/cross-validation intervals, reveals they were particularly effective in keeping close track to inflation and potentially identifying turning points during recent inflationary periods. The study reveals further accuracy improvements from including longer lags of SPE data, as they tend to capture critical dynamics in inflation trends. However, the limitations of factor models, which underperformed compared to models that select individual indicators, suggest that the nuanced information within specific SPE indicators is crucial for precise forecasting. Additionally, heterogeneity in forecasting accuracy across HICP components was detected, with some evident complexities of forecasting energy and services inflation during recent shocks. Following these component specific inaccuracies and despite some gains in terms of pooling individual components forecast errors, SPE data were still found to be more effective in directly predicting inflation than aggregating individual component forecasts. These findings affirm the utility of SPE data as a powerful tool for inflation forecasting and provide valuable insights for future research and policymaking.

References

European Commission. *The Joint Harmonised EU Programme of Business and Consumer Surveys User Guide.* Available from: http://ec.europa.eu/economy_finance/db_indicators/surveys11283_en.htm.