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Analyzing Financial Conditions and Forecasting Performance

A Comparative Study of Four European Economies

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Abstract

In this analysis we examine the financial conditions of four countries and evaluate the forecasting ability of various models in each of these countries. We describe many variables for each economy, we create a Financial Conditions Index and perform forecasting cross-validation in many settings. Finally, we construct our own methods and evaluate them, indicating avenues for future research.

1 Introduction

This academic project presents a comprehensive analysis of the financial conditions and forecasting performance in four designated European economies: Belgium (BE), Spain (ES), Netherlands (NL), and Hungary (HU). The study employs a rigorous methodology that encompasses data description, the construction of a Financial Conditions Index using Principal Component Analysis (PCA) and forecasting cross-validation. Additionally, variable selection techniques including Ridge and Lasso, as well as variable reduction techniques such as PCA and Partial Least Squares (PLS), are utilized to enhance the accuracy of the forecasts. We also construct some new methods which we present towards the end of the analysis.

The initial stage of the project involves a meticulous data description process. This includes presenting summary statistics and generating informative plots to provide a comprehensive understanding of the data and enable meaningful comparisons between the target variables across the economies. To capture the multidimensional nature of financial conditions, the project leverages PCA to construct a Financial Conditions Index. By applying PCA to all variables, underlying dimensions are extracted, allowing for a concise representation of the overall financial conditions in each economy. This index serves as a valuable tool for further analysis and forecasting. In the forecasting cross-validation phase, advanced variable selection techniques like Ridge and Lasso are employed. Ridge regression effectively handles multicollinearity by introducing a penalty term, enabling the identification of the most relevant predictors. Lasso regression, on the other hand, promotes sparse solutions by driving some coefficients to zero, facilitating variable selection. Multiple models are generated using these techniques, and their respective forecasts are meticulously evaluated, ranked, and compared to determine the most accurate approach. Furthermore, variable reduction techniques, namely PCA and PLS, are applied to create additional forecasting models. These techniques reduce the dimensionality of the data while retaining crucial information. The forecasts generated by these reduced models are assessed, with particular attention given to the loadings of each variable, allowing for a comprehensive analysis of their contributions to the forecasting process. In addition, the project explores model averaging, which combines forecasts from various models to mitigate individual model biases and improve overall accuracy. The performance of these average forecasts is evaluated and compared against individual models to determine their effectiveness in predicting financial conditions. To account for different forecasting horizons, ranging from short-term (h=1) to long-term (h=12), the project examines how forecast errors vary across the horizons. This analysis enables the identification of the optimal forecasting approach for each specific horizon, considering the unique characteristics of each economy.

In conclusion, this project employs a meticulous methodology, encompassing PCA, Ridge and Lasso variable selection, and PCA and PLS variable reduction, to comprehensively analyze the financial conditions and forecast the performance of the designated European economies. By leveraging these sophisticated techniques, the study aims to provide valuable insights, robust predictions, and actionable recommendations for financial analysts and policymakers in their decision-making processes.

2 Data Description

The primary focus of this analysis pertains to the economies of Belgium (BE), Spain (ES), Netherlands (NL), and Hungary (HU), encompassing the time period spanning from 30/06/2008 to 31/12/2022.

The dependent variable (Y) is the Industrial Production, which refers to the output of industrial establishments and covers sectors such as mining, manufacturing, electricity, gas and steam and air-conditioning. This indicator is measured in an index based on a reference period that expresses change in the volume of production output.

Our independent variables are Hard and Soft variables from Eurostat. A comprehensive review of each one of them is provided in the Appendix in *Table 15*.

The project commences with a comprehensive data description process, entailing the calculation of summary statistics to elucidate the central tendencies, dispersions, and distributions of the variables. In addition, plots and visualizations are generated to facilitate a comparative analysis of the target variables across the aforementioned European economies. These graphical representations play a crucial role in the identification of discernible patterns, trends, and potential associations among the variables.

2.1 Distributions

All four density plots exhibit distributions that are approximately normal or near normal; however, they differ in terms of their kurtosis, which refers to the shape of the distribution's peak, and their variance, which indicates the spread of the data, as seen in *Figure 1* .

The density plot of Belgium (BE) displays a bell-shaped distribution with a relatively short and compact form. This suggests that the data exhibits a low variance, indicating that the values are closely clustered around the mean. The maximum density value of 0.13, in comparison to the other plots, signifies a more even distribution of values across the range of the variable.

In the second plot, Spain (ES), we also observe a bell-shaped distribution; however, it is notably tall and narrow. This indicates a low standard deviation, suggesting that a significant portion of the data points are located in close proximity to the mean. With a maximum density value of 0.4, which is the highest among the plots, there is a higher likelihood of a value occurring in close proximity to the mean of the distribution.

The third plot, Hungary (HU), exhibits a bell-shaped distribution with a slight skewness, implying a subtle degree of asymmetry in the data. It is relatively shorter compared to the other plots, indicating a lower variance. The maximum density value of 0.18 suggests that while there is some concentration of data around the mean, it is less pronounced compared to the density plot of Spain (ES).

The fourth plot, Netherlands (NL), demonstrates a bell-shaped distribution with a maximum density value of 0.21. Without further elaboration on the skewness or kurtosis, it can be inferred that this plot represents a relatively symmetric distribution with a moderate spread of values around the mean.

2.2 Boxplots

Addition to the density plot above, a boxplot analysis was conducted to further enhance the understanding of the distributions in Spain (ES), Belgium (BE), Netherlands (NL), and Hungary (HU). The boxplots, as seen in *Figure 2* , provided insights into the central tendency, variability, and potential outliers in the data. Notably, the boxplots revealed that the medians for all countries were centered around 0, suggesting a normal distribution and a similar central tendency in terms of the dataset's mean. However, variations in the quantiles were observed, indicating differences in the spread of the data. For Spain (ES), the interquantile range (IQR) extended from approximately -0.5 to 0.5, indicating a relatively narrow spread of values. Belgium (BE) exhibited a wider interquantile range (IQR), approximately -2 to 2, suggesting a broader distribution with a larger spread of values. Hungary (HU) and the Netherlands (NL) displayed narrower interquantile range (IQR), approximately -1.3 to 1.3 and -1 to 1, respectively, indicating relatively tighter distributions and a more concentrated range of values.

In conclusion, by combining a boxplot with a density plot, we can gain a more comprehensive understanding of the distributional properties of the data in each country. The boxplot provides information about the quartiles, median, and potential outliers, while the density plot visualizes the shape and spread of the distribution.

2.3 Industrial Production Plots

Several factors can influence industrial production. The overall state of the economy, including factors like GDP growth, inflation rates, interest rates, and consumer spending, can significantly influence industrial production. During periods of economic expansion, industrial production tends to increase as demand for goods and services rises. Government policies play also a crucial role in shaping industrial production. Policies related to taxation, regulation, trade, investment incentives, and infrastructure development can impact the cost of production, market access, and overall business environment, thereby influencing industrial production. Global demand for goods and services, as well as international trade dynamics, can significantly influence industrial production. Expanding international markets, trade agreements, and shifts in global consumer preferences can create opportunities for increased production. Finally, the availability and cost of inputs such as raw materials, energy, and labor can affect industrial production. Fluctuations in commodity prices, changes in labor market conditions, and disruptions in supply chains, like those caused by natural disasters or geopolitical events, can impact production levels.

In this setting, as shown in *Figure 8*, the industrial production in Spain exhibited a pattern of variability throughout the years. In the aftermath of the global financial crisis in 2008, Spain encountered a substantial decline in its industrial output. However, subsequent years witnessed a gradual recuperation. Prior to the advent of the COVID-19 pandemic, indications of growth in Spain's industrial production were discernible. Nevertheless, the pandemic inflicted a severe blow to industrial activity, leading to a sharp contraction in production.

In a similar manner the global financial crisis of 2008 adversely affected Hungary, causing a contraction in its industrial output, as *Figure 7* illustrates. Following the crisis, Hungary embarked on a gradual recovery trajectory and witnessed periods of growth. Prior to the COVID-19 pandemic, Hungary's industrial production generally exhibited an upward trend on the whole, although with many ups and downs. Nevertheless, the pandemic disrupted supply chains and precipitated reduced demand, resulting in a decline in industrial production.

Figure 5 depicts the industrial production in Belgium. Belgium boasts a well-developed industrial sector characterized by fluctuations in production over time, influenced by both domestic and global factors. The country faced challenges during the financial crisis in 2008; however, it demonstrated a relatively swift recovery. Prior to the onset of the COVID-19 pandemic, Belgium's industrial production exhibited overall stability or growth. Nonetheless, the pandemic exerted adverse effects on industrial activities, leading to disruptions and diminished output.

The Netherlands, renowned for its robust industrial base and emphasis on manufacturing and export-oriented industries, demonstrated resilience and growth in industrial production over the years. As it is shown in *Figure 6*, although the country experienced a downturn during the financial crisis in 2008, it rebounded and showcased consistent expansion in industrial production. However, the outbreak of the COVID-19 pandemic significantly impacted the Dutch economy, including industrial production. Imposed restrictions, disruptions in supply chains, and a reduced demand environment exerted a negative influence on output. So on the whole global financial crisis of 2008 and the COVID-19 pandemic were events with great influence on the industrial production of all countries under examination, although the degree of their impacts vary across them.

2.4 Other Key Variable Plots

The variables in question were selected based on a specific interest in the industrial production sector. To interpret the variables and gain insights, two types of plots were employed: a time series plot and a bar plot. The time series plot provides insights into temporal trends, while the bar plot facilitates a comparative analysis of the production levels among Belgium, Spain, Netherlands, and Hungary. This combined approach enhances the understanding of the variables' dynamics and aids in drawing meaningful conclusions related to the industrial production sector.

2.4.1 SD1

The first industrial variable of interest, SD1 (Production development observed over the past 3 months), was analyzed using the time series plot in *Figure 9*. The plot indicates that Spain has experienced the highest level of production development among the four countries over the past 3 months. This suggests that Spain's industrial production has shown significant growth or improvement during this period. Compared to Spain, Belgium's production development appears to be relatively lower. However, it demonstrates a stable pattern over the observed period, indicating consistent and reliable growth in industrial production. The time series plot reveals a steady upward trend for the Netherlands. Although the level of production development may not be as high as Spain or Belgium, the plot illustrates a consistent and gradual increase over the observed period. This implies sustained growth and improvement in industrial production in the Netherlands. In contrast to the other countries, Hungary's production development exhibits a negative trend. This suggests a decline or decrease in industrial production during the observed 3-month period. Further investigation may be necessary to identify the factors contributing to this negative trend in Hungary.

On the other hand, the bar plot (*Figure 10*) was utilized to represent the same production development variables but with a focus on the comparative magnitudes among the four countries of interest. The bar for Spain is the tallest among all countries, indicating the highest production development. Spain has experienced significant growth or improvement in industrial production over the past three months. Although Hungary's bar appears to be shorter than Spain's, it is the second tallest in the plot. However, the negative values indicate that Hungary's production development is below zero. This suggests a decline or decrease in industrial production over the observed period in Hungary. The bar for Belgium is shorter than Hungary's bar, indicating a lower production development. However, unlike Hungary, Belgium's production development is positive, suggesting some level of growth or improvement in industrial production. The bar for the Netherlands is the shortest among all countries with a positive value.

2.4.2 SD14

To understand the business activity of Spain (ES), Belgium (BE), Netherlands (NL), and Hungary (HU), we analyzed the variable SD14, which represents business activity expectations over the next 3 months.

The time series plot in *Figure 11* indicates that Belgium has the highest level of business activity expectations among the four countries. This suggests that businesses in Belgium anticipate significant growth or improvement in their activities over the next 3 months. Although Spain's values appear negative, it is important to note that negative values in this context may represent a decrease in expectations rather than a negative business activity itself. The plot also indicates a stable upward trend, suggesting that the expectations are gradually increasing, albeit from a lower starting point. Netherlands (NL) demonstrates a consistent and gradual increase in the business activity expectations. While the level of expectations may not be as high as Belgium or Spain, the stable upward trend suggests a reliable and steady growth in business activities over the next 3 months. Hungary's business activity expectations exhibit the most variability with significant ups and downs. This suggests a higher level of uncertainty or volatility in the business environment of Hungary compared to the other countries.

Based on the observations from the bar plot in *Figure 12*, Belgium (BE) has the highest mean value. The bar plot indicates that Belgium has the highest mean value among the four countries, suggesting the highest level of business activity expectations. The difference between Belgium's mean value and the mean values of the other countries is quite significant, emphasizing a strong expectation for business activity growth in Belgium. In contrast to the other countries, Spain's bar shows a negative mean value, indicating a decrease or decline in business activity expectations. Although the mean value is negative, it is important to note that this does not necessarily imply negative business activity itself, but rather a reduction in expectations compared to the baseline. The bar plot reveals that Netherlands has a positive mean value, indicating an overall expectation of business activity growth. While the mean value may not be as high as Belgium, it suggests a positive outlook for business activities in the Netherlands. The bar plot shows that Hungary has the lowest mean value among the four countries, indicating lower business activity expectations compared to the others. This suggests a relatively lower level of anticipated growth or improvement in business activities in Hungary.

2.4.3 SD33

The variable SD33, denoted as "Unemployment Expectations over the next 12 months," is of interest for examining the anticipated changes in unemployment rates in the countries under consideration.

The time series plot in *Figure 13* indicates that Belgium experiences constant fluctuations in unemployment expectations over the next 12 months. The mean values go through periods of increase and decrease, suggesting varying levels of optimism or concern regarding unemployment in Belgium. Hungary and Spain show a similar pattern in their unemployment expectations. This suggests that both countries have comparable trends in their expectations of unemployment over the next 12 months. It could indicate a shared economic environment or similar factors influencing unemployment expectations in these countries. The plot reveals that Netherlands has higher volatility in its unemployment expectations compared to the other countries. This suggests a greater level of uncertainty or variability in the anticipated unemployment rates over the next 12 months in the Netherlands.

All countries have negative mean values: The bar plot in *Figure 14* shows that the mean values of unemployment expectations for all four countries are negative. This indicates an overall expectation of a decrease or decline in employment prospects over the next 12 months in these countries. Among the four countries, Belgium has the shortest mean value for unemployment expectations. This suggests a relatively lower level of anticipated increase in unemployment compared to the other countries. Spain and Hungary have larger mean values compared to Belgium, indicating a higher level of anticipated increase in unemployment. This suggests a relatively more pessimistic outlook for employment prospects in these countries compared to Belgium. The bar plot indicates that Netherlands has a medium-sized mean value for unemployment expectations. This suggests a moderate level of anticipated increase in unemployment compared to Belgium, Spain, and Hungary.

2.4.4 HD8

The variable HD8 represents the turnover and volume of sales in wholesale and retail trade, specifically focusing on monthly data for retail sales. In simpler terms, it provides information about the amount of money generated and the volume of sales within the retail sector on a monthly basis.

Based on the observations from the time series plot in *Figure 15*, the following interpretations can be made. The plot indicates that Hungary's turnover and volume of retail sales initially had zero mean values. This suggests a relatively low level of sales activity or revenue generation in the beginning. However, over time, the mean values show a stable increase, indicating a gradual improvement in the turnover and volume of sales in the retail sector. This suggests a positive trend and growth in retail sales in Hungary. The time series plot reveals that Belgium's turnover and volume of retail sales exhibit considerable fluctuations in the mean values. This indicates variability in the sales activity and revenue generation within the retail sector. The significant fluctuations could be attributed to various factors impacting the retail industry in Belgium. The plot shows that Spain's turnover and volume of retail sales occasionally have big negative values during specific periods. These negative values indicate a decline or decrease in sales activity and revenue generation within the retail sector during those particular periods. The time series plot indicates that the turnover and volume of retail sales in the Netherlands follow a stable increasing trend over time. This suggests consistent growth in sales activity and revenue generation within the retail sector. However, in the year 2020, there is a significant spike or notable increase in the mean values, indicating a substantial surge in the turnover and volume of retail sales. This increase could be attributed to specific factors impacted the retail industry in the Netherlands during that period.

The bar plot in *Figure 16* clearly illustrates that Hungary exhibits the highest values in terms of turnover and volume of sales, surpassing the other countries. This suggests that Hungary's wholesale and retail trade sector experiences a relatively larger amount of sales activity and revenue generation compared to the other countries. Spain, on the other hand, shows relatively high values in terms of turnover and volume of sales, following Hungary. However, it is noteworthy that the mean values for Spain are negative. This indicates that, on average, the retail sales in Spain are below zero or experiencing a decline in terms of turnover and volume. This negative trend suggests a challenging or contracting retail market in Spain. In contrast, the bar plot reveals that both Netherlands and Belgium exhibit similar values in terms of turnover and volume of sales. The lengths of their respective tails are comparable, indicating comparable levels of sales activity and revenue generation within the wholesale and retail trade sectors of these countries. This implies a relatively stable performance in the retail markets of Netherlands and Belgium.

2.4.5 Key Points

In summary, these findings provide valuable insights into the economic dynamics of the countries under study. Spain demonstrates strong production growth and business activity expectations, albeit with occasional negative values. Belgium exhibits stability in production development, high business activity expectations, and fluctuations in turnover and sales volume. The Netherlands shows steady growth in production development, stable business activity expectations, and a notable increase in turnover and sales volume in 2020. Hungary experiences a decline in production development but shows a positive trend in turnover and sales volume.

3 Financial Conditions Index

As we already discussed, PCA is a statistical method that aims to capture the maximum amount of variation in a dataset by transforming the original variables into a set of new, uncorrelated variables, called principal components. The first principal component is computed by maximizing the variance incorporated and hence the information from the predictors. In our project, the first principal component, "financial conditional index" could be interpreted as a derived feature that attempts to capture as much of the variance in the original macro data as possible. Therefore, it can be interpreted as an indicator of all the starting variables. From *Figure 17* to *Figure 20*, a "Financial Conditional Index" is extracted with PCA from all variables, including the response variable Y (Industrial Production) for Belgium, Spain, Hungary and Netherlands. As we can see in the four diagrams, the FCI is positively correlated with our y's. Deviations occur in instances where Industrial Production experiences a negative shock, as in 2009 financial crisis or in mid 2020 with COVID 19. Despite those deviations, when the economy stabilizes, we observe that the FCI begins to follow again Industrial Production and retain a positive correlation throughout.

Figures present the relationship between PCA1 and industrial production for Belgium, Netherlands, Hungary, and Spain. Typically, the Financial Condition Index aligns with industrial production, however, divergence is observed during crisis years such as 2008-2009 and 2020-2022. Interestingly, in Spain, no significant divergence is seen during 2008-2009, underscoring the varied economic responses to global events.

4 Methodology

The main aim of this report is to evaluate in pseudo-real time the predictive performance of various models from different estimating methodologies, that can be grouped in two main approaches: variable selection and variable or dimensionality reduction. To provide a comprehensive insight of how these approaches work and why they are used according to literature, we assume that $y_t,\ t = 1, 2, \ldots, T$ is our target variable and $x_t = (x_{1\mathrm{t}}, x_{2\mathrm{t}}, \ldots, x_{\mathrm{Nt}})'$ a set of potential predictors, with N being very large, while we consider a simple linear relationship form as equation (1) indicates. The most popular estimation method for a relationship like this in equation (1) is the ordinary least squares (OLS) method. When the number of observations are much greater than the number of potential predictors, that is $T >> N$, the least squares estimates will have low bias and also low variance, meaning that the estimates will perform well on unseen data and will therefore have improved prediction accuracy.

$$Y_t = a + \sum_{i=1}^{N} \beta_i X_{it} + u_t, \quad u_t \sim \mathrm{iid}(0, \sigma_u^2) \tag{1}$$

However, in cases where the number of observations (T) is not much greater than the number of possible predictors (N), the OLS estimates will have increased variance and the model will suffer from the so called over-fitting problem and therefore low prediction accuracy. Overfitting occurs because the model tries to fit the noise or random variations in the data, leading to poor generalization to new, unseen data. The model becomes too complex and captures the noise rather than the true underlying relationships between the predictors and the response variable. Additionally, in extreme cases where $N > T$, the OLS estimation method is not even feasible, since the covariance matrix of the predictors cannot be inverted, something that is required to estimate the regression coefficients in OLS estimation method.

To mitigate overfitting in the presence of a large number of predictors, several approaches can be considered. The two most popular are the sparse or penalized regression and the dimensionality reduction or factor extraction. The first one involves fitting a model involving all N predictors but also introduces a penalty term to the OLS objective function. In this way the estimated coefficients are shrunk towards zero relative to the least squares estimates in order to exploit the bias-variance trade-off relationship. That is, the shrinkage has the effect of reducing variance at the cost of a negligible increase in bias leading to enhanced prediction accuracy. Here three methodologies can be applied that differentiate regarding the introduced penalty term: Ridge, Lasso and Elastic Net. This setting of sparse regression can also be used to perform variable selection as we will explain later. The second approach of dimensionality reduction entails dimensionality reduction of the predictor matrix, by generating a substantially smaller set of regressors. This reduced set of regressors can subsequently be employed to generate forecasts using conventional methods. The most well-known methodologies for dimensionality reduction is the Principal Component Analysis (PCA) and the Partial Least Squares (PLS).

4.1 Main Methods

4.1.1 Penalized Regression

As we said this setting, relies on the trade-off relationship between bias and variance. Specifically, it attempts to decrease variance of the estimates by accepting a negligible increase in bias. This is performed with a penalty term introduced to the OLS objective function, known as RSS (Residual Sum of Squares) as shown in equation (2) below, where R(f) denotes the penalty term.

$$\text{RSS} = \sum_{t=1}^{T} \left(y_t - a - \sum_{i=1}^{N} \beta_i x_{it} \right)^2 + \lambda R(f) \tag{2}$$

This penalty term varies according to what penalized regression method is employed as shown in *Table 4.1.1.*

Method	**Regularization Term**
Ridge	$R(f) = \sum_{i=1}^{N} \beta_i^2$
Lasso	$R(f) = \sum_{i=1}^{N} \lvert\beta_i\rvert$
Elastic Net	$R(f) = \sum_{i=1}^{N} a\beta_i^2 + (1-a)\lvert\beta_i\rvert$

Table 1: Regularization Techniques and Terms

Notes:

- $\lambda \geq 0$ is a tuning parameter to be determined separately. It serves to control the relative impact of these two terms on the regression coefficient estimates. When $\lambda = 0$, the penalty term has no effect, and penalized regression will produce the least squares estimates. However, as $\lambda \to \infty$, the impact of the shrinkage penalty grows, and the penalized regression coefficient estimates will approach zero. Unlike least squares, which generates only one set of coefficient estimates, penalized regressions will produce a different set of coefficient estimates for each value of λ. Selecting a good value for λ is critical. This is mainly done using cross-validation (either k-fold cross-validation with $k = 5$ or 10 or the special case where $k = T$ (number of observations), that is the Leave One Out Cross Validation (LOOCV).

- The shrinkage penalty is applied to $\beta_1, \beta_2, \ldots, \beta_N$ but not to the intercept α. We want to shrink the estimated association of each variable with the response and not the intercept, which is simply a measure of the mean value of the response when all the N covariates are zero.

- The standard least squares coefficient estimates are scale invariant. In simply terms, it is possible that the predictors are measured in different scale, therefore for those with larger scale the coefficient will be smaller and for those with smaller scale the coefficient will be larger. Therefore, it is best to apply penalized regressions after standardizing the predictors, that means we have to subtract the mean and divide with the standard deviation. It is important to note that this transformation does not change the variability or in the other words the information that is concentrated in each variable i.e., the movement of each variable remains unchanged.

The usefulness of penalized regressions in the context of large data sets is also related with the ability to perform variable selection, that is necessary due to the fact that some or many of the potential predictors are in fact not associated with our variable of interest (the response Y), leading to unnecessary complexity and less interpretability in the resulting model. Ridge regression does have one obvious disadvantage that it is it will include all N predictors in the final model. The penalty used in Ridge will shrink all of the coefficients towards zero, but it will not set any of them exactly to zero (unless $\lambda \to \infty$). This may not be a problem for prediction accuracy, but it can create a challenge in model interpretation in settings in which the number of variables p is quite large. The Lasso overcomes this disadvantage, as the different penalty term used in Lasso also shrinks the coefficient estimates towards zero but also has the effect of forcing some of the coefficients estimates to be exactly equal to zero when the tuning parameter λ is sufficiently large (this comes from the fact that the derivatives when minimizing the objective function of the Lasso can lead to assign some coefficients with exactly zero.) Hence, the Lasso performs variable selection, resulting in models that are generally much easier to interpret than those produced by Ridge regression. We say that the Lasso yields sparse models—that is, models that involve only a subset of the variables. Elastic Net can perform both variable selection and feature shrinkage because it combines the benefits of both Ridge and Lasso by including the penalties of both these methods, providing a flexible approach for variable selection. Although we cannot perform exact variable selection with the Ridge regression this does not mean that we cannot perform it at all. Obviously, we can manually set some coefficients equal to zero, those with estimates very close to zero, where closer to zero is defined as below a specific threshold that the researcher chooses. However, this is consider as crude method for variable selection.

4.1.2 Dimensionality Reduction

Dimensionality reduction involves reducing the dimensionality of the predictor matrix by generating a significantly smaller set of regressors. It is also known as factor extraction methods due to the idea that our target variable is affected by some unobserved factors and combining all the N possible predictors we might obtain useful insight of these unobserved factors.

Principal Component Analysis (PCA) is a popular approach for deriving a low-dimensional set of features from a large set of variables. PCA is an unsupervised approach, since it involves only a set of features $x_1, x_2, \ldots, x_N$ and no associated response Y. Apart from producing derived variables for use in supervised learning problems, PCA also serves as a tool for data visualization, in that if we wanted to examine the whole phenomenon described by the initial N predictors including the target variable y_t, we would have to examine numerous plots. However, after the principal components have been computed we could plot the first principal component to obtain useful insights for the phenomenon as a whole, examining only one single plot. In economic literature this is referred to as coincident indicator.

If we consider that we have a set of available variables and we want to summarize their information in one single variable, one possible way to do it is to take a linear combination of these variables. The main problem about linear combinations is how the weights for each variable will be assigned. Since we want to summarize all the initial variables for example in a single one variable and by doing so to be able to examine the overall phenomenon that these variables describe we want this one variable to capture the most of the "information" of all the initial variables or in other words the most of the variability of the initial X's. This is the way in which the weights (or as they called loadings) that will be used in the linear combination, are chosen in PCA, that is the loadings are chosen in order the index-component we will generate to explain the maximum possible variability of all the initial variables.

Specifically, the first principal component of a set of features $x_1, x_2, \ldots, x_N$ is the normalized linear combination of the features (as shown in Equation (3)) that has the largest variance. Equation (3) indicates the first principal component as the linear combination of the N possible predictors. It is necessary to normalize our N predictors to have zero-mean and unit variance (as it is in penalized regressions), that is, to subtract the mean and divide by the standard deviation of each variable. The elements $\phi_{11}, \ldots, \phi_{N1}$ are referred to as the loadings of the first principal component.

$$Z_1 = \phi_{11}X_1 + \phi_{21}X_2 + \ldots + \phi_{N1}X_N \tag{3}$$

Together, the loadings make up the first principal component's loading vector $\phi_1 = (\phi_{11}, \phi_{21}, \ldots, \phi_{N1})$. We constrain the loadings so that their sum of squares is equal to 1 since, otherwise, setting these elements to be arbitrarily large in absolute value could result in an arbitrarily large variance. If we do not impose this constraint, variables with large scales would receive small weights, while variables with small scales would receive large weights. In other words, the first principal component loading vector solves the optimization problem as shown in Equation (4) below.

$$\max_{\phi_1} \left\{ \frac{1}{T} \sum_{t=1}^{T} \left(\sum_{i=1}^{N} \phi_{i1} x_{it} \right)^2 \right\}$$
$$\text{subject to} \quad \sum_{i=1}^{N} \phi_{i1}^2 = 1$$

After the first principal component Z_1 of the features has been determined, we can find the second principal component Z_2. The procedure for determining the second principal component can be described as follows: We regress x_1 on the first principal component Z_1 and keep the residuals (that is, the part of x_1 that is not explained by the first factor). We then regress x_2 on Z_1 and keep the residuals, and so on for all variables x_N. In other words, we find the unexplained part from the first factor for each variable. Finally, we perform PCA on the residuals obtained from the previous step. This process is repeated to determine all the principal components, which can be as many as the initial variables. Practically, principal components are computed using the spectral decomposition of the $N \times N$ covariance matrix Σ.

Partial Least Squares is a method that is employed to address PCAs main disadvantage, namely, it being an unsupervised learning method. This means that we extract the linear combinations of X's without taking into account the response y_t that we mainly are interested to explain or predict. To solve this problem, we can use the method of Partial Least Squares, which is a supervised machine learning method. The main idea to extract the factors in PLS methodology is practically the same, in that we take as a factor the linear combination of the initial variables which they again need to be standardized. However, the loading for each variable in each PLS factor are now chosen in order the PLS factors to be those linear combinations of $x_1, x_2, \ldots, x_N$ that give the maximum covariance between y_t and each PLS factor, while they are orthogonal to each other, that is that as before with the PCA, after determine the first PLS factor, we regress $x_1, x_2, \ldots, x_N$ on this first PLS factor and we keep the residuals and then we perform the same procedure using instead of $x_1, x_2, \ldots, x_N$ the estimated residuals from the previous step to determine the second PLS factor. In a similar manner we determine all the PLS factors (which can be as many as the initial predictor variables).

4.2 Further Methods

4.2.1 Simple/Naive Models

First we begin with some simple models including:

- The so called “naïve” model, that is we take as forecast the last observation or in other words the forecasted value for tomorrow is the value of the target variable today.
- Average models, that is models that use as forecast the average of the last three and the last 12 observations, namely AVG3 and AVG12 respectively.
- We also include as a model the average of the three aforementioned simple models. So here the forecast for tomorrow is the average forecast of these simple models.

4.2.2 Time-Series Models

The second category of simple models rely on simple time series models, that is AR, MA and ARMA, for which the general form for p and q lags is given in equations (5), (6) and (7). Specifically, here we include:

- Autoregressive models with one and two lags, that is AR(1) and AR(2) and their average forecast as AR average model.
- Moving Average models with one and two lags, that is MA(1) and MA(2) and their average forecast as MA average model.
- Autoregressive Moving Average models, specifically ARMA(1,1), ARMA(2,2) and ARMA(3,3) and their average forecast as ARMA average model.
- We also include as a model the average of all the simple time series models. So here the forecast for tomorrow is the average forecast of all these simple time series models (AR, MA and ARMA).

4.2.3 Linear Regression

In the context of predictive regression we first include the following models:

- Linear regression model using only one possible predictor that has been chosen randomly.
- The model proposed for ‘’all subsets selection method”. In cases where the total number of explanatory variables is not extremely large, as in our case of the forty nine possible predictors we can run all possible linear subset regression models and use some criterion to find the “best” model. The “best” subset regression model can be found by using two steps. First, we fix the number of variables in the model and find the “best” model within this class (e.g. for k=1, we will find the best model for all possible simple

regression models). Next, we compare the best subset regression models found within a specific class (i.e. for different k-subset models), and pick the overall "best" model. Various criteria can be used at each step of the algorithm, here we use the Bayesian Information Criterion (BIC).

- We also include as a model the average of these two models. So here the forecast for tomorrow is the average forecast obtained from these two models.

4.3 Forecasting Cross-Validation Structure

The forecasting cross-validation algorithm works as follows:

- We leave out a number of observations T_{out} of 3 years (out-of-sample size), in order to use them for the evaluation of the forecasting output of the various models and we decide the length of our rolling window (W) to be 2 years.
- For the first round of estimation and forecasting the sample used is for t=1,2,...,(T-$T_{out} - h + 1$), where h is the forecasting horizon. Then, we estimate the parameters and produce the forecasts of the various models.
- We repeat the previous step in a recursive manner, while keeping the sample size (window) the same throughout the process.

Here we use data from June 2008 to December 2022 (monthly data), while we use h=1,3,6,12 as forecasting horizons. After we have computed the forecasts of each model we evaluate the forecasting performance of the various models using the root mean squared forecast error (RMSFE) statistic.

5 New Methods Constructed

Additionally to the already existing methods, we propose two new ones, "Time-Varying PCA/PLS" and "Mean Adaptive Forecasting PCA/PLS". We examine the efficiency of these models at a subsection in the end and we continue the rest of the project without them, since they haven't been validated or approved by research and we don't want to contaminate our results with something wrong. As shown later, our new methods actually perform the best out of all when we test it.

5.1 Adaptive Forecasting PCA/PLS

Adaptive Forecasting is a method that already exists, but we were heavily inspired from it in the creation of the two following methods. The equation for AFPCA is the following:

$$\hat{y}_{t+1|t}^{\text{AFPCA}} = \hat{y}_{t+1|t}^{\text{PCA}}\left(\frac{1}{\text{FE}_t^{\text{PCA}}}\right) + y_t^{\text{PCA}}\left(1 - \frac{1}{\text{FE}_t^{\text{PCA}}}\right) \tag{4}$$

AFPCA observes the forecasting error at time t. If the FE from the PCA is high, it weighs less the prediction of PCA at time $t+1$ and gives some weight at the true value of y at time t.

5.2 Time-Varying PCA/PLS

The idea behind the Time-Varying PCA or PLS is that we don't have to restrict ourselves at the forecasting error of the one period prior, since we have all prior forecasting errors. This is especially useful in PCA settings where the forecasts are particularly sensitive to the variables chosen with high weight in each period. For example, in our setting, it could be that PCA heavily weighs the SD33 (Unemployment expectations) and predicts reasonably well. However, at one point and for some periods, the SD33 remains very stable, leading the PCA to not choose it at the next period (since it selects variables with the maximum variance). Hence, despite the fact that SD33 continues to explain/impact our Y, it is discarded from our model. With Time-Varying PCA though, we weigh more the variables chosen when the Forecast error was really small, meaning the time when SD33 was included in the PCA, thus alleviating the above problem. The TVPCA equation is provided as:

$$\hat{y}^{\text{TVPCA}}_{t+1|t} = \hat{y}^{\text{PCA}}_{t+1|t}\left(\frac{\sum_{i=1}^{t} \text{FE}^{\text{PCA}}_{i}}{\text{FE}^{\text{PCA}}_{t}}\right) + \ldots + y^{\text{PCA}}_{2}\left(\frac{\sum_{i=1}^{t} \text{FE}^{\text{PCA}}_{i}}{\text{FE}^{\text{PCA}}_{1}}\right) \tag{5}$$

5.3 Mean Adaptive Forecasting PCA/PLS

The Mean Adaptive Forecasting PCA/PLS is something similar to Adaptive Forecasting. It has again, two parts that we weigh between. In simple AF the first part was the prediction produced by the PCA and the assigned weight was determined by the FE of the previous period. The second part used to be the dependent lagged variable. In our new method, the second part is essentially the mean of our series at time t and the weights are assigned based on the mean forecast error, in relation with the FE at time t. The MAFPCA is described as:

$$\hat{y}^{\text{AFPCA}}_{t+1|t} = \hat{y}^{\text{PCA}}_{t+1|t}\left(\frac{\text{FE}^{\text{PCA}}_{t} + \text{meanFE}^{\text{PCA}}_{t}}{\text{FE}^{\text{PCA}}_{t}}\right) + \mu^{\text{PCA}}_{t}\left(\frac{\text{FE}^{\text{PCA}}_{t} + \text{meanFE}^{\text{PCA}}_{t}}{\text{meanFE}^{\text{PCA}}_{t}}\right) \tag{6}$$

6 Forecasting

6.1 Shrinkage: Variable Selection

6.1.1 Selected Variables

In this concise report, we leverage shrinkage methods, including LASSO, Ridge, Elastic Net (with mix ratios of 0.2, 0.5, 0.8), and Adaptive LASSO, to identify the key variables selected by each model. Our analysis spans forecasting models for four countries, providing insights into the variable preferences of each technique.

In *Figure 22*, the variable selection for the Netherlands shows notable consistency across shrinkage methods. LASSO and Elastic Net models highlight "Production in Construction (HD4)" and "Price Expectations over the next 3 months (SD10)". Ridge includes these and "Money market interest rates (HD6)", while Adaptive Lasso adds "Employment Expectations over the next 3 months (SD3)" among others. The consistent selection of certain variables across diverse models is an encouraging outcome, reinforcing the robustness of these variables in the forecasting process.

Figure 21 reveals a strong consistency in variable selection for Belgium across shrinkage methods. Both LASSO and ELNET-0.8 prominently feature "Business activity expectations over the next three months (SD14)". Similarly, Ridge, ELNET-0.5, ELNET-0.2, and Adaptive Lasso also highlight this variable, with Ridge and ELNET-0.2 selecting a wider set. Notably, "Consumer Confidence indicator (SD26)" and "Major purchases over the next 12 months (consumer) (SD34)" are common picks for ELNET-0.5, ELNET-0.2, and Adaptive Lasso. The consistent selection of these variables across models underlines their importance in the forecasting process.

Figure 23, all models for Hungary, singularly highlight the variable "Assessment of the current level of stocks of finished products (SD6)". Even in Ridge's 22-variable selection, this particular variable emerged as the most weighted underscoring its prominence in the forecasting process.

In *Figure 24*, the variable selection for Spain shows some prevalent choices across different models. LASSO, ELNET-0.5, ELNET-0.2, ELNET-0.8 and Adaptive Lasso all highlight "Volume of stocks currently held (SD12)" and "Unemployment rate (HD5)". Additionally, "Evolution of the current overall order books (SD8)" is a common choice in Ridge, ELNET-0.5, and ELNET-0.2 selections. The recurring selection of these variables across different models underscores their significant role in the forecasting process for Spain.

6.1.2 Model Ranking

In our analysis we employ 6 different shrinkage models and we rank them based on the average performance of each model for all four economies, as seen in *Table 2*. We observe that Ridge performs the best out of all models. Interestingly, the models closer to Ridge perform the best after that, namely, Elastic-Net(0.2) and Elastic-Net(0.5). LASSO and Elastic-Net(0.8) come after that while Adaptive Lasso with inputs the coefficients of Ridge, comes last as the worst performing model, surprisingly.

6.2 Dimension Reduction: Loadings

6.2.1 PCA Loadings

Our Principal Component Analysis (PCA) across four economies uncovers a universal Financial Conditions Index (FCI) as the first principal component, PCA(1). The FCI, with major contributions from variables such as "Unemployment expectations over 12 months (SD33)", "Business activity expectations over the next 3 months (SD14)", "Employment expectations over the next 3 months (SD15)", and "Economic sentiment indicator (SD23)", consistently captures substantial economic variation across all economies. The PCA Loadings can be seen from *Figure 25* to *Figure 28*. This uniformity in high loading variables signifies the robustness of our FCI as a fundamental economic indicator in all investigated economies. The second principal component, PCA(2), accounts for remaining unexplained variance, providing a secondary insight into financial conditions. The consistency of these findings across diverse economies underscores the PCA's capacity to isolate crucial economic indicators. An observation of particular interest in *Figure 28*, which pertains to Spain, is the notably low weights assigned to the variables "Production in industry (HD1)", "Exports (HD2)", and "Building activity over the past 3 months (SD7)". In the context of PCA, these low loadings suggest these variables have a minimal impact on the industrial production. This may be reflective of the economic structure of Spain, where industrial production may not play as significant a role compared to other economic activities.

6.2.2 PLS Loadings

In our analysis, we utilize the Partial Least Squares (PLS) method, a statistical approach which seeks to find directions that concurrently explain both the response variable and the predictors. Similar to Principal Component Analysis (PCA), the components in PLS are orthogonal, meaning they are uncorrelated with each other.

Figures 29 through *32* present the PLS1 and PLS2 loadings, which represent distinct types of variation in our predictors that explain the response variable. The sign of the loading is indicative of the direction of the relationship with the component, with variables of the same sign being positively correlated with each other. *Figure 30*, which pertains to the Netherlands, the variables "Construction Confidence Indicator (SD23)" and "Economic Sentiment Indicator (SD24)" display the largest loadings in PLS1, suggesting a significant role in explaining the response variable. Turning our attention to Belgium, in *Figure 29*, the variable "Assessment of the current level of stocks of the finished products (SD6)" emerges as the one with the largest loading for PLS1, indicating its key role in the model. *Figure 31*, illustrates the PLS1 loadings for Hungary, where the variable "Business activity (sales) development over the past 3 months (SD11)" exhibits the highest loading, signifying its prominence in the model.Lastly, in *Figure 32*, which represents Spain, the variable "Unemployment rate (HD5)" possesses the highest loading for PLS1, highlighting its substantial influence on the model.

This analysis provides a comprehensive understanding of how different variables, through their loadings, contribute to the PLS components in explaining the response variable for each country

6.2.3 Model Ranking

In our analysis we employ 8 different models Dimension Reduction models and rank them. We use PCA and PLS for the first 3 components in each method and the ones with components determined by cross-validation, again for both methods, as seen in *Table 3*. As expected, the two best performing models are the two determined by cross-validation, while PCA(1), our financial conditions index, follows after that. The performance is evaluated using the average forecast error from all the economies.

6.3 Forecasting h step-ahead

Tables 4 through *7* encapsulate the results of our forecasting procedure, focusing on four distinct future periods: 1 period ahead, 3 periods ahead, 6 periods ahead, and 12 periods ahead. The accuracy of these forecasts is quantified using the Root Mean Square Forecast Error (RMSFE), a well-established measure for forecasting accuracy. The RMSFE is computed as the square root of the mean of the squared discrepancies between forecasted and actual values.

By computing RMSFE it allows us to compare the performance of different models and offers insights into how forecasting accuracy alters as we extend our predictive reach. For each forecast horizon, the model that exhibits the lowest RMSFE is typically regarded as the most accurate. This does not preclude the possibility of different models outperforming others at different horizons, thereby adding complexity to the comparative analysis.

As we move forward into the future, it is generally expected that the RMSFE will increase, mirroring the inherent difficulties in longer-term prediction. This is clearly observed in *Table 4* and *Table 7*, where the "Column mean" (the average RMSFE across all models), for Belgium and Spain , displays an upward trajectory as the forecast horizon expands. This suggests that the challenge of predicting the industrial production for each country escalates as we forecast further into the future.

However, an intriguing counter-intuitive pattern is detected in Figures *Table 5* and *Table 6*. Specifically, for h=1, h=3, and h=6 in *Table 6*, and for h=1 and h=3 in *Table 5*, the average RMSFE, for Hungary and Netherlands, diminishes as the forecast horizon extends. This suggests that, on average, our models are exhibiting enhanced accuracy when predicting further into the future. Such an uncommon trend necessitates further exploration to comprehend the unique model and data characteristics that contribute to this phenomenon.

An interesting divergence between mean and median RMSFE is noticeable in *Table 4*, *Table 6*, and *Table 5*, suggesting that the RMSFE distribution for Belgium, Hungary and Netherlands, at these horizons may be skewed or contain outliers. This pattern is indicative of a right-skewed distribution, where a small number of models with exceptionally high RMSFEs exert an upward influence on the mean. Even though the majority of our models demonstrate relatively low RMSFEs (as indicated by the lower median), the presence of a few underperforming models may inflate the mean RMSFE.

For a forecast horizon of 1 month, PCA and PLS models perform the best for all countries. With an increased horizon of 3 months, Time-Series models have the most effective forecasts for all countries except Spain, where Ridge there has a slightly smaller forecast error than the MA models. In the 6-month forecast horizon, 2 countries are predicted better by Elastic Net and 2 countries from Time-Series models. However, in all cases, the forecast errors are very close between the models, meaning that a slight change of sample could yield the opposite. In the longest forecast horizon of 12 months, the countries again are divided between Time-Series and Dimension Reduction methods.

6.4 Forecasting 1 step-ahead

6.4.1 All Models

In *Table 8*, we employ a comprehensive approach to model selection, aiming to identify a universally fitting model that would perform optimally across all countries under consideration. This strategy is particularly useful when forecasting for a new country where we can leverage the insights gleaned from the models used for the existing countries.

The model average RMSFE, which is calculated as the mean of RMSFEs of a particular model across all countries, serves as a reliable metric for this purpose. A lower model average RMSFE signifies a better performance in forecasting across the countries.

Our analysis suggests that the PCA_CV model stands out as the most fitting model for this general forecasting approach. It achieves the lowest average RMSFE, marking it as the most accurate model on average across all countries. Therefore, PCA_CV is identified as the optimal choice when a universally fitting model is needed for industrial production forecasting.

In our process to identify the best performing model across countries, we benchmark models based on their average RMSFE relative to the AR(1) model. Specifically, for Belgium, the best model is PLS(2) while the Naive model underperforms, as shown in *Table 37*. Hungary's data, presented in *Table 39*, exhibits the PCA_CV as the top model and ARMA(3,3) as the least efficient. For Spain, highlighted in *Table 40*, the PCA_CV outperforms all others, while the adaptive_lasso(ridge) lags behind. Lastly, for the Netherlands, depicted in *Table 38*, the pls_avg model takes the lead while the Naive model trails.

6.4.2 Predictive Ability of Best Performing Model

As we have already mentioned the model that uses the number of principal components proposed by cross-validation has the best forecasting performance, that is it has the smallest RMSFE, for all the four economies under examination. To illustrate how this model performs we plot for each country the forecasts obtained by this model along with the actual true values in *Figures 33* to *36*. Starting from Belgium in *Figure 33* we can identify three periods of different performance by the model. Specifically, the first period starts from our starting point of evaluation, that is the beginning of 2020 and ends in the about the third quarter of the same year. During this period as it is shown in the figure the forecasts are moving together in direction and rather close in terms of distance from the true values of industrial production. The second period goes approximately until the half of 2021 and is a period of poor forecasts at least in terms of distance from the true values, although the model succeeds in capturing the direction of the variable. Finally, the last period which continuous to the end of the evaluation period of our forecasting exercise, seems to encompass good forecasts from an overall perspective.

Turning to the Netherlands, the period of good performance of the model is presented basically in the second half of our evaluation period that is from 2022 to the end, as it is shown from *Figure 34*, while we can identify poor forecasts in terms of distance and direction from the actual values from the beginning of our evaluation period (year 2020) until the third quarter of 2021.

Looking at *Figure 35*, regarding Hungary we see that the forecasts do not follow the actual values, at least in contrast to what we saw for the previous countries. In each of the years 2020, 2021 and 2022 we can see periods with good and bad performance spread through the evaluation period. The worst forecasting performance is detected between the last quarter of 2021 and the first quarter of 2022, where the model some ups and downs of the variable.

Finally, moving to the results for Spain, the model presents overall a good forecasting performance of the industrial production, as it is shown in *Figure 36*. Although, for the first half of 2020 the model provide forecasts with some small ups and downs while the true values follow an increasing trend, it manages to capture this overall increasing trend during this period. There are some small periods of bad forecasts in terms of direction relative to the direction of the actual values, as these in the first half of 2021 an the last quarter of 2022 but also a remarkable approximation of the true values both in direction and distance in the middle of 2022.

6.4.3 Different Types of Models

We now present the best model, according to relative RMSFE, of each model category for all the four economies, as *Table 9* indicates. Starting with Belgium the model that uses as forecast the average of the 12 last observations, (AVG12) performs best among the simple models.

AR(1) model prevails among the simple time-series models with relative RMSFE equal to 1 (as this is the benchmark model), that is 0.085 smaller than the respective relative RMSFE of the AR(2) model which is the next well performed model in this category of models, as shown in *Table 10*.

In the context of predictive regression, the model proposed by best subset selection (forward method) performs better than the simple linear regression model with one variable randomly chosen, as seen in *Table 11.*

In sparse regression, the best two models are the models proposed from the Ridge regression and the Elastic Net with parameter alpha equal to 0.2 and with relative RMSFE of 0.95 and 0.99 respectively, as seen in *Table 12.*

From the category of Factor models, the models with components selected by cross-validation, performed the best, as previously discussed in the corresponding section and as seen in *Table 13.*

Finally, in the model averaging setting, the average of the models with PCA factors has the smallest relative RMSFE out of all, while the average of PLS models follow slightly behind, as seen in *Table 14.* In PLS settings we normally expect smaller forecast errors than in PCA settings. However, in model averaging, we might include PLS models, constructed from components with lower predictive ability, because PLS has this asymmetry in its components where we don't know which components would perform the best a priori, as is the case with PCA. Furthermore, our results seem to be heavily influenced the forecasts in Hungary, where for some reason that should be researched further, PLS performs a lot worse than PCA, thus increasing the average PLS error from all countries.

6.5 Forecasting with New Methods

In *Table 41* and *Table 42* we observe the RMSFE of all the models used, calculated for one country (Belgium) with 1 step-ahead prediction. We have added many new models, as well as our own models that we created. Interestingly enough, the 4 best performing models are constructed by us and they are AFPLS(2), MAFPLS(2), MAFPLS model's average and AFPLS model's average. Then, the two consistently successful models from previous applications are PLS model's average and PLS(2), before we see again our models in TVPLS model's average and TVPLS(2).

7 Conclusions

In our analysis, we conducted forecasts for four European economies using a combination of existing literature models (36 in total) and two new models developed by us. The evaluation of forecasting performance was carried out across four different forecasting horizons and separately for various types of models. Additionally, we examined the variables selected by Sparse methods and the loadings from Dimension reduction methods to gain insights into the dynamics of each economy. Descriptive work was also included to provide readers with information about the unique characteristics of each economy. Furthermore, we constructed a Financial Conditions Index, which allowed us to identify interesting patterns in the time-series data of each country.

Based on our results, the PCA model, with components determined through cross-validation, emerged as the best performing model on average in our overall sample, for a 1-month forecasting horizon. As the forecasting horizons increased, time-series and shrinkage models demonstrated more efficient predictions. For researchers interested in specific countries, we also identified the best performing models tailored to each country. The performance of the PCA model's average, outperformed other static model averaging methods, gaining a slight advantage over the PLS model's average. Our newly developed method, Mean Adaptive Forecasting PLS(2), performed surprisingly well, falling just behind the Adaptive Forecasting PLS(2) model in the sample we tested. Finally, our newly constructed Financial Conditions Index displayed a reasonable alignment with the Industrial Production of each country, with minor deviations during major economic downturns.

8 References

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9 Appendix

9.1 Figures

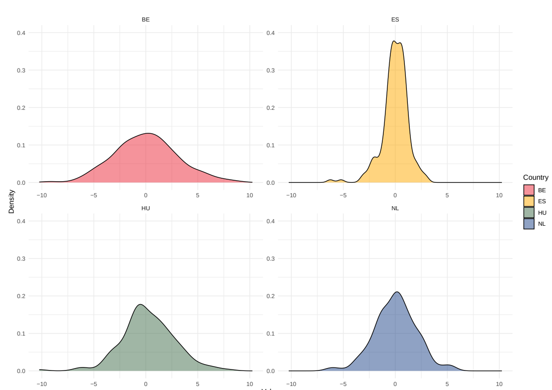

Figure 1: Distributions

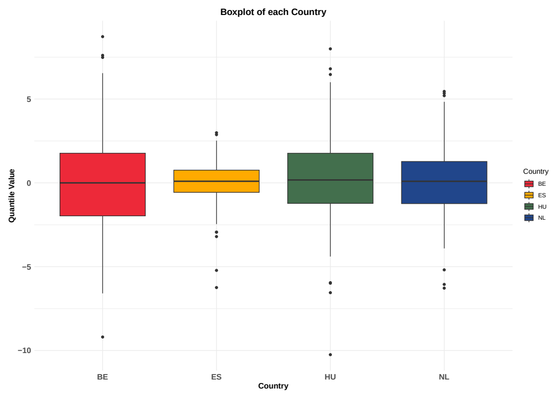

Figure 2: Boxplots

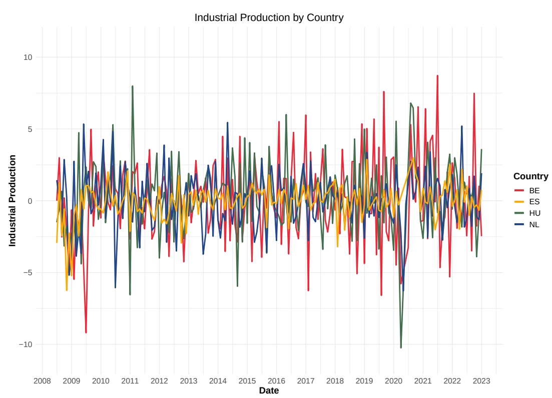

Figure 3: Industrial Prod. Plot (together)

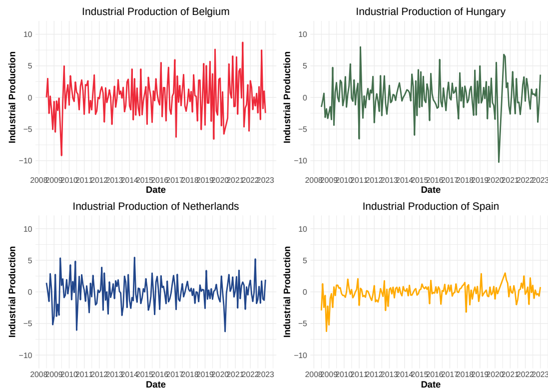

Figure 4: Industrial Prod. Plot (combined)

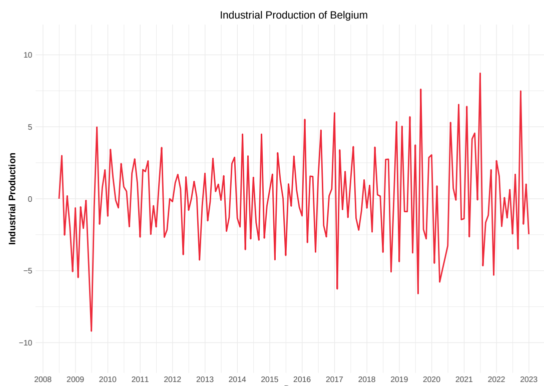

Figure 5: Belgium: Industrial Production

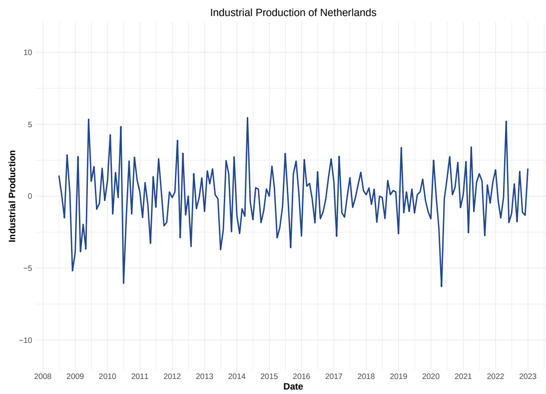

Figure 6: Netherlands: Industrial Production

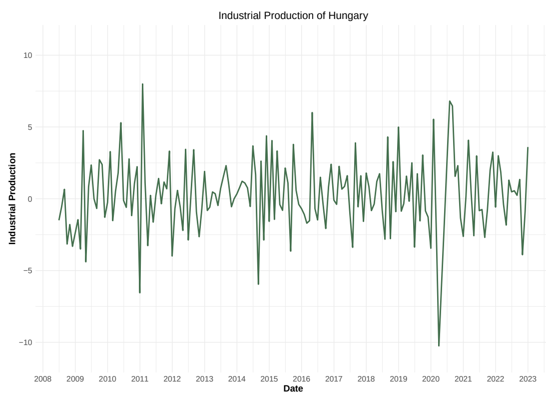

Figure 7: Hungary: Industrial Production

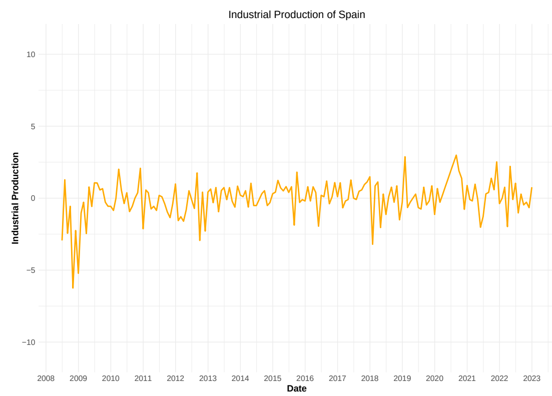

Figure 8: Spain: Industrial Production

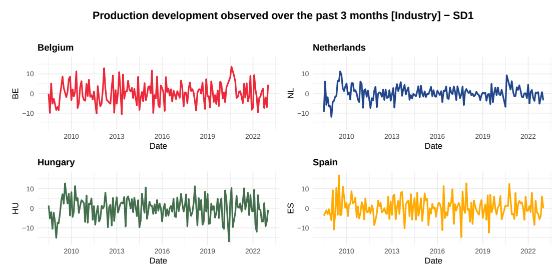

Figure 9: SD1: Time-Series

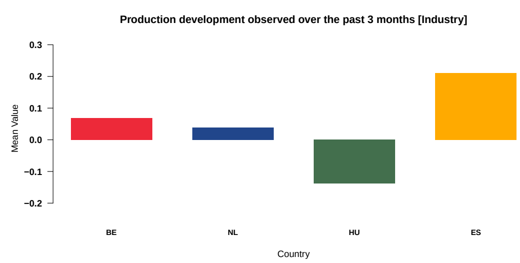

Figure 10: SD1: Barplot

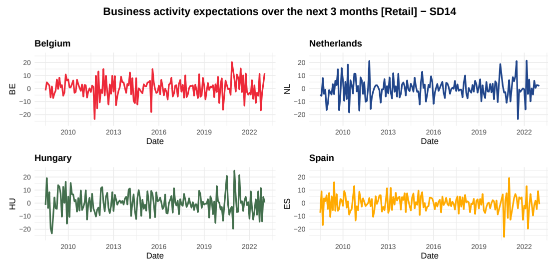

Figure 11: SD14: Time-Series

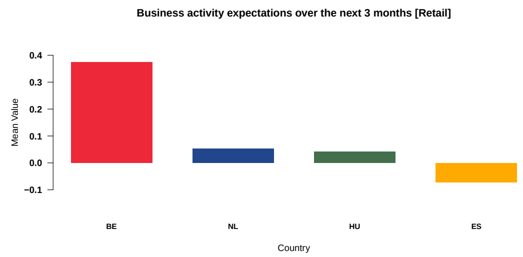

Figure 12: SD14: Barplot

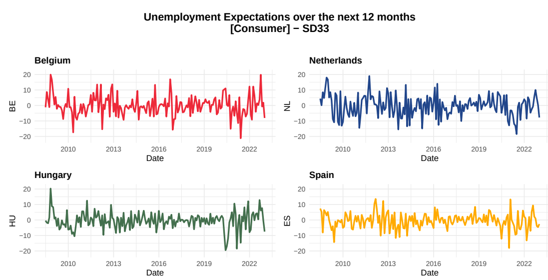

Figure 13: SD33: Time-Series

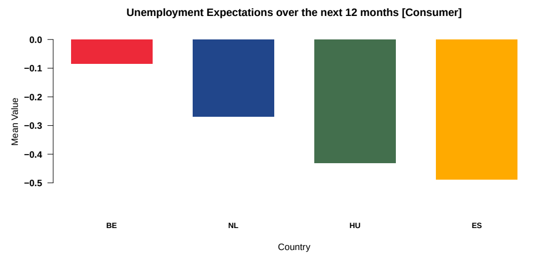

Figure 14: SD33: Barplot

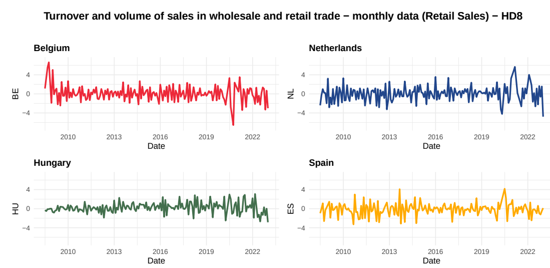

Figure 15: HD8: Time-Series

Figure 16: HD8: Barplot

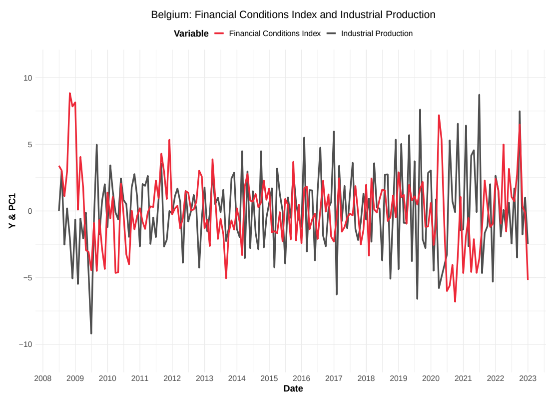

Figure 17: Belgium - PCA1

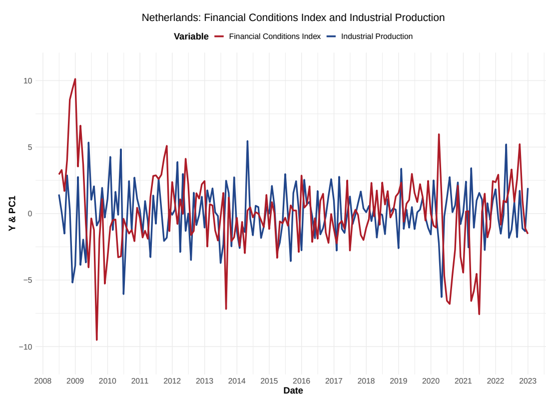

Figure 18: Netherlands - PCA1

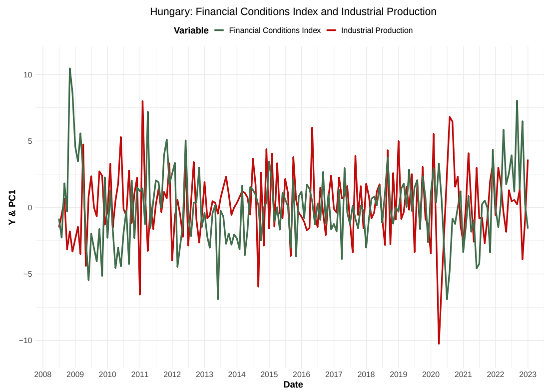

Figure 19: Hungary - PCA1

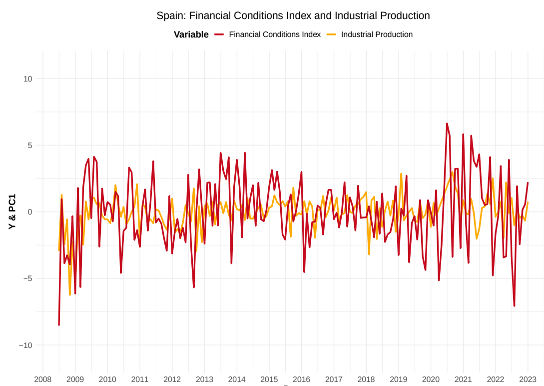

Figure 20: Spain - PCA1

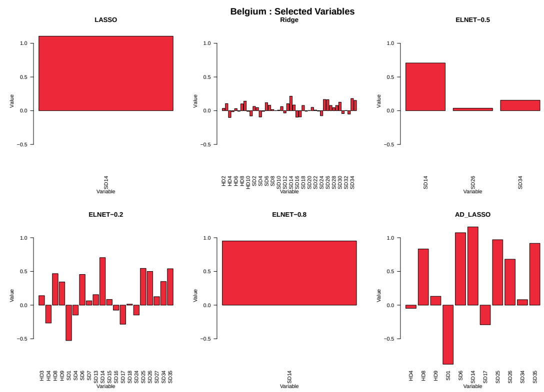

Figure 21: Belgium - Shrinkage Variable Selection

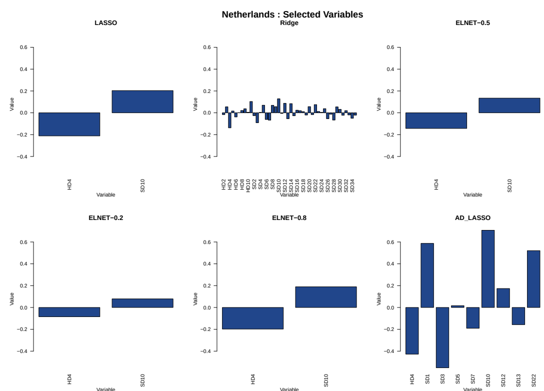

Figure 22: Netherlands - Shrinkage Variable Selection

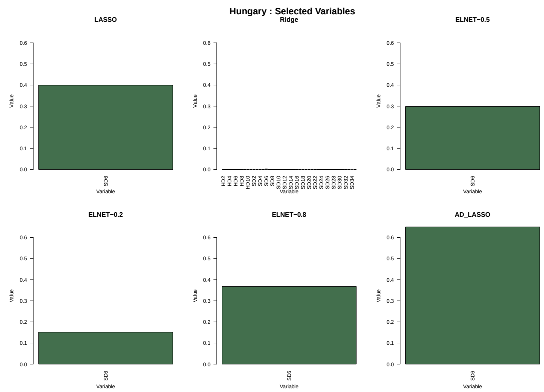

Figure 23: Hungary - Shrinkage Variable Selection

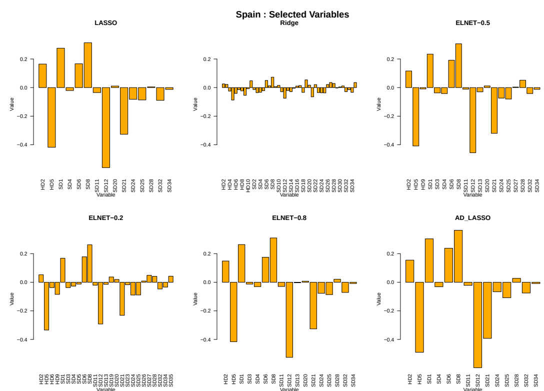

Figure 24: Spain - Shrinkage Variable Selection

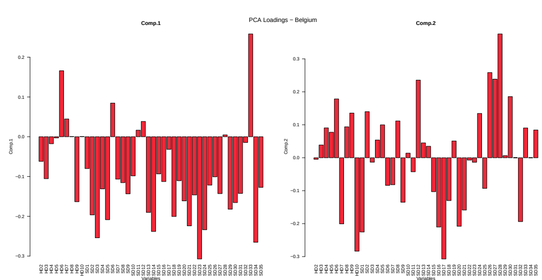

Figure 25: Belgium - PCA Loadings

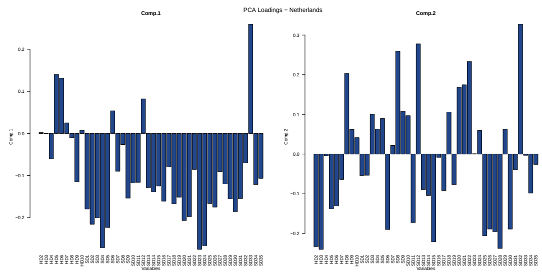

Figure 26: Netherlands - PCA Loadings

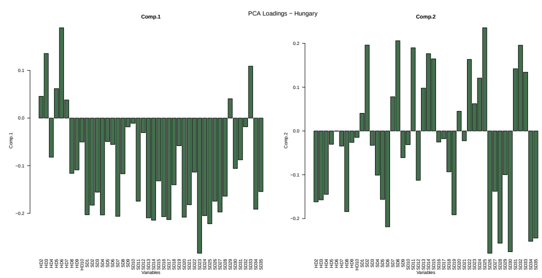

Figure 27: Hungary - PCA Loadings

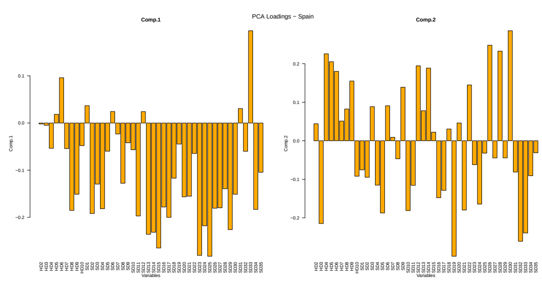

Figure 28: Spain - PCA Loadings

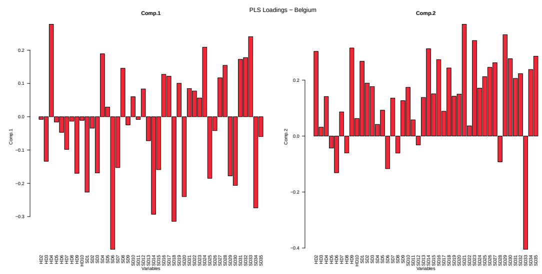

Figure 29: Belgium - PLS Loadings

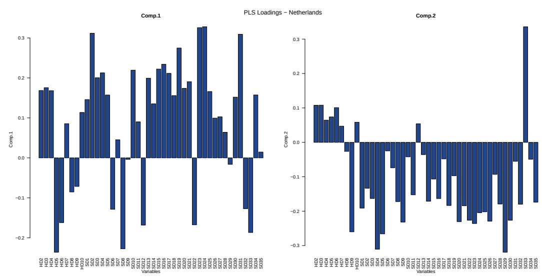

Figure 30: Netherlands - PLS Loadings

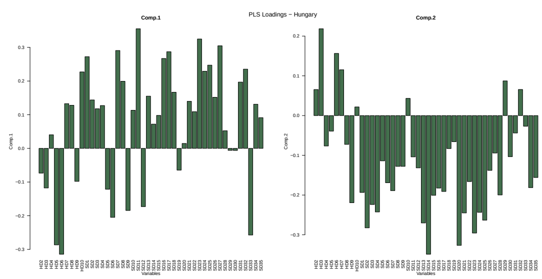

Figure 31: Hungary - PLS Loadings

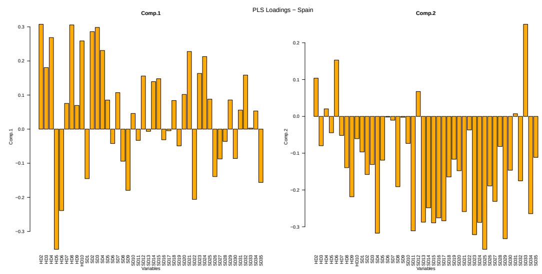

Figure 32: Spain - PLS Loadings

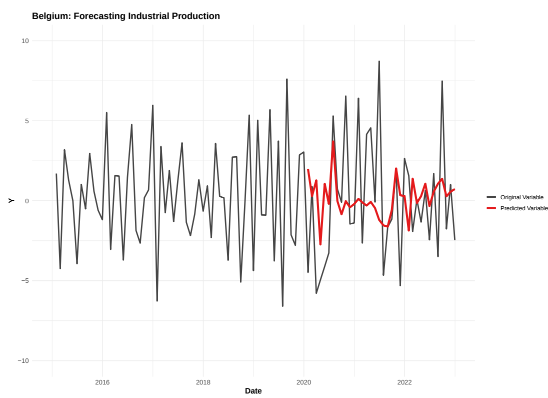

Figure 33: Belgium - Predicted vs True

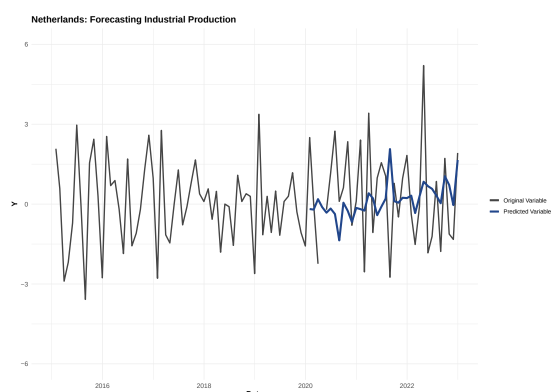

Figure 34: Netherlands - Predicted vs True

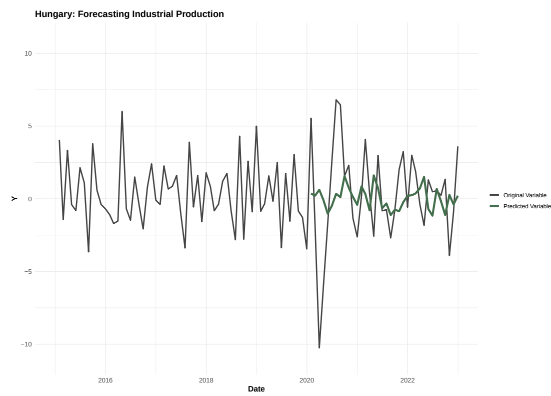

Figure 35: Hungary - Predicted vs True

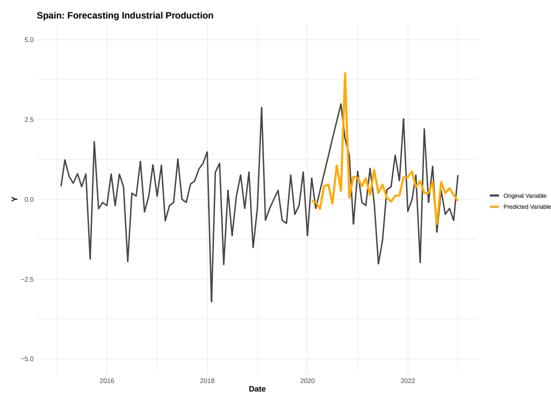

Figure 36: Spain - Predicted vs True

9.2 Tables

	Model	BE	HU	ES	NL	Row_Average
1	Ridge	0.9543	0.9367	0.9325	0.9749	0.9496
4	EL_NET(0.2)	1.0302	1.1443	1.0157	1.0476	1.0594
3	EL_NET(0.5)	0.9938	1.1087	1.0683	1.0795	1.0626
2	LASSO	1.0034	1.0678	1.1325	1.0516	1.0638
5	EL_NET(0.8)	1.0059	1.1221	1.1314	1.0422	1.0754
6	ADAPT_LASSO(ridge)	1.0495	1.1880	1.1402	1.1056	1.1208

Table 2: Ranked Shrinkage Models

	Model	BE	HU	ES	NL	Row_Average
7	PCA_CV	0.9626	0.9150	0.9172	0.9721	0.9417
8	PLS_CV	0.9964	0.9501	0.9631	0.9694	0.9697
1	PCA(1)	1.0018	0.9252	0.9966	1.0230	0.9867
5	PLS(2)	0.8520	1.1667	0.9939	0.9530	0.9914
2	PCA(2)	1.0756	0.9741	1.0656	1.0204	1.0339
4	PLS(1)	1.0379	1.0783	1.0025	1.0515	1.0425
3	PCA(3)	1.0740	1.0107	1.0801	1.0551	1.0550
6	PLS(3)	0.9489	1.1372	1.1262	1.0357	1.0620

Table 3: Ranked Dimension Reduction Models

	Model	1_step	3_step	6_step	12_step	Row_Average
1	True	0	0	0	0	0
2	NAIVE	5.8680	4.9376	5.1574	6.7366	5.6749
3	AVG3	4.1066	4.3943	4.1269	5.0172	4.4112
4	AVG12	4.0586	4.1252	4.0535	4.0139	4.0628
5	AR(1)	3.9449	3.9303	3.7946	3.7856	3.8638
6	AR(2)	4.2815	3.9378	3.7955	3.7632	3.9445
7	MA(1)	4.3591	3.8292	3.8020	3.7460	3.9341
8	MA(2)	4.4890	3.8167	3.7992	3.7895	3.9736
9	ARMA(1,1)	4.3351	3.9322	3.8064	3.7533	3.9568
10	ARMA(2,2)	4.2992	3.8518	3.9072	3.7810	3.9598
11	ARMA(3,3)	4.8124	4.4024	3.9545	3.8460	4.2538
12	LIN_REGR_1	4.3395	5.5916	6.6204	21.2150	9.4416
13	BEST_SUBSET	3.8689	3.8798	3.8819	4.0139	3.9111
14	Ridge	3.7648	3.8858	3.8495	4.1459	3.9115
15	LASSO	3.9584	4.7386	3.8152	5.3345	4.4617
16	EL_NET(0.5)	3.9203	4.5373	3.7855	5.1056	4.3372
17	EL_NET(0.2)	4.0639	4.4129	3.8296	4.7839	4.2726
18	EL_NET(0.8)	3.9683	4.7063	3.8153	5.2989	4.4472
19	ADAPT_LASSO(ridge)	4.1403	5.4920	4.8940	6.4140	5.2351
20	PCA(1)	3.9521	3.8450	4.3097	7.2670	4.8435
21	PCA(2)	4.2433	4.1145	4.8666	6.4104	4.9087
22	PCA(3)	4.2369	4.0864	5.1775	5.9873	4.8720
23	PLS(1)	4.0943	4.2300	4.2885	4.4277	4.2601
24	PLS(2)	3.3610	4.4080	4.4166	5.2524	4.3595
25	PLS(3)	3.7433	4.4758	4.2480	5.2111	4.4196
26	PCA_CV	3.7974	4.0819	4.1884	6.7101	4.6944
27	PLS_CV	3.9306	4.1990	4.0094	4.3516	4.1227
28	Naive_avg	4.4502	4.1665	4.1180	5.0497	4.4461
29	AR_avg	4.0961	3.9215	3.7914	3.7742	3.8958
30	MA_avg	4.2680	3.8223	3.7998	3.7672	3.9143
31	ARMA_avg	4.3331	3.9778	3.8715	3.7914	3.9934
32	Lin_Reg_avg	4.0452	4.5577	4.6956	10.8643	6.0407
33	Shrinkage_avg	3.8801	4.5583	3.7913	5.0388	4.3171
34	PCA_avg	3.8593	3.8720	4.4404	6.2757	4.6118
35	PLS_avg	3.5875	4.1895	4.1019	4.3079	4.0467
36	Time_Series_avg	4.1931	3.8969	3.8244	3.7792	3.9234
37	Column_Mean	4.0181	4.1335	4.0730	5.3003	
38	Column_Median	4.0791	4.1199	3.9308	4.6058	
39	Best Model	PLS(2)	MA(2)	EL_NET(0.5)	MA(1)	

Table 4: Belgium: RMSFE per h step-ahead

	Model	1_step	3_step	6_step	12_step	Row_Average
1	True	0.0000	0.0000	0.0000	0.0000	0.0000
2	NAIVE	3.1438	3.0434	2.8653	2.5532	2.9014
3	AVG3	2.5423	2.2892	2.4453	2.3227	2.3998
4	AVG12	2.1601	2.1435	2.1498	2.1007	2.1385
5	AR(1)	2.2139	2.0779	2.1121	2.1009	2.1262
6	AR(2)	2.2495	2.1110	2.1191	2.1012	2.1452
7	MA(1)	2.3473	2.1007	2.0936	2.1008	2.1606
8	MA(2)	2.3393	2.1107	2.1081	2.1033	2.1654
9	ARMA(1,1)	2.2329	2.1084	2.1500	2.1166	2.1520
10	ARMA(2,2)	2.5664	2.0361	2.1372	2.0997	2.2098
11	ARMA(3,3)	2.6126	2.5355	2.2787	2.1694	2.3990
12	LIN_REGR_1	2.2212	2.2564	2.8943	15.2240	5.6490
13	BEST_SUBSET	2.1256	2.1019	2.1127	2.1007	2.1102
14	Ridge	2.1582	2.1553	2.1171	2.0927	2.1308
15	LASSO	2.3281	2.3139	2.3174	2.3174	2.3192
16	EL_NET(0.5)	2.3900	2.3680	2.3166	2.3463	2.3552
17	EL_NET(0.2)	2.3192	2.3194	2.2023	2.2031	2.2610
18	EL_NET(0.8)	2.3072	2.4294	2.3141	2.3589	2.3524
19	ADAPT_LASSO(ridge)	2.4476	3.7956	2.4691	2.5216	2.8085
20	PCA(1)	2.2648	2.3389	2.3804	2.1075	2.2729
21	PCA(2)	2.2590	2.3292	2.3668	2.4326	2.3469
22	PCA(3)	2.3360	2.5067	2.5809	3.0429	2.6166
23	PLS(1)	2.3279	2.2754	2.2039	2.3345	2.2854
24	PLS(2)	2.1099	2.2880	2.3322	2.3353	2.2664
25	PLS(3)	2.2930	2.3356	2.4882	2.3585	2.3688
26	PCA_CV	2.1520	2.2239	2.3126	2.1265	2.2038
27	PLS_CV	2.1461	2.2556	2.2556	2.2273	2.2211
28	Naive_avg	2.4712	2.3405	2.3275	2.1693	2.3271
29	AR_avg	2.2194	2.0878	2.1154	2.1010	2.1309
30	MA_avg	2.3358	2.1055	2.1007	2.1020	2.1610
31	ARMA_avg	2.3695	2.1631	2.1604	2.1187	2.2029
32	Lin_Reg_avg	2.1621	2.1426	2.3323	7.8371	3.6186
33	Shrinkage_avg	2.2994	2.4200	2.2522	2.2632	2.3087
34	PCA_avg	2.1317	2.2604	2.3221	2.2413	2.2389
35	PLS_avg	2.0968	2.2086	2.2410	2.1699	2.1791
36	Time_Series_avg	2.2801	2.1125	2.1260	2.1066	2.1563
37	Column_Mean	2.2489	2.2414	2.2250	2.6947	
38	Column_Median	2.2866	2.2560	2.2539	2.1696	
39	Best Model	PLS_avg	ARMA(2,2)	MA(1)	Ridge	

Table 5: Netherlands: RMSFE per h step-ahead

	Model	1_step	3_step	6_step	12_step	Row_Average
1	True	0.0000	0.0000	0.0000	0.0000	0.0000
2	NAIVE	3.8382	5.0165	4.7406	4.9059	4.6253
3	AVG3	3.9897	4.5181	3.9274	4.0613	4.1241
4	AVG12	3.5481	3.5909	3.3447	3.3596	3.4608
5	AR(1)	3.6926	3.3824	3.3145	3.2738	3.4158
6	AR(2)	4.0694	3.5495	3.3422	3.2770	3.5595
7	MA(1)	3.7774	3.4055	3.3239	3.2799	3.4467
8	MA(2)	4.2151	3.3954	3.3174	3.2821	3.5525
9	ARMA(1,1)	4.0060	3.4571	3.3252	3.2780	3.5166
10	ARMA(2,2)	4.4315	4.0033	3.3976	3.3372	3.7924
11	ARMA(3,3)	4.4579	4.2643	3.4078	3.2988	3.8572
12	LIN_REGR_1	3.5957	3.6926	3.6736	28.9390	9.9752
13	BEST_SUBSET	3.3888	3.4235	3.3318	3.3596	3.3759
14	Ridge	3.4589	3.5142	3.4130	3.3031	3.4223
15	LASSO	3.9429	3.7329	3.9121	3.9068	3.8737
16	EL_NET(0.5)	4.0942	3.7036	3.5928	3.6548	3.7613
17	EL_NET(0.2)	4.2256	3.7007	3.5322	3.4472	3.7264
18	EL_NET(0.8)	4.1436	3.7386	3.7737	3.8699	3.8814
19	ADAPT_LASSO(ridge)	4.3869	3.7558	4.1566	4.9454	4.3112
20	PCA(1)	3.4163	3.6791	3.5423	4.8224	3.8650
21	PCA(2)	3.5970	3.7457	3.6253	4.7806	3.9372
22	PCA(3)	3.7322	3.7681	3.8557	5.6004	4.2391
23	PLS(1)	3.9818	3.6899	3.3183	3.7126	3.6756
24	PLS(2)	4.3083	4.7514	3.6642	5.9337	4.6644
25	PLS(3)	4.1990	4.2200	3.6989	6.4961	4.6535
26	PCA_CV	3.3787	3.4947	3.5161	3.6396	3.5073
27	PLS_CV	3.5083	3.6491	3.6237	3.4270	3.5521
28	Naive_avg	3.4666	4.1437	3.7403	3.8561	3.8017
29	AR_avg	3.8577	3.4449	3.3269	3.2753	3.4762
30	MA_avg	3.9670	3.4003	3.3206	3.2810	3.4922
31	ARMA_avg	4.1784	3.8057	3.3453	3.2865	3.6540
32	Lin_Reg_avg	3.4312	3.5397	3.4532	14.8995	6.3309
33	Shrinkage_avg	3.9511	3.6404	3.6720	3.6851	3.7372
34	PCA_avg	3.3850	3.5649	3.5667	4.2366	3.6883
35	PLS_avg	3.8292	3.9049	3.4478	4.1776	3.8399
36	Time_Series_avg	3.9945	3.5569	3.3270	3.2799	3.5396
37	Column_Mean	3.7624	3.6623	3.4686	4.8103	
38	Column_Median	3.9003	3.6845	3.4846	3.6472	
39	Best Model	PCA_CV	AR(1)	AR(1)	AR(1)	

Table 6: Hungary: RMSFE per h step-ahead

	Model	1_step	3_step	6_step	12_step	Row_Average
1	True	0	0	0	0	0
2	NAIVE	1.4882	1.6604	1.8109	1.9221	1.7204
3	AVG3	1.2425	1.4975	1.5614	1.5368	1.4596
4	AVG12	1.3373	1.3850	1.3471	1.2680	1.3343
5	AR(1)	1.3447	1.3088	1.3261	1.2564	1.3090
6	AR(2)	1.3694	1.3012	1.3408	1.2578	1.3173
7	MA(1)	1.4203	1.2939	1.3147	1.2542	1.3208
8	MA(2)	1.4222	1.2976	1.3183	1.2593	1.3243
9	ARMA(1,1)	1.3770	1.5180	1.5852	1.4827	1.4907
10	ARMA(2,2)	1.4472	1.5936	1.6046	1.5360	1.5453
11	ARMA(3,3)	1.4973	1.6184	1.6229	1.8637	1.6506
12	LIN_REGR_1	1.3082	1.3075	2.6891	3.9774	2.3205
13	BEST_SUBSET	1.2411	1.2806	1.2919	1.2680	1.2704
14	Ridge	1.2539	1.2748	1.2654	1.3953	1.2974
15	LASSO	1.5228	1.3529	1.2174	1.4144	1.3769
16	EL_NET(0.5)	1.4365	1.4008	1.2655	1.6474	1.4375
17	EL_NET(0.2)	1.3658	1.4258	1.2789	1.6048	1.4188
18	EL_NET(0.8)	1.5213	1.3543	1.2128	1.4002	1.3722
19	ADAPT_LASSO(ridge)	1.5332	1.5479	1.4131	1.8334	1.5819
20	PCA(1)	1.3401	1.2970	1.3316	1.3985	1.3418
21	PCA(2)	1.4328	1.3060	1.3435	1.6428	1.4313
22	PCA(3)	1.4524	1.5701	1.6381	2.1032	1.6910
23	PLS(1)	1.3480	1.3405	1.4104	1.5270	1.4065
24	PLS(2)	1.3365	1.5732	1.4384	1.7868	1.5337
25	PLS(3)	1.5144	1.5836	1.5945	1.9757	1.6670
26	PCA_CV	1.2333	1.5059	1.3096	1.1482	1.2993
27	PLS_CV	1.2951	1.3362	1.3057	1.3538	1.3227
28	Naive_avg	1.2392	1.4113	1.4839	1.4959	1.4076
29	AR_avg	1.3495	1.3010	1.3325	1.2569	1.3100
30	MA_avg	1.3984	1.2957	1.3165	1.2567	1.3168
31	ARMA_avg	1.4157	1.5266	1.5474	1.5742	1.5160
32	Lin_Reg_avg	1.2481	1.2823	1.7445	2.1633	1.6096
33	Shrinkage_avg	1.4097	1.3592	1.2511	1.5137	1.3834
34	PCA_avg	1.2726	1.3580	1.3189	1.4654	1.3537
35	PLS_avg	1.3023	1.4185	1.4036	1.5574	1.4204
36	Time_Series_avg	1.3536	1.3432	1.3673	1.3418	1.3515
37	Column_Mean	1.3353	1.3674	1.4057	1.5483	
38	Column_Median	1.3597	1.3562	1.3422	1.4893	
39	Best Model	PCA_CV	Ridge	EL_NET(0.8)	PCA_CV	

Table 7: Spain: RMSFE per h step-ahead

	Model	BE	HU	ES	NL	Model_Average
1	PCA_CV	0.9626	0.9150	0.9172	0.9721	0.9417
2	BEST_SUBSET	0.9807	0.9177	0.9230	0.9601	0.9454
3	Ridge	0.9543	0.9367	0.9325	0.9749	0.9496
4	PCA_avg	0.9783	0.9167	0.9464	0.9629	0.9511
5	Lin_Reg_avg	1.0254	0.9292	0.9282	0.9766	0.9649
6	PLS_avg	0.9094	1.0370	0.9685	0.9471	0.9655
7	PLS_CV	0.9964	0.9501	0.9631	0.9694	0.9697
8	PCA(1)	1.0018	0.9252	0.9966	1.0230	0.9867
9	AVG12	1.0288	0.9609	0.9945	0.9757	0.9900
10	PLS(2)	0.8520	1.1667	0.9939	0.9530	0.9914
11	AR(1)	1.0000	1.0000	1.0000	1.0000	1.0000
12	LIN_REGR_1	1.1000	0.9738	0.9729	1.0033	1.0125
13	AR_avg	1.0383	1.0447	1.0036	1.0025	1.0223
14	Naive_avg	1.1281	0.9388	0.9216	1.1162	1.0262
15	PCA(2)	1.0756	0.9741	1.0656	1.0204	1.0339
16	Shrinkage_avg	0.9836	1.0700	1.0484	1.0386	1.0351
17	PLS(1)	1.0379	1.0783	1.0025	1.0515	1.0425
18	Time_Series_avg	1.0629	1.0818	1.0067	1.0299	1.0453
19	AVG3	1.0410	1.0805	0.9240	1.1483	1.0485
20	ARMA(1,1)	1.0989	1.0849	1.0240	1.0086	1.0541
21	PCA(3)	1.0740	1.0107	1.0801	1.0551	1.0550
22	AR(2)	1.0853	1.1020	1.0184	1.0161	1.0555
23	EL_NET(0.2)	1.0302	1.1443	1.0157	1.0476	1.0595
24	MA(1)	1.1050	1.0230	1.0563	1.0603	1.0611
25	PLS(3)	0.9489	1.1372	1.1262	1.0357	1.0620
26	EL_NET(0.5)	0.9938	1.1087	1.0683	1.0795	1.0626
27	MA_avg	1.0819	1.0743	1.0399	1.0551	1.0628
28	LASSO	1.0034	1.0678	1.1325	1.0516	1.0638
29	EL_NET(0.8)	1.0059	1.1221	1.1314	1.0422	1.0754
30	ARMA_avg	1.0984	1.1316	1.0528	1.0703	1.0883
31	MA(2)	1.1379	1.1415	1.0577	1.0567	1.0984
32	ADAPT_LASSO(ridge)	1.0495	1.1880	1.1402	1.1056	1.1208
33	ARMA(2,2)	1.0898	1.2001	1.0762	1.1592	1.1313
34	ARMA(3,3)	1.2199	1.2073	1.1135	1.1801	1.1802
35	NAIVE	1.4875	1.0394	1.1068	1.4201	1.2634
	Column_Mean	1.0476	1.0480	1.0214	1.0448	1.0405
	Column_Median	1.0379	1.0678	1.0157	1.0357	1.0453

Table 8: Ranking by Average Performance between Countries

	Model	BE
10	PLS(2)	0.8520
6	PLS_avg	0.9094
25	PLS(3)	0.9489
3	Ridge	0.9543
1	PCA_CV	0.9626
4	PCA_avg	0.9783
2	BEST_SUBSET	0.9807
16	Shrinkage_avg	0.9836
26	EL_NET(0.5)	0.9938
7	PLS_CV	0.9964
11	AR(1)	1.0000
8	PCA(1)	1.0018
28	LASSO	1.0034
29	EL_NET(0.8)	1.0059
5	Lin_Reg_avg	1.0254
9	AVG12	1.0288
23	EL_NET(0.2)	1.0302
17	PLS(1)	1.0379
37	**Median**	1.0379
13	AR_avg	1.0383
19	AVG3	1.0410
36	**Mean**	1.0476
32	ADAPT_LASSO(ridge)	1.0495
18	Time_Series_avg	1.0629
21	PCA(3)	1.0740
15	PCA(2)	1.0756
27	MA_avg	1.0819
22	AR(2)	1.0853
33	ARMA(2,2)	1.0898
30	ARMA_avg	1.0984
20	ARMA(1,1)	1.0989
12	LIN_REGR_1	1.1000
24	MA(1)	1.1050
14	Naive_avg	1.1281
31	MA(2)	1.1379
34	ARMA(3,3)	1.2199
35	NAIVE	1.4875

Figure 37: Ranking by Performance for Belgium

	Model	NL
6	PLS_avg	0.9471
10	PLS(2)	0.9530
2	BEST_SUBSET	0.9601
4	PCA_avg	0.9629
7	PLS_CV	0.9694
1	PCA_CV	0.9721
3	Ridge	0.9748
9	AVG12	0.9757
5	Lin_Reg_avg	0.9766
11	AR(1)	1.0000
13	AR_avg	1.0025
12	LIN_REGR_1	1.0033
20	ARMA(1,1)	1.0086
22	AR(2)	1.0161
15	PCA(2)	1.0204
8	PCA(1)	1.0230
18	Time_Series_avg	1.0299
25	PLS(3)	1.0357
37	**Median**	1.0357
16	Shrinkage_avg	1.0386
29	EL_NET(0.8)	1.0421
36	**Mean**	1.0448
23	EL_NET(0.2)	1.0476
17	PLS(1)	1.0515
28	LASSO	1.0516
27	MA_avg	1.0551
21	PCA(3)	1.0551
31	MA(2)	1.0567
24	MA(1)	1.0603
30	ARMA_avg	1.0703
26	EL_NET(0.5)	1.0795
32	ADAPT_LASSO(ridge)	1.1056
14	Naive_avg	1.1162
19	AVG3	1.1483
33	ARMA(2,2)	1.1592
34	ARMA(3,3)	1.1801
35	NAIVE	1.4201

Figure 38: Ranking by Performance for Netherlands

	Model	HU
1	PCA_CV	0.9150
4	PCA_avg	0.9167
2	BEST_SUBSET	0.9177
8	PCA(1)	0.9252
5	Lin_Reg_avg	0.9292
3	Ridge	0.9367
14	Naive_avg	0.9388
7	PLS_CV	0.9501
9	AVG12	0.9609
12	LIN_REGR_1	0.9738
15	PCA(2)	0.9741
11	AR(1)	1.0000
21	PCA(3)	1.0107
24	MA(1)	1.0230
6	PLS_avg	1.0370
35	NAIVE	1.0394
13	AR_avg	1.0447
36	**Mean**	1.0480
28	LASSO	1.0678
37	**Median**	1.0678
16	Shrinkage_avg	1.0700
27	MA_avg	1.0743
17	PLS(1)	1.0783
19	AVG3	1.0805
18	Time_Series_avg	1.0818
20	ARMA(1,1)	1.0849
22	AR(2)	1.1020
26	EL_NET(0.5)	1.1087
29	EL_NET(0.8)	1.1221
30	ARMA_avg	1.1316
25	PLS(3)	1.1372
31	MA(2)	1.1415
23	EL_NET(0.2)	1.1443
10	PLS(2)	1.1667
32	ADAPT_LASSO(ridge)	1.1880
33	ARMA(2,2)	1.2001
34	ARMA(3,3)	1.2073

Figure 39: Ranking by Performance for Hungary

	Model	ES
1	PCA_CV	0.9172
14	Naive_avg	0.9216
2	BEST_SUBSET	0.9230
19	AVG3	0.9240
5	Lin_Reg_avg	0.9282
3	Ridge	0.9325
4	PCA_avg	0.9464
7	PLS_CV	0.9631
6	PLS_avg	0.9685
12	LIN_REGR_1	0.9729
10	PLS(2)	0.9939
9	AVG12	0.9945
8	PCA(1)	0.9966
11	AR(1)	1.0000
17	PLS(1)	1.0025
13	AR_avg	1.0036
18	Time_Series_avg	1.0067
23	EL_NET(0.2)	1.0157
37	**Median**	1.0157
22	AR(2)	1.0184
36	**Mean**	1.0214
20	ARMA(1,1)	1.0240
27	MA_avg	1.0399
16	Shrinkage_avg	1.0484
30	ARMA_avg	1.0528
24	MA(1)	1.0563
31	MA(2)	1.0577
15	PCA(2)	1.0656
26	EL_NET(0.5)	1.0683
33	ARMA(2,2)	1.0762
21	PCA(3)	1.0801
35	NAIVE	1.1068
34	ARMA(3,3)	1.1135
25	PLS(3)	1.1262
29	EL_NET(0.8)	1.1314
28	LASSO	1.1325
32	ADAPT_LASSO(ridge)	1.1402

Figure 40: Ranking by Performance for Spain

	Model	BE	HU	ES	NL	Row_Average
1	NAIVE	1.4875	1.0394	1.1068	1.4201	1.2634
2	AVG3	1.0410	1.0805	0.9240	1.1483	1.0485
3	AVG12	1.0288	0.9609	0.9945	0.9757	0.9899
4	Column_Mean	1.1858	1.0269	1.0084	1.1814	
5	Column_Median	1.0410	1.0394	0.9945	1.1483	
6	Best Model	AVG12	AVG12	AVG3	AVG12	

Table 9: Naive Models - RMSFE

	Model	BE	HU	ES	NL	Row_Average
1	AR(1)	1	1	1	1	1
2	AR(2)	1.0853	1.1020	1.0184	1.0161	1.0555
3	MA(1)	1.1050	1.0229	1.0563	1.0603	1.0611
4	MA(2)	1.1379	1.1415	1.0577	1.0567	1.0984
5	ARMA(2,2)	1.0898	1.2001	1.0762	1.1592	1.1313
6	ARMA(3,3)	1.2199	1.2073	1.1135	1.1801	1.1802
7	Column_Mean	1.1063	1.1123	1.0537	1.0787	
8	Column_Median	1.0974	1.1218	1.0570	1.0585	
9	Best Model	AR(1)	AR(1)	AR(1)	AR(1)	

Table 10: Time Series Models - RMSFE

	Model	BE	HU	ES	NL	Row_Average
1	LIN_REGR_1	1.1000	0.9738	0.9729	1.0033	1.0125
2	BEST_SUBSET	0.9807	0.9177	0.9230	0.9601	0.9454
3	Column_Mean	1.0404	0.9458	0.9479	0.9817	
4	Column_Median	1.0404	0.9458	0.9479	0.9817	
5	Best Model	BEST_SUB	BEST_SUB	BEST_SUB	BEST_SUB	

Table 11: Linear Regression Models - RMSFE

	Model	BE	HU	ES	NL	Row_Average
1	Ridge	0.9543	0.9367	0.9325	0.9749	0.9496
2	LASSO	1.0034	1.0678	1.1325	1.0516	1.0638
3	ELNET(0.5)	0.9938	1.1087	1.0683	1.0795	1.0626
4	ELNET(0.2)	1.0302	1.1443	1.0157	1.0476	1.0595
5	ELNET(0.8)	1.0059	1.1221	1.1314	1.0422	1.0754
6	ADAPT_LASSO(ridge)	1.0495	1.1880	1.1402	1.1056	1.1208
7	Column_Mean	1.0062	1.0946	1.0701	1.0502	
8	Column_Median	1.0047	1.1154	1.0998	1.0496	
9	Best Model	Ridge	Ridge	Ridge	Ridge	

Table 12: Shrinkage Models - RMSFE

	Model	BE	HU	ES	NL	Row_Average
1	PCA(1)	1.0018	0.9252	0.9966	1.0230	0.9867
2	PCA(2)	1.0756	0.9741	1.0656	1.0204	1.0339
3	PCA(3)	1.0740	1.0107	1.0801	1.0551	1.0550
4	PLS(1)	1.0379	1.0783	1.0025	1.0515	1.0425
5	PLS(2)	0.8520	1.1667	0.9939	0.9530	0.9914
6	PLS(3)	0.9489	1.1372	1.1262	1.0357	1.0620
7	PCA_CV	0.9626	0.9150	0.9172	0.9721	0.9417
8	PLS_CV	0.9964	0.9501	0.9631	0.9694	0.9697
9	Column_Mean	0.9936	1.0197	1.0182	1.0100	
10	Column_Median	0.9991	0.9924	0.9996	1.0217	
11	Best Model	PLS(2)	PCA_CV	PCA_CV	PLS(2)	

Table 13: Dimension Reduction Models - RMSFE

	Model	BE	HU	ES	NL	Row_Average
1	AR_avg	1.0383	1.0447	1.0036	1.0025	1.0223
2	MA_avg	1.0819	1.0743	1.0399	1.0551	1.0628
3	ARMA_avg	1.0984	1.1316	1.0528	1.0703	1.0883
4	Shrinkage_avg	0.9836	1.0700	1.0484	1.0386	1.0351
5	PCA_avg	0.9783	0.9167	0.9464	0.9629	0.9511
6	PLS_avg	0.9094	1.0370	0.9685	0.9471	0.9655
7	Time_Series_avg	1.0629	1.0818	1.0067	1.0299	1.0453
8	Column_Mean	1.0218	1.0509	1.0095	1.0152	
9	Column_Median	1.0383	1.0700	1.0067	1.0299	
10	Best Model	PLS_avg	PCA_avg	PCA_avg	PLS_avg	

Table 14: Model Averaging Models - RMSFE

	X	RMSFE
1	True	0.00
50	AFPLS(2)	3.33
51	MAFPLS(2)	3.39
69	MAFPLS_avg	3.40
68	AFPLS_avg	3.40
72	PLS_all_avg	3.41
48	PLS(2)	3.44
67	TVPLS_avg	3.45
49	TVPLS(2)	3.48
71	PCA_all_avg	3.49
63	PLS_avg	3.49
7	AR(3)	3.56
58	MA_avg	3.57
59	ARMA_avg	3.59
36	AFPCA(1)	3.59
70	Time_Series_avg	3.59
5	AR(1)	3.62
34	PCA(1)	3.64
15	ARMA(1,1)	3.64
28	Ridge	3.65
16	ARMA(1,2)	3.65
11	MA(2)	3.65
10	MA(1)	3.66
55	PLS_CV	3.66
6	AR(2)	3.66
52	PLS(3)	3.68
35	TVPCA(1)	3.68
62	PCA_avg	3.69
65	AFPCA_avg	3.69
57	AR_avg	3.74
27	BEST_SUBSET	3.74
61	Shrinkage_avg	3.74
29	LASSO	3.74
20	ARMA(2,1)	3.75
21	ARMA(3,1)	3.75
22	ARMA(6,1)	3.75

Figure 41: Ranking by Performance for Belgium incl. New Models (1/2)

	X	RMSFE
23	ARMA(12,1)	3.75
37	MAFPCA(1)	3.76
64	TVPCA_avg	3.76
46	AFPLS(1)	3.76
47	MAFPLS(1)	3.77
17	ARMA(1,3)	3.77
30	EL_NET(0.5)	3.77
32	EL_NET(0.8)	3.79
45	TVPLS(1)	3.80
42	PCA(3)	3.81
43	TVPCA(3)	3.82
66	MAFPCA_avg	3.84
53	TVPLS(3)	3.84
44	PLS(1)	3.87
39	TVPCA(2)	3.87
40	AFPCA(2)	3.88
12	MA(3)	3.89
13	MA(6)	3.92
38	PCA(2)	3.93
41	MAFPCA(2)	3.94
60	Lin_Reg_avg	3.96
4	AVG12	3.98
3	AVG3	4.00
31	EL_NET(0.2)	4.04
33	ADAPT_LASSO(ridge)	4.06
19	ARMA(1,12)	4.07
14	MA(12)	4.10
25	LIN_REGR_2	4.13
24	LIN_REGR_1	4.23
18	ARMA(1,6)	4.28
8	AR(6)	4.33
56	Naive_avg	4.44
54	PCA_CV	4.61
26	LIN_REGR_6	5.10
9	AR(12)	5.14
2	NAIVE	5.94

Figure 42: Ranking by Performance for Belgium incl. New Models (2/2)

9.3 Data Review

9.3.1 Data Table

Label	Series
HD2	Euro area 19 international trade [EXPORTS] - monthly data
HD3	Euro area 19 international trade [IMPORTS] - monthly data
HD4	Production in construction - monthly data
HD5	Unemployment Rate
HD6	Money market interest rates [3MONTHYIELD] - monthly data
HD7	Euro yield curves [10YEARYIELD] - monthly data
HD8	Turnover and volume of sales in wholesale and retail trade - monthly data (RetailSales)
HD9	Euro/ECU [USD] exchange rates - monthly data
HD10	Corresponding Equity Index
HD11	Corresponding Volatility Index
HD12	Spread [10Y-3M=HD7-HD6]
SD1	Production development observed over the past 3 months [Industry]
SD2	Production expectations over the next 3 months [Industry]
SD3	Employment expectations over the next 3 months [Industry]
SD4	Assessment of order-book levels [Industry]
SD5	Assessment of export order-book levels [Industry]
SD6	Assessment of the current level of stocks of finished products [Industry]
SD7	Building activity development over the past 3 months [Construction]
SD8	Evolution of the current overall order books [Construction]
SD9	Employment expectations over the next 3 months [Construction]
SD10	Price expectations over the next 3 months [Construction]
SD11	Business activity (sales) development over the past 3 months [Retail]
SD12	Volume of stocks currently hold [Retail]
SD13	Expectations of the number of orders over the next 3 months [Retail]
SD14	Business activity expectations over the next 3 months [Retail]
SD15	Employment expectations over the next 3 months [Retail]
SD16	Business Situation over the past 3 months [Services]
SD17	Evolution of Demand over the past 3 months [Services]
SD18	Expectation of Demand over the next 3 months [Services]
SD19	Evolution of Employment over the past 3 months [Services]
SD20	Expectation of Employment over the next 3 months [Services]
SD21	Euro-zone Business Climate Indicator - monthly data
SD22	Construction confidence indicator
SD23	Economic sentiment indicator
SD24	Industrial confidence indicator
SD25	Retail Confidence Indicator
SD26	Consumer Confidence Indicator
SD27	Financial situation over the last 12 Months [Consumer]
SD28	Financial situation over next 12 Months [Consumer]
SD29	General economic situation over the last 12 months [Consumer]
SD30	General economic situation over the next 12 months [Consumer]
SD31	Price Trends over the last 12 months [Consumer]
SD32	Price Trends over the next 12 months [Consumer]
SD33	Unemployment Expectations over the next 12 months [Consumer]
SD34	Major purchases over next 12 months [Consumer]
SD35	Savings over the next 12 months [Consumer]

Table 15: Extended Table

9.3.2 Date Extended Explanation

We have categorize the ten hard variables in six categories as shown below.

- Production and Industry (3 variables): This category includes variables related to production in the industrial sector, such as " Production in industry - monthly data, (HD1) ", "Production in construction - monthly data, (HD4)" and "Turnover and volume of sales in wholesale and retail trade - monthly data (Retail Sales) (HD8) ". These variables provide insights into the level of activity in the manufacturing, construction, and wholesale/retail trade sectors, which are key contributors to economic growth and employment.

- International Trade (2 variables): This category includes variables related to international trade, such as "Euro area 19 international trade [EXPORTS] - monthly data, (HD2)" and "Euro area 19 international trade

[IMPORTS] - monthly data, (HD3) ". These variables provide information on the value of goods and services exported and imported by the euro area countries, which can indicate the level of international economic activity and trade relationships.

- Labor Market (1 variable): This category includes variables related to the labor market, such as "Unemployment Rate (HD5)". This variable provides insights into the percentage of the labor force that is unemployed, which is an important indicator of the overall health of the labor market and the economy.

- Interest Rates (2 variables): This category includes variables related to interest rates, such as "Money market interest rates [3 MONTH YIELD] - monthly data, (HD6)" and "Euro yield curves [10 YEAR YIELD] - monthly data (HD7)". These variables provide information on the cost of borrowing and lending, as well as the long-term interest rates and risk associated with investing in government bonds.

- Exchange Rates (1 variable): This category includes variables related to exchange rates, such as "Euro/ECU [USD] exchange rates - monthly data (HD9)". This variable provides information on the relative value of the euro currency compared to other currencies, which can have implications for international trade and investment.

- Market Expectations (1 variable): This category includes variables related to market expectations, such as "Spread [10Y - 3M] (HD10)". This variable measures the difference in yield between long-term government bonds and short-term treasury bills, which can provide insights into the market's expectation of future economic conditions and inflation.

In the same way we have categorized the thirty-five remaining soft variables in seven categories as shown and described below.

- 1. Production-related variables (2 variables): These variables are related to the level of production in the industrial sector, both in the past and expected in the future and include: "Production development observed over the past 3 months [Industry] (SD1)" and "Production expectations over the next 3 months [Industry] (SD2)".

- 2. Employment-related variables (5 variables): These variables are related to the expected change in employment levels in various sectors, reflecting the hiring plans and perceived demand for labor and include : "Employment expectations over the next 3 months [Industry] (SD3)", "Employment expectations over the next 3 months [Construction] (SD9)", "Employment expectations over the next 3 months [Retail] (SD15)", "Evolution of Employment over the past 3 months [Services] (SD19)" and "Expectation of Employment over the next 3 months [Services] (SD20)"

- 3. Order-book and demand-related variables (8 variables): These variables are related to the assessment of order-book levels, demand, and stock levels in different sectors, providing insights into the capacity utilization, inventory management, and expected number of orders and include: “Assessment of order-book levels [Industry] (SD4)”, “Assessment of export order-book levels [Industry] (SD5)”,”Evolution of the current overall order books [Construction] (SD8)”, “Volume of stocks currently hold [Retail] (SD12)”, “Expectations of the number of orders over the next 3 months [Retail] (SD13)”, “Business Situation over the past 3 months [Services] (SD16)”, “Evolution of Demand over the past 3 months [Services] (SD17)”, and “Expectation of Demand over the next 3 months [Services] (SD18)”.

- 4. Business activity and sales-related variables (2 variables): These variables are related to the sales volume and business activity in the retail sector, both in the past and expected in the future and include: “Business activity (sales) development over the past 3 months [Retail] (SD11)” and “Business activity expectations over the next 3 months [Retail] (SD14)”.

- 5. Confidence-related variables (6 variables): These variables provide measures for business confidence and confidence in various sectors of the economy illustrating the overall sentiment in each field. They are based on surveys of various industries, businesses, and consumers and professionals and experts of industries. This category includes the following variables: “Euro-zone Business Climate Indicator - monthly data (SD21)”, “Construction confidence indicator (SD22)”, “Economic sentiment indicator (SD23)”, “Industrial confidence indicator (SD24)”, “Retail Confidence Indicator (SD25)” and “Consumer Confidence Indicator (SD26)”.

- 6. Consumers’ perceptions and expectations (8 variables): These variables constitute measures of consumers’ perceptions over a past period and expectations over a future period regarding financial and economic situation, the price trends, unemployment, major purchases and savings. This category includes: “Financial situation over the last 12 months [Consumer] (SD27)”, “Financial situation over the next 12 months [Consumer] (SD28)”, “General economic situation over the last 12 months [Consumer] (SD29)”, “General economic situation over the next 12 months [Consumer] (SD30)”, “Price Trends over the last 12 months [Consumer] (SD31)”, “Price Trends over the next 12 months [Consumer] (SD32)”, “Unemployment Expectations over the next 12 months [Consumer] (SD33)”, “Major purchases over next 12 months [Consumer] (SD34)” and “Savings over the next 12 months [Consumer] (SD35)”.

- 7. Other variables (4 variables): Here we have assigned the remaining variables. These are: “Assessment of the current level of stocks of finished products [Industry] (SD6)”. This variable provides an assessment of the current level of stocks of finished products in the industrial sector. It measures whether the current stock level is high, low or stable, and reflects the industry's inventory management. "Building activity development over the past 3 months [Construction] (SD7)". This variable measures the change in building activity in the construction sector over the past three months. It indicates whether the construction activity has increased, decreased or remained stable during this period. "Price expectations over the next 3 months [Construction] (SD10)" This variable measures the expected change in prices in the construction sector over the next three months. It indicates the industry's pricing strategy and reflects the perceived demand for construction services. The last variable is the "Volume of stocks currently hold [Retail] (SD12)" and measures the level of stock held by retailers at the time of the survey.