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Economic Research

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Advances in inflation forecasting with Random Forests

New machine learning methods improve inflation forecasting. So-called random forest models allow the processing of large amounts of data and expose concealed relationships. We present the methods and test the forecast quality. The calculations show, for example, that euro area inflation could exceed the ECB's target of 2% in the coming year.

Why a new model?

In recent years, machine learning techniques have become increasingly popular across various scientific fields – including econometrics and statistics. New methods promise speedy processing of large amounts of data and the discovery of concealed relationships. For a long time, however, artificial intelligence algorithms were regarded as a “black box” whose calculations could neither be inspected nor edited. New techniques make the mechanics of the algorithms visible. On top of that, the calculation methods can also be used so flexibly that transparency of the forecast is enhanced.

For these reasons, we are introducing a purely data-driven model that uses two machine learning techniques: The Least Absolute Shrinkage and Selection Operator (LASSO) in combination with Random Forest models. Recent academic studies (such as this [paper](#)) have shown that a combination of these methods have improved forecasts overall.

This model processes around 75 independent time series – and their numerous time lags – and estimates the main components of inflation with a forecast horizon of up to 12 months. Despite the high forecasting quality of these methods, the pure data model will continue to form only one, albeit important, component of our inflation forecasts. We supplement the data model with structural calculations and empirical values. The longer the forecasting horizon, the greater the importance of structural considerations.

Models forecast the components of inflation

We deliberately do not forecast inflation as a whole using all available data. In order to increase transparency and interpretability, the focus of the forecast is on the components of inflation: Energy, food and beverages, non-energy goods and services. In addition, we do not use all available independent variables in an all-encompassing calculation. Instead, the procedure divides the independent variables into six groups and estimates one inflation component with each of the indicator groups. Chart 1 illustrates

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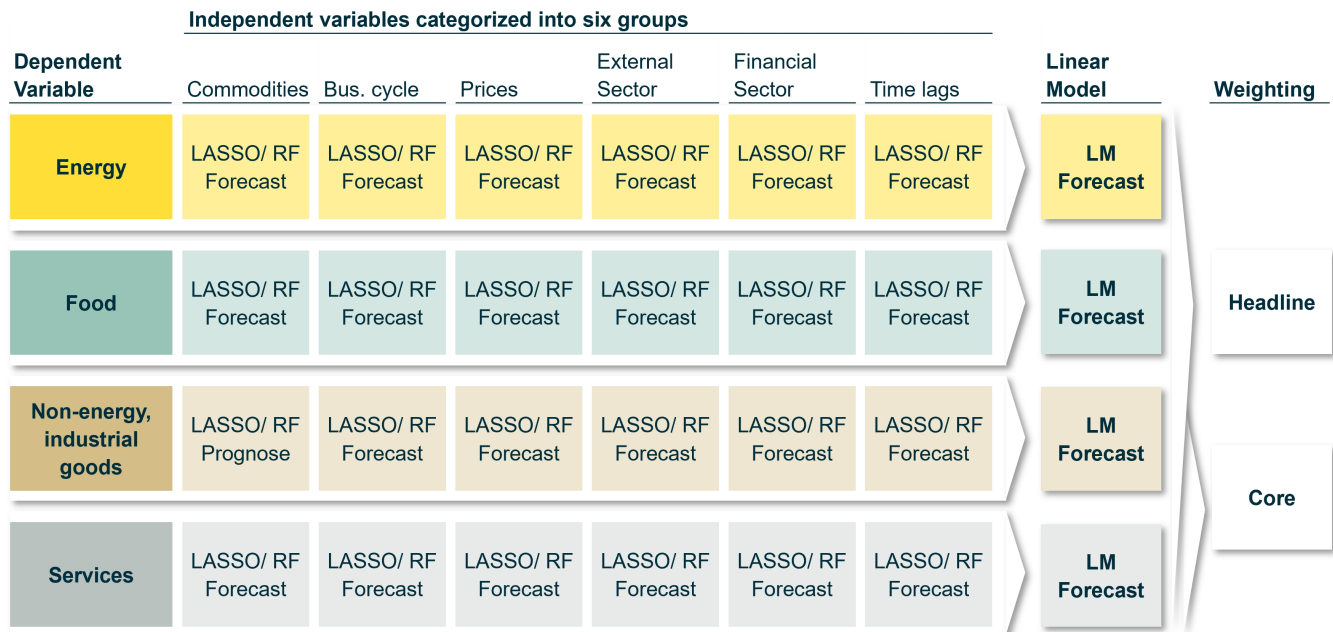


this process, as well as the following steps, which are explained below. The groups of indicators are based on a study by the Dutch central bank and are categorized as follows:

- Prices of energy sources and commodities as well as electricity prices (abbreviated here as "**commodities**")
- Economic indicators and economic indicators on the business cycle ("**bus. cycle**")
- Price indicators and survey results on price trends ("**prices**")
- Foreign trade prices and international transportation costs ("**external sector**")
- Financial market indicators including the price development of inflation swaps ("**financial sector**")
- Historical, or time-delayed, dependent time series ("**time lags**")

Chart 1 - Six indicator groups forecast inflation components

Illustration



Source: Commerzbank Research

The number of indicators per group varies from eight in the financial sector to 17 in the external sector. Strictly speaking, the new method therefore does not consist of one model, but of 24 models for four dependent variables and six independent variable groups. This makes it much easier to interpret the results.

Preparing the data

When using large amounts of data and powerful algorithms from the field of machine learning, typically, there exist two risks: Overfitting, i.e. improving the estimates in the training dataset without an actual improvement in predictive quality, and spurious correlation between independent and dependent variables without actual causal (or at least Granger) causality. Starting with the selection and preparation of the data, preventative measures are taken along the way to mitigate said risks. For example, we only consider independent variables that either influence inflation on the basis of



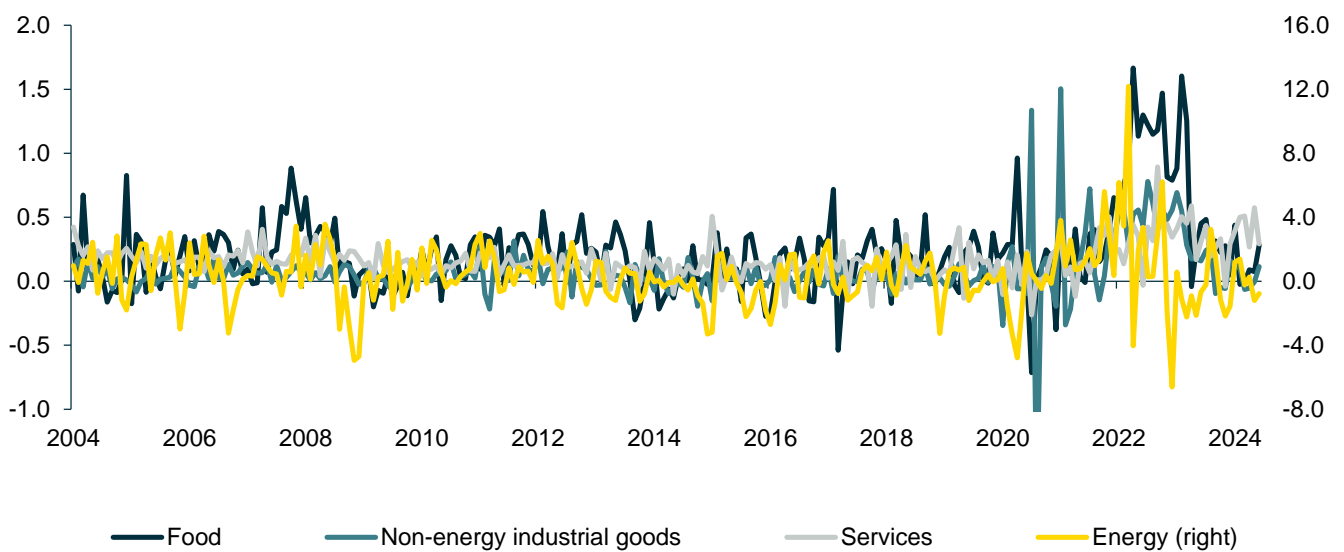
economic plausibility or at least have a clear lead time. For example, we include China's export prices of electronic goods. Since euro area economies import a significant proportion of the electronics they consume from China, export prices have a lead time relative to inflation in the euro area.

In order to exploit the entire lead time of the temporal relationship, the calculations take into account lags of up to twelve months. Furthermore, to reduce the number of independent variables (and the risk of spurious correlation), the maximum lag depends on the pair of dependent and independent variables: For example, inflation in the euro area certainly correlates with a shorter time lag with German import prices than with Chinese export prices. For this reason, fewer lags for import prices (six months) than for export prices (nine months) are included in the calculation. In addition, the publication of data with a time lag also limits the number of time lags available. This is because if European industrial production is published with a time lag of around two months, it cannot be used for an even shorter forecast horizon. A variable with a publication delay of two months and a maximum period of nine months would be included in the algorithm described below with seven time lags of two to nine months.

In addition to calculating the lags, this step also involves adjusting the time series for seasonal influences using the X-13 method, extracting the statistical trend using the one-sided Hodrick-Prescott filter [1] and converting to month-over-month rates. The latter mainly concerns time series that can be interpreted as absolute levels. This does not apply to inflation expectations or corporate yields, for example. The choice of previous month rates as opposed to previous year rates is intended to render the time series more stationary (Chart 2), which facilitates the identification of intra-year trends and allows us to calculate eleven additional observations. The training phase generally covers twenty years from 2004 to 2024, depending on the availability of the explanatory variables.

Chart 2 - Dependent time series show stationarity

Sub-components of the euro area harmonized consumer price index, month-over-month changes in %



Source: Commerzbank Research

Selection and random forest forecast



An important step before the actual forecast is the careful selection of optimal lags and Hodrick-Prescott filter levels using the Least Absolute Shrinkage and Selection Operator (LASSO). This is one of the most common selection procedures in econometrics and goes back to a [study](#) from 1996. Formula (1) illustrates the procedure. Of the up to 36 time series resulting from twelve maximum lags and three filtering stages, the LASSO selects the up to three most suitable time series of an independent variable. This approach reduces the number of time series. However, an independent variable, x_i , will always be represented by a time series, i.e. a filter-lag combination, j , in the last forecasting step.

$$\hat{\beta}_i = \arg \min_{\beta} \left[\sum_{t=1}^T \left(y_{t+h} - \sum_{j=1}^N \beta_{ij} x_{tij} \right)^2 + \lambda \sum_{j=1}^N |\beta_{ij}| \right] \quad \text{with } \lambda \geq 0 \quad (1)$$

For the following forecasting step, we opted for the Random Forest method due to the machine learning algorithm's great flexibility. The Random Forest is also garnering more and more popularity in econometrics. In addition to its flexibility, such as the attribute of not requiring variables to be normalized, the random forest is also characterized by a strong, non-linear calculation method. This takes account of empirical observations that inflation is only affected above certain threshold values. For example, producers could compensate for fluctuations in input prices of up to 2% compared to the previous year by adjusting their profit margin. Above this threshold, however, producers have to pass on the costs. The random forest method maps these and other non-linearities and makes a forecast for the dependent variable, y_t , with the forecast horizon, h :

$$\hat{y}_{t+h}^{Commodities} = \text{RandomForest}(\mathbf{X}^{Commodities}); \quad \text{with } \mathbf{X} = \begin{cases} x_{i=1,j} & , \text{ if } \hat{\beta}_{i=1,j} \neq 0 \\ x_{i=2,j} & , \text{ if } \hat{\beta}_{i=2,j} \neq 0 \\ \dots & \end{cases} \quad (2)$$

A decision tree forms the basis for the random forest calculation. The decision tree first searches for a threshold value (also known as a decision criterion) of an independent variable that divides the observations into two groups. If observations fall below this threshold, they fall into the first group. If observations exceed the threshold value, they fall into the second group. A threshold value of a second independent variable further divides the two observation groups into a total of four groups. A forecast can already be derived from this: An additional observation can be sorted into one of the four groups based on the two decision criteria. The forecast for the new observation is then the average of the dependent variable of the observations in this specific group. This process works for all dependent variables and is illustrated here for the development of goods prices (Chart 3). Here, the global container shipping freight rate and German import prices are shown as independent variables.



Chart 3 - A decision tree forms the basis of random forests

Illustration only



Source: Commerzbank Research

A decision tree selects the variables and threshold values used such that the square of the forecast errors of the previously unused variables is minimized. A random forest, in turn, reiterates hundreds of decision trees (750 in this specification) with slightly different combinations of independent variables and forms the average forecast value of the hundreds of decision trees to produce a forecast.

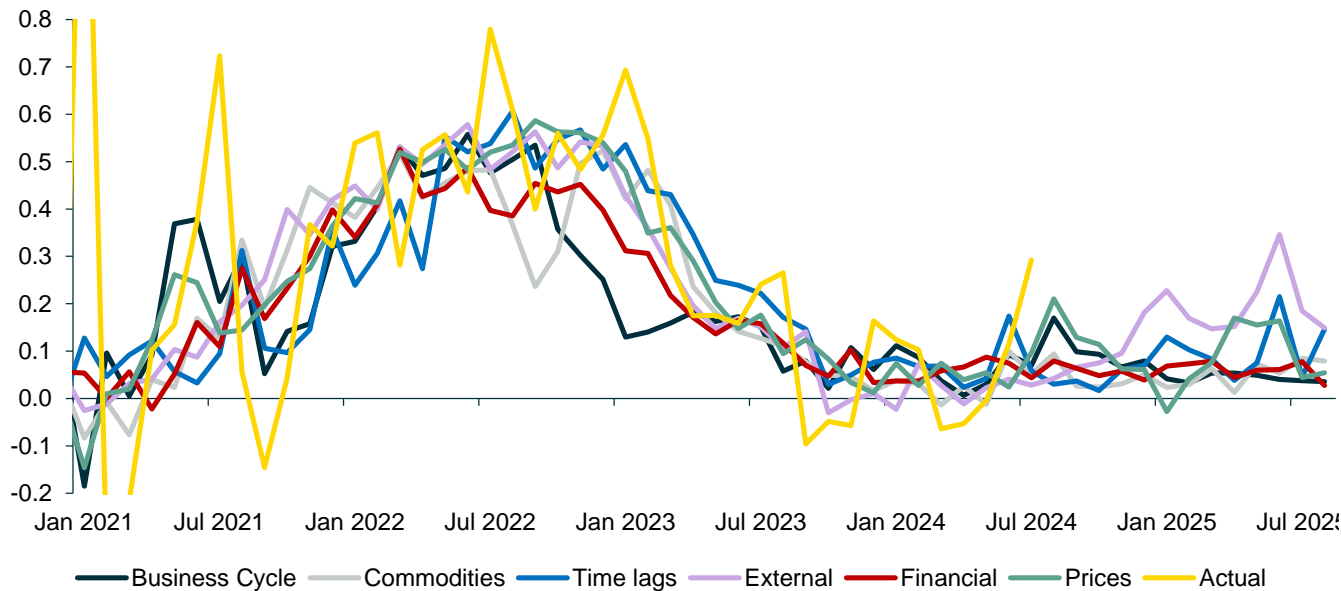
Evaluation and combination of results

We also evaluate the forecasts of the random forests. This is essential in order to compare the forecast quality of the new method with benchmarks. For this purpose, the algorithm examines the months from January 2017 to June 2024 and estimates inflation for each individual month in independent runs. Here, the tested target month is excluded in the training phase of this run. [2] Nevertheless, the training phase extends over approximately twenty years. Due to the out-of-sample method used, the simulated forecasts should be interpreted as forecasts the Random Forest would have produced if a connection of very high energy prices (as in 2022) with inflation had been observed in the training period. This test procedure is carried out for each combination of inflation component and indicator group. For the dependent variable of goods excluding energy, we accordingly test the six forecasts on the basis of the respective indicator groups (Chart 4). While the yellow line shows the actual observed value of the good's pre-month rate, the blue line shows, for example, the forecast based on the time lags- indicators (\hat{y}_t _{time lags}).



Chart 4 - Forecast models for goods' prices

Out-of-sample forecasts for monthly changes in non-energy industrial goods prices, in %; until July 2024 h=0, afterwards increasing in forecast horizon.



Source: ECB, Commerzbank-Research

Obviously, the simulated forecasts correlate very strongly with each other and provide a narrow corridor for the estimate overall. This is not surprising, as the indicators also correlate with each other across groups. The price of oil price futures (in the indicator group of commodities) is also likely to influence the input prices of the purchasing managers' indices in the manufacturing sector (in the indicator group of prices) with a time lag. In contrast, the previous month's realized rate is very volatile and often oscillates above and below the forecasts. With a longer forecast horizon, however, the forecasts tend to diverge - as here for the summer months in 2025.

Now, the question arises whether and how these six forecasts should be combined in order to obtain a single forecast line for inflation. Due to the aforementioned synchronization of the forecasts, the problem of so-called multicollinearity emerges. A simple average of the forecasts is therefore likely to distort the result. For this reason, we calculate a linear model with the out-of-sample forecasts as independent variables for each forecast horizon. At this point, we deliberately specify the linear model without a constant as shown in formula (3) so as not to include an automatic return to the mean in the estimation.

$$y_{t+h} = \kappa_1 \hat{y}_{t+h|t}^{Commod.} + \kappa_2 \hat{y}_{t+h|t}^{Bus.cycle} + \kappa_3 \hat{y}_{t+h|t}^{prices} + \kappa_4 \hat{y}_{t+h|t}^{external} + \kappa_5 \hat{y}_{t+h|t}^{finance} + \kappa_6 \hat{y}_{t+h|t}^{time lags} + \epsilon_{t+h} \quad (3)$$

Due to multicollinearity, the regression coefficients cannot be interpreted as causal. However, the estimated time series of inflation is reliable and corrects the synchronization of the forecasts. [3]

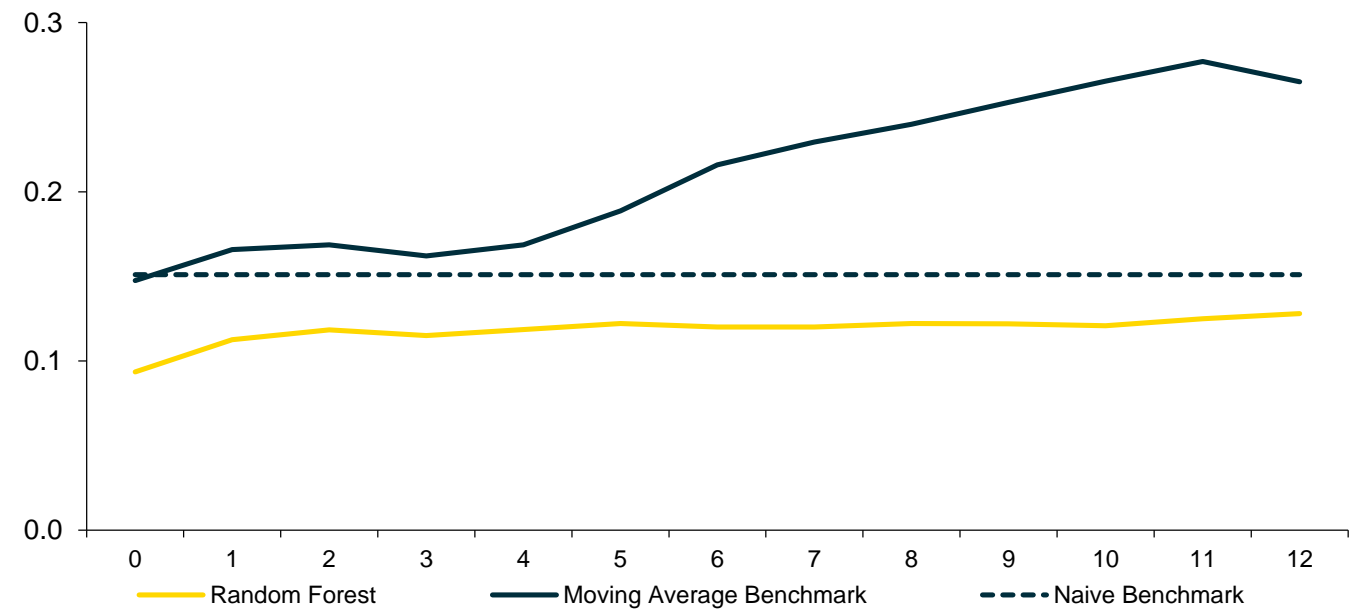
The final step is to combine the forecasts for the components of inflation into the overall inflation rate or the core inflation rate. To do this, we calculate an average of the forecasts weighted by the significance of the component according to Eurostat. In a final evaluation step, we derive the average absolute estimation error compared to the



historical values from the forecast overall inflation rate. This is lowest for the current month, the forecast horizon $h=0$, at 0.09 percentage points and increases up to the forecast horizon of one year (Chart 5). By comparison, the average inflation rate since 2017 has been 0.30%. To additionally assess the forecasting quality of the new model, we compare the forecasts with two simple benchmark models. The first benchmark consists of the average of the previous month's historical changes, the second consists of the moving average of the last three months. The new forecasting model estimates the previous month's rates of inflation with less error than the two benchmark models over the entire forecasting horizon of up to 12 months. However, as the Random Forest model only has slightly smaller estimation errors than the historical average at a forecast horizon of 12 months, we only use the new model up to this point.

Chart 5 - New forecast model beats benchmarks

Average absolute deviation between model forecasts and overall consumer price index; x-axis: forecast horizon in months; in percentage points of m/m rates



Source: Commerzbank-Research

Results and discussion

If the previous year's inflation rate is calculated purely using the model results, a wave-like inflation can be seen until the end of 2024 (Chart 6). Initially, the previous year's rate falls to around 2% in September 2024 and then rises again to 2.8% by the end of the year. The model forecast only settles at 2% in the course of the coming year. The fact that this corresponds exactly to the ECB target is pure coincidence. The central bank target or the historical average inflation rate are entirely excluded in the model.

Despite the above-mentioned forecast quality, we do not incorporate the model results into our inflation forecast without restrictions. This is due to three limitations of the Random Forest model and our methods:

Firstly, the model could underestimate the influence of variables that have influenced several indicator groups in the past but only initially impact one indicator group. Freight rates in the container ship network are probably a primary example for this. During the coronavirus pandemic, freight rates had already risen significantly and were included directly in the external indicator group, but also had an indirect impact on input prices. Although the current increase in transportation costs is already captured in the freight



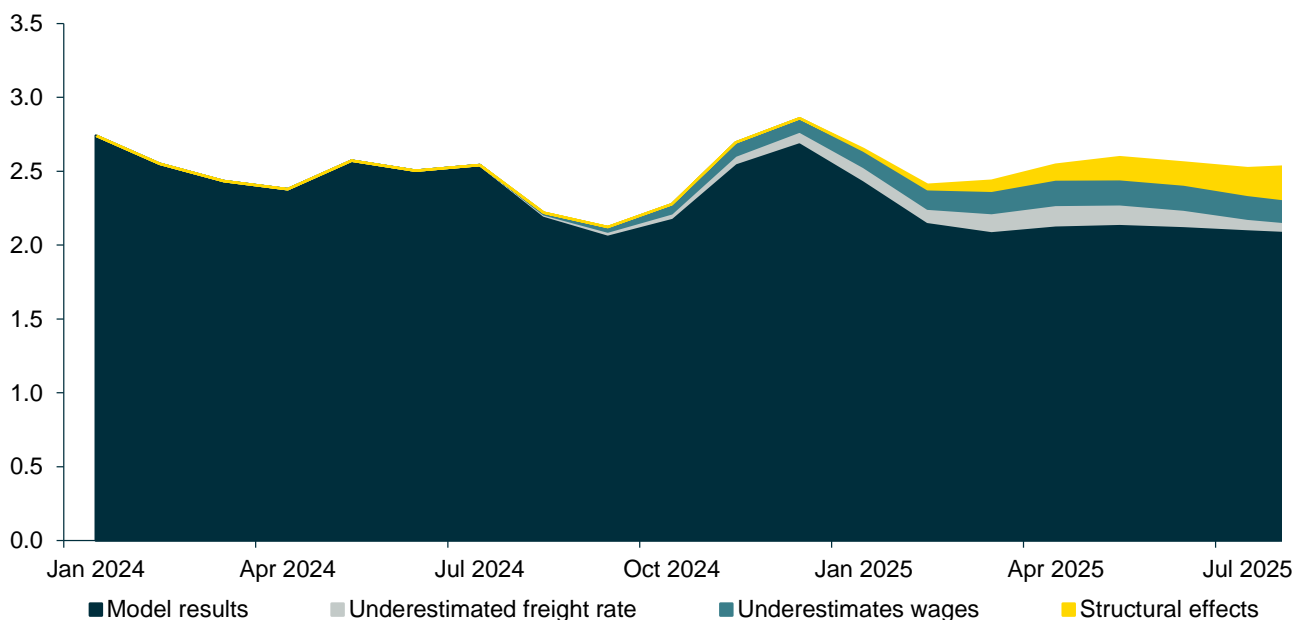
rate time series used, it is probably not yet fully reflected in input prices. We therefore manually add a positive freight rate effect to the model.

Secondly, the Random Forest model underestimates (overestimates) the effect of variable values that exceed (fall below) the historically observed values. This applies to labor costs, which are currently rising more strongly than observed in the past. The Random Forest model could certainly collect those monthly observations in the branches of decision trees for which the largest wage developments have fallen the most. The forecast value based on this branch is then the average of inflation in these monthly observations. However, a new observation is assigned to precisely this branch, even if the wage increase and the potential effect on inflation in this month is higher than in the past. Here, too, we supplement the model forecasts with a manual addition, thereby increasing the inflation forecast.

Thirdly, the Random Forest model – just like all other non-structural models – cannot calculate future trends that have not been realized in the past. These include future effects that are based on deglobalization or decarbonization. While in the past China’s accession to the World Trade Organization and the resulting globalization have dampened consumer prices, a future reversal of this trend as a result of geopolitical tensions is likely. Decarbonization is also expected to influence inflation at a faster pace in the future than in the past. The introduction of the CBAM (Carbon Border Adjustment Mechanism) is just one example here, which has no precedent in the past. Due to these additions, expected inflation for the end of the forecast period rises to around 2.5%.

Chart 6 - Limitations could bias forecasts downwards

Forecasts for euro area headline inflation, year-over-year rates in %



Source: Commerzbank Research

Model will serve as the basis for future forecasts

The new forecasting model combines various machine learning methods and calculates reliable forecasts that can still be tracked transparently. Despite the ability to process a large amount of data, the grouping of variables in particular allows for easier interpretation. Overall, the forecast quality, tested in an out-of-sample procedure, clearly beats simple benchmarks. This holds for inflation as a whole, as well as the inflation components of services, goods excluding energy, and food and beverages. Only the



model forecasts for the energy component are worse than a naive benchmark using a forecast horizon of more than one month. However, this illustrates the risk in using the forecast model blindly. In our analyses, we always combine the pure model results with structural models and empirical values. We also supplement the model results if a limitation of the model becomes apparent. For this reason, we augmented the model's output as a consequence of the increased freight rates and wages, as well as structural effects generated by deglobalization and decarbonization. The longer the forecast horizon, the more important the influence of structural considerations becomes. This is another reason why we do not expect inflation to fall back to the ECB's target of 2.0% in the coming year.

[1] The standard procedure of the Hodrick-Prescott filter is two-sided and takes into account past and future data points for the trend extraction. This would make the simulated forecast output appear better than it actually is. Therefore, we use the one-sided version, which constructs a local linear trend from past data points using a Kalman filter and thus explicitly does not consider future data points. ([back](#))

[2] This method corresponds to the "leave-one-out-out-of-sample" (LOO) method. This is less restrictive than an "expanding window" or "rolling window" version and could underestimate the effect of structural breaks. However, the LOO method has the advantage that the high-inflation phase of previous years can always be used to identify the relevant variables and threshold values. This means that the estimation error of the test phase is also a better indication of the estimation error of the coming months, as the high-inflation phase of recent years is now always available for the estimation. ([back](#))

[3] The Principle Components Regression (PCR) method is considered to be particularly reliable in reducing the distortion in the case of strong multicollinearity. In this case, PCR produces almost identical results to the more easily interpretable and significantly simpler linear model. ([back](#))



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