A Comparative Study of Machine Learning Models for Forecasting Key Macroeconomic Indicators: how COVID-19 Betrayed Expectations

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Abstract

This paper compares various machine learning models for forecasting macroeconomic indicators, with a focus on the Euro Area economy. Utilizing a high-dimensional dataset spanning from 2000 to 2019, the study explores Bayesian shrinkage, Principal Component Regression, and a Factor-Adjusted Regularized Model Selection (FarmSelect). The models aim to forecast GDP, Wage and Salaries, and the Energy Producer Price Index, addressing challenges like cross-sectional dependencies in the data. Findings highlight that while Ridge regression and PCR performed well for GDP and Wage and Salaries forecasts, FarmSelect was more effective in forecasting Energy PPI. A counterfactual analysis of 2020 is undertaken, simulating economic forecasts in the absence of the COVID-19 pandemic. The monetary policies enacted during the pandemic are presented and they are compared with those that would have been more appropriate in the counterfactual scenario.

Contents

1 Introduction

The Euro Area (EA) economy is characterized by a complex interplay among various economic indicators, such as inflation, interest rates, industrial production, and labor market metrics. These indicators are interdependent and evolve over time, reflecting both domestic and global economic influences. Forecasting macroeconomic variables like GDP at the EA level involves navigating this high-dimensional, interconnected dataset—a task that is challenging due to the strong cross-sectional and serial dependencies within economic variables. Standard econometric models can struggle under these conditions, as they are often overwhelmed by the correlation present in the data.

To address these complexities, this study leverages Bayesian shrinkage methods and factor-adjusted approaches. The aim is to isolate the essential drivers of few key macroeconomic variables from the larger set of economic indicators while reducing noise from collinear or redundant variables. Specifically, we use Bayesian shrinkage with Gaussian and Double-Exponential priors in order to perform variable aggregation and variable selection, and we compare it to Principal Component Regression (PCR), in line with De Mol, Giannone, and Reichlin 2008. Afterwards, through the factor-adjusted model presented by Fan, Ke, and Wang 2020, we adjust for common influences shared across indicators, ensuring that our model focuses on the more idiosyncratic drivers of our target variables. This adjustment is crucial for high-dimensional data, where dependencies among variables can obscure true predictive relationships.

Our dataset, which spans from 2000 to 2019, consists of quarterly economic data for the EA, containing 118 variables. By excluding the COVID-19 period, this time-frame enables us to develop baseline forecasts free from pandemic disruptions, allowing a later comparison to assess how COVID-19 betrayed economic expectations.

The analysis follows a twofold approach:

1. **Bayesian Shrinkage and PCR Comparisons**: Using Bayesian shrinkage, we perform Ridge and LASSO regressions and compare the results to PCR. Thus, we investigate how reliable are these models in forecasting macroeconomic variables in the presence of serial and cross-sectional dependence.

2. **Factor Adjustment and Dimensionality Reduction**: By removing the influence of common latent factors from the regressors, FarmSelect shall enhance both model interpretability and predictive performance by solving the issue of multicollinearity. The focus on identifying the unique contribution of each predictor—once decorrelated via few pervasive factors—enables more reliable variable selection.

This study aims to test the effectiveness of Factor-Adjusted Regularized Model for high-dimensional economic data, while also comparing Bayesian shrinkage methods with Principal Component Regression. The main contribution of this paper is to expand upon existing research by offering a comprehensive comparison of machine learning methodologies and conducting a counterfactual analysis to explore the potential economic outcomes had the COVID-19 crisis not occurred. Through our forecasts, we will speculate on "what would have been" in the absence of the pandemic, also discussing monetary policy implications.

2 Methodology

In this section, we outline the econometric and machine learning techniques applied to address the high-dimensional structure of our macroeconomic dataset for the Euro Area. Our approach leverages a combination of Bayesian shrinkage and factor-adjusted selection methods to effectively manage multicollinearity and cross-sectional dependency within the data. We detail each technique's implementation and theoretical grounding, demonstrating how they contribute to robust forecasting and counterfactual analysis in the context of macroeconomic indicators.

2.1 Empirics

The analysis begins with a large dataset containing quarterly and monthly macroeconomic time series for the Euro Area (EA) as a whole, namely *"EA-MD-QD: Large Euro Area and Euro Member Countries Datasets for Macroeconomic Research"* by Barigozzi and Lissona 2024 [1]. We retain only the quarterly variables and truncated the time series prior to the COVID-19 crisis. This subset selection aligns with our forecasting objective: to compare our forecasts for macroeconomic variables against actual outcomes during the crisis. This approach provides a counterfactual that demonstrates how, despite statistical effectiveness, forecasts may fail to capture unexpected global shocks, potentially leading to misguided policies and prompting central banks to respond with unconventional tools. Following these adjustments, the dataset, referred to as EA-MD-QD, was reduced to 79 observations spanning from January 2000 to December 2019. The EA-MD-QD dataset enables automated de-seasonalization and aggregation of EA data at the quarterly level, with additional transformations applied to ensure stationarity. In particular, we point out and comment the transformations implemented to our variables of interest, in order to interpret their values accordingly in the results.

- For GDP and Wage and Salaries, the logarithmic differencing multiplied by 100,

$$100 \times \Delta \log(x_t)$$

  which represents approximately the percentage change in the original series between quarter t and $t-1$;

- For Energy PPI, a heavier transformation was implemented to ensure stationarity, which is the second-order log differencing,

$$\Delta^2 \log(x_t),$$

  indicating the change in the growth rate between quarter t and $t-1$. Therefore, its sign shows whether the growth rate of the Energy PPI is accelerating, if positive, or decelerating, if negative.

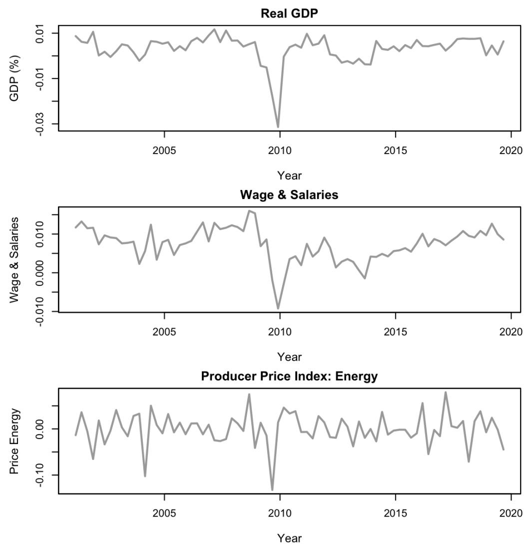

Figure 1: Stationary Target Macroeconomic Indicators

In line with the methodology used by De Mol, Giannone, and Reichlin 2008, our model smooths the dependent variable by applying a moving average to reduce the volatility caused by short-term fluctuations. We aim to make one-year-ahead forecasts (where $h = 4$) using quarterly data, meaning that our forecasts look four quarters into the future. To capture the most relevant trends while minimizing overfitting, we use a rolling window approach with a span of 14 years (56 trimesters). At each time t, model parameters are re-estimated using the latest

[1] Note that a description of the variables ID used in this paper is provided in the Data description PDF file available in the replication package.

14 years of available data. According to De Mol, Giannone, and Reichlin 2008, including lagged regressors does not significantly impact the qualitative results or improve forecast accuracy. Therefore, we set $p = 0$, where p represents the number of lags for the predictor variables in the regression, thus preferring a simpler specification of the model. All procedures operate on standardized data to ensure comparability and stability of the input features. For interpretability, we reapply the original mean and standard deviation to the forecasts.

2.2 Econometric models

To address the high-dimensionality problem inherent in large panels of time series data, this study aims to effectively extract the underlying signal necessary for reliable forecasting. A crucial prerequisite for this analysis is the presence of strong cross-sectional, as it will be highlighted in the descriptive analysis. The primary objective is to conduct a robust and consistent comparison of various forecasting models applied to macroeconomic variables, focusing on the Euro Area data. Specifically, our goal is to evaluate and identify the most suitable forecasting approach for key macroeconomic indicators, such as GDP and Wage and Salaries, thereby enhancing the predictive capabilities for these aggregates.

2.2.1 Bayesian Shrinkage

Our analysis starts with Bayesian shrinkage methods as suggested by De Mol, Giannone, and Reichlin 2008 in *"Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components?"*. Whenever econometric analysis involves high dimensional data, as in the present case, Bayesian methods can offer a solution to the curse of dimensionality problem by imposing priors. Generally, this approach uses specific priors, such as Gaussian or Double-Exponential (Laplace) distributions. De Mol, Giannone, and Reichlin demonstrate that the results from these prior specifications are correlated, leading to approximately equivalent outcomes.

The similarity between Bayesian shrinkage methods and Principal Component Regression can be explained by the way PCR assigns weights to the dominant factors in the data. Specifically, PCR gives unit weights to the main principal components (associated with the largest eigenvalues of the covariance matrix) while assigning zero weights to the remaining components. As both the cross-sectional and the time series dimension grow large ($n \to \infty, T \to \infty$), the dominant eigenvalues become increasingly distinct, allowing a clearer separation from the smaller ones. Bayesian shrinkage with a Gaussian prior achieves a similar effect because it relies on the covariance structure of X_t. The Gaussian prior enforces smooth shrinkage, reducing coefficients associated with weaker linear combinations of the predictors while retaining those aligned with the directions of greatest variance in the covariance matrix, thereby emphasizing the principal components. Therefore, under the Gaussian prior, variable aggregation is achieved, since the posterior mode solution assigns non-zero coefficients to all covariates in the panel. Conversely, Bayesian shrinkage under a Double-Exponential prior, which corresponds to the LASSO estimator, induces sparsity by focusing only on the largest non-zero parameters and ignoring weaker components. It is worth noticing that, if the large panel includes many relevant variables, this approach can perform worse than Bayesian shrinkage with a Gaussian prior.

We replicated a similar analysis on the EA dataset, following their criteria for setting the amount of shrinkage in a large cross-section by imposing the same priors. Although these two methods approach shrinkage differently, in De Mol, Giannone, and Reichlin 2008 they produce similar results, as only a few variables capture the essential covariance structure in highly correlated datasets. However, the LASSO estimator can present an issue in terms of stability, as variable selection may be inconsistent in this context and selected variables are not stable over different trials. To address this limitation, we propose enhancing LASSO by introducing a Factor-Adjusted Regularized Model (FARM), which accounts for collinearity and improves the robustness of variable selection.

Theoretical framework Let us start from the definition of the relationship between prior and posterior. If we set X as the vector of regressors and we treat β as a vector of random variables, Bayes law gives:

$$P(\beta|X,Y) = P(Y|X,\beta)\cdot P(\beta)$$
$$\texttt{posterior} = \texttt{likelihood}\cdot\texttt{prior}$$

If we take the logarithm:

$$\log P(\beta|X,Y) = \log P(Y|X,\beta) + \log P(\beta).$$

De Mol, Giannone, and Reichlin 2008 explain how the choice between a Gaussian and a Double-Exponential prior leads to two distinct modeling approaches: variable aggregation and variable selection.

Gaussian prior for variable aggregation A Gaussian prior $\beta \sim N(0,\tau^2)$ leads to variable aggregation by assigning non-zero coefficients to all variables, similar to Principal Component Regression (PCR) but with progressively smaller weights on variables associated with smaller eigenvalues. Unlike PCR, which assigns unit weights to dominant components and zero to others, a Gaussian prior smoothly includes all variables in the model, albeit with diminishing influence. Computationally, a Gaussian prior leads to a Ridge regression problem, solved through penalized least squares with a penalty on the squared coefficient.

If we assume a linear model

$$y = X\beta + u \quad \text{with} \quad E[uu'|X] = \sigma^2 I,$$

the log-likelihood is given by

$$\log P(Y|X,\beta) \approx -\frac{n}{2}\log\sigma^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(y_i - x_i\beta)^2.$$

The Gaussian prior is expressed as

$$\log P(\beta) \approx -\frac{1}{2}\log\tau^2 - \frac{1}{2}\frac{\beta^2}{\tau^2}.$$

Consequently, the log posterior is given by

$$\log P(\beta|X,Y) = -\frac{1}{2}\log\tau^2 - \frac{n}{2}\log\sigma^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(y_i - x_i\beta)^2 - \frac{1}{2}\frac{\beta^2}{\tau^2}.$$

The posterior mode, which maximizes this expression over β, corresponds to the Ridge regression solution, where the optimal regularization parameter is given by $\lambda = \frac{\sigma^2}{\tau^2}$. This also represents the posterior mean. The larger the value of λ, the stronger the penalty applied. When $\lambda = 0$, no penalty is applied, and the ridge estimate of β is identical to the ordinary least squares (OLS) estimate of β.

Double-Exponential prior for variable selection In contrast to the Gaussian prior, a Double-Exponential prior encourages sparsity by concentrating probability mass near zero and in the tails, favoring coefficients that are either large or exactly zero. This promotes variable selection, where only a few variables with strong effects remain in the model, making the results potentially more interpretable, especially in economic contexts. In terms of optimization, a double-exponential prior results in a Lasso regression, penalizing the absolute values of coefficients to achieve sparsity.

From the mathematical point of view, assuming a linear model and a Laplace (or Double-Exponential) prior, we have:

$$\log P(\beta) \approx -\log\tau - \frac{|\beta|}{\tau}.$$

The log posterior is then given by

$$\log P(\beta|X,Y) = -\log \tau - \frac{n}{2}\log \sigma^2 - \\ - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(y_i - x_i\beta)^2 - \frac{|\beta|}{\tau},$$

which is maximized over β by the posterior mode, leading to the lasso solution, with $\lambda = \frac{\sigma^2}{\tau}$. This is not the posterior mean, which in general is not sparse. As in the case of Gaussian prior, higher values of λ imply a stronger penalization, and absence of penalization means going back to the OLS case.

2.2.2 Factor-Adjusted Regularized Selection Model Theory

In order to consistently recover the true model when covariates are highly correlated, we draw inspiration from the approach taken by Fan, Ke, and Wang 2020 in their paper titled *Factor-Adjusted Regularized Model Selection*. In fact, traditional model selection methods like LASSO assume that covariates are only weakly correlated across cross-sectional observations and are serially independent. Fan, Ke, and Wang 2020 apply this model to the Stock and Watson dataset on financial aggregates, where the correlation among regressors is very high. By utilizing factor models, the problem with model selection in presence of highly correlated covariates is overcome by transforming them into weakly correlated or uncorrelated idiosyncratic components. As is typically the case, as both n and T approach infinity ($n, T \to \infty$), the consistency of the methodology increases. To illustrate this phenomenon, the authors empirically increase the sample size.

Therefore, for our purposes, FarmSelect can be implemented to improve the robustness of forecasts generated through LASSO. As shown by Fan, Ke, and Wang 2020 in a toy example, LASSO tends to struggle with accurate variable selection when correlations among predictors are high. High correlation influences the forecasts in three main ways, each negatively impacting the model's ability to consistently identify the true active set in variable selection methods:

- **Model size**: Higher correlation often leads to an increase in the number of variables included in the selected model.
- **Early selection of irrelevant variables**: When correlation is high, the model is more prone to mistakenly incorporate non-relevant regressors early in the selection process.
- **Model selection consistency**: High correlation can also reduce the model's reliability in consistently identifying relevant variables across iterations.

Formally, the FarmSelect approach is typically divided into two steps, based on the assumption that covariates can be generated by the following approximate factor model

$$\mathbf{x}_t = \mathbf{B}\mathbf{f}_t + \mathbf{u}_t$$

where $\mathbf{f}_t$ is a $K \times 1$ vector of latent factors, $\mathbf{B}$ is a $p \times K$ matrix of factor loadings, and $\mathbf{u}_t$ is a $p \times 1$ vector of idiosyncratic components that are uncorrelated with $\mathbf{f}_t$. The two steps followed by Fan, Ke, and Wang 2020 are:

- **Estimation of the approximate factor model**: The approximate factor model is generally estimated using principal component analysis, which we have adopted due to its applicability in high-dimensional settings.
- **Lifting step**: Once factors and their impact on each variable that drive high correlation among covariates are identified, each predictor is "cleaned," that is decorrelated via a few pervasive latent factors. Thus we retain only the weakly correlated component relevant to explaining the dependent variable:

$$\hat{\mathbf{u}}_t = \mathbf{x}_t - \hat{\mathbf{B}}\hat{\mathbf{f}}_t$$

After the lifting step, existing algorithms that generate solution paths for LASSO can be directly applied, given that there is no more presence of cross-sectional dependence invalidating the model selection process.

3 Descriptive analysis

As a foundation for our forecasting analysis, we begin with a descriptive study designed to identify the key conditions necessary for applying the statistical techniques and address the inherent challenges of selecting macroeconomic variables in the Euro Area. This initial step is crucial to ensure the robustness and relevance of our methodology. Conducting machine learning analyses requires a thorough examination of the high-dimensional dataset, particularly to verify the presence of fundamental conditions for the methodologies chosen. Our preliminary analysis reveals that the data demonstrates both cross-sectional and serial dependency. Understanding these dependencies informs the structure of our analysis, as factor models—such as PCA and FarmSelect—leverage the aggregated variance within the data to enhance forecast accuracy and ensure consistency in variable selection.

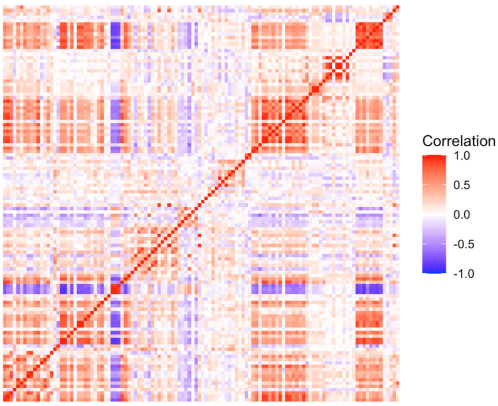

Figure 2: Cross-Sectional Correlation

As illustrated by the correlation Heatmap in Figure 2, the stationarized data displays a substantial degree of cross-sectional linear dependency among the economic indicators in our dataset. Hence, we can claim that the first condition for a relevant cross-sectional correlation is met.

Before discussing the serial correlation in the dataset, we briefly comment the reason behind our target variable selection, commenting specifically their autocorrelation. The variables selected for forecasts were chosen based on two primary criteria: their relevance to Central Bank policy calibration for inflation control and economic stability, and their sensitivity to both endogenous shocks—such as the American subprime mortgage crisis or the European sovereign debt crisis—and exogenous shocks, like the COVID-19 pandemic.

1. **Gross Domestic Product (GDP):** As a key indicator of economic health, accurate GDP forecasts are then essential for anticipating inflationary pressures or recessions and inform monetary policy decisions. As shown in Figure 4, GDP is significantly impacted during crises, contracting sharply in response to recessions caused by economical financial disruptions. These declines reflect reduced consumer demand, lower business investment, and rising unemployment, underscoring its susceptibility to economic shocks.

2. **Energy Producer Price Index:** Energy prices are among the primary drivers of inflation in Europe and are thus of critical importance to central banks. These prices are particularly sensitive to external shocks, such as geopolitical conflicts in oil-producing regions or significant shifts in demand, as evidenced during endogenous financial crises. Their volatility can lead to widespread economic ripple effects, making them a key focus for inflation management strategies.

3. **Wages and Salaries:** In macroeconomic terms wages have a dual character. On the one hand, they represent the largest cost factor to enterprises; on the other hand, they are the principal source of income for households. Hence, they are direct contributor to inflation through both demand-side and the supply-side. Central

banks analyze wage dynamics to assess inflationary trends and labor market conditions, which are pivotal for shaping monetary policy. While less volatile than energy prices, wages can be influenced by prolonged economic downturns and structural shifts in the labor market.

These variables are not equally impacted by crises. Energy prices typically exhibit the highest volatility, often serving as an initial trigger for broader inflationary trends. GDP follows, showing pronounced fluctuations during periods of economic instability, while wages tend to be more stable but still responsive to prolonged economic challenges as the time series in Figure 3 shows.

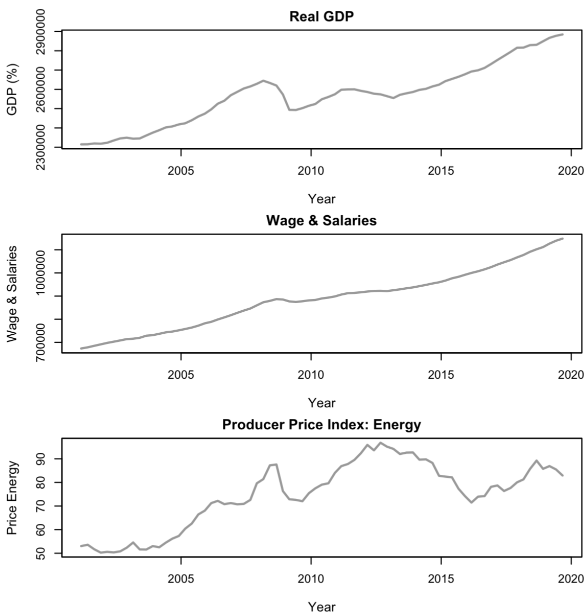

Figure 3: Non-Stationary Macroeconomic Indicators

For the selected dependent variables, we provide the Autocorrelation and Partial Autocorrelation functions, which graphs are provided in the Appendix. As shown in Figure 19, variables we want to forecasts exhibit correlation over time. These plots offer insights into the temporal structure of economic aggregates, capturing essential dependencies across different time horizons. The autocorrelation across various lags, as observed in GDP and Wage and Salaries, decays rapidly to zero. This empirically confirms that these time series are stationary.

The PACF values refine this analysis, helping to identify the most significant lags, which for GDP and Wage and Salaries appear to be at lag 1.

This initial exploration of the data highlights the complexity and interconnected nature of Euro Area economic indicators, emphasizing the need for a careful balance between dimensionality reduction and regularization. By systematically isolating the core drivers of the dependent variables while accommodating variable dependencies, we can enhance the predictive accuracy of our models.

An important consideration, as mentioned in the criteria for selecting target variables, is the impact that financial crises have had on the European economy.

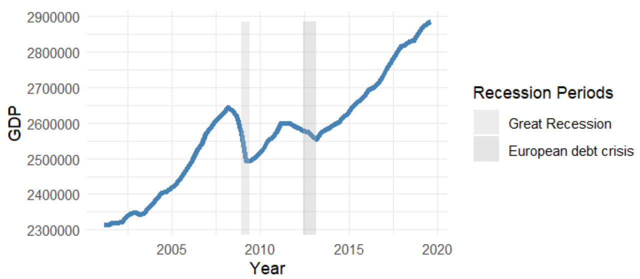

Figure 4: EA Quarterly Real GDP with Recession Periods

The 2008 subprime mortgage crisis, which had severe repercussions on the real economy, and the subsequent 2012 sovereign debt crisis in Europe, are part of our training set. As shown in Figure 4, the economy experienced significant recessions during these events, which negatively impact the training set. Consequently, the results obtained from our analyses are expected to be influenced by the distortions introduced by these endogenous shocks.

4 Results

In this section we analyse the results obtained from Bayesian Shrinkage methods and FarmSelect by looking at the Mean Squared Forecast Error (MSFE) and in particular at their ability to perform better than a random walk for the three macro-variables chosen (i.e. GDP, Wage and Salaries, Energy Producer Price Index). The optimal parameters will be determined for each model, and their forecasting performances will be compared to select the most accurate one for each target variable. Finally, this model will be used to create a counterfactual scenario for the year 2020, which is characterized by the outbreak of COVID-19.

4.1 Bayesian Shrinkage

Following the methodology outlined by Stock and Watson 2002, our analysis focuses on forecasting a single time series at a time in a setting with a large number of predictors ($N = 118$) and a relatively small number of time series observations ($T = 56$). The forecast results in the tables are reported as the MSFE relative to the benchmark Naive Random Walk model[2] during the evaluation period, which spans from 2015:Q1 to 2019:Q4.

$$\text{MSFE ratio} = \frac{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_{t,\text{model}}\right)^2}{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_{t,\text{RW}}\right)^2} \quad (1)$$

This evaluation period was chosen due to the limited number of time periods available in our quarterly dataset and it is used to assess model performance.

PCR As in De Mol, Giannone, and Reichlin 2008, our baseline model is Principal Component Regression. This approach involves computing the principal components of the predictor matrix X_t within a rolling window of size 56 periods. A pre-specified number of principal components ($r = 1, 3, 5, 10, 25, 40, 50$) is then selected to serve as regressors in the forecasting equation for the target variables. The dynamic forecasting model is specified as follows:

$$y_{t+h} = \theta' Z_t + \varepsilon_{t+h}, \quad (2)$$

where y_{t+h} is the $T \times 1$ vector of dependent variables being forecasted at horizon h, Z_t represents the $r \times T$ matrix of the chosen subset of principal components at time t, θ is the $r \times 1$ vector of regression coefficients, and ε_{t+h} is the vector of error terms.

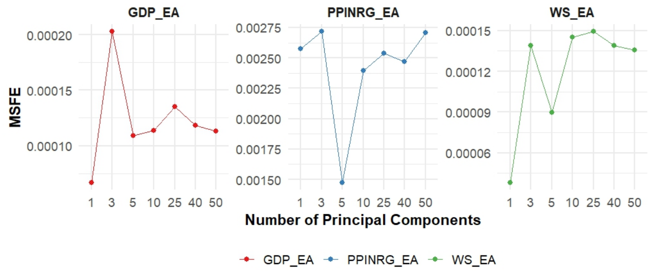

Figure 5: MSFE estimates in absolute form for Principal Component Regression

For the GDP forecast, the model with a single principal component achieves the lowest MSFE, suggesting the importance of model low-dimensionality. Increasing the number of components leads to a rapid rise in MSFE ($r = 3$), with performance improving only marginally including more principal components. A similar pattern is evident for Wages and Salaries, where the most low-dimensional specification ($r = 1$) yields superior results, while additional components introduce redundant predictors, degrading forecast accuracy.

Interestingly, for the Energy Producer Price Index, the model with five principal components achieves the lowest MSFE, suggesting that a moderate level of dimensionality is optimal for capturing the underlying dynamics of this variable. However, further increases in the number of components lead to declining performance.

	Number of Principal Components						
	1	**3**	**5**	**10**	**25**	**40**	**50**
GDP	0.599	1.812	0.973	1.015	1.206	1.060	1.011
WS	0.283	1.027	0.663	1.072	1.103	1.028	1.005
PPINRG	1.085	1.144	0.622	1.010	1.070	1.040	1.139

Table 1: MSFE ratio for different numbers of Principal Components from the PCR estimate

As shown in Table 1, these MSFE ratios reinforce the importance of low-dimensional models, with ratios

[2] In line with De Mol, Giannone, and Reichlin 2008, the Naive Random Walk is defined as a model that applies a moving average filter to the time series and uses the mean of the filtered values as the forecast.

below 1 indicating better performance relative to the Random Walk benchmark.
Notably, the superior performance of compact models for GDP and Wages and Salaries aligns with the findings of De Mol, Giannone, and Reichlin 2008, although their best performing model for the most recent evaluation period uses a higher number of principal components. This difference may be explained by the smaller difference between the number of observations in the rolling window and the number of variables. In their study, the time observations were 120 and the number of regressors 131. Moreover, another source of misalignment could be the distinct nature of their target variables (i.e. Industrial Production and Consumer Price Index), which may require a different balance between model complexity and low-dimensionality.

Overall, in our high-dimensional setting where the number of predictors far exceeds the number of observations, the low-dimensionality induced by PCR proves beneficial by retaining only the most predictive linear combinations of the regressors, thus preventing overfitting.

Bayesian Shrinkage with Gaussian Prior Regarding the model performance of the i.i.d. Gaussian prior, which corresponds to the estimates generated by penalized Ridge regression, we utilized the in-sample observations for the first 14 years ($T = 56$, from 2000:Q2 to 2014:Q1) to tune the optimal regularization parameter, ν.

Following the Bayesian shrinkage approach outlined in De Mol, Giannone, and Reichlin 2008, we selected ν based on a pre-specified level of in-sample residual variance, κ, which quantifies the variance left unexplained by the model for the target variable. This method balances the trade-off between model complexity and overfitting risk. Extreme values of κ were excluded from consideration. Specifically, $\kappa = 1$ was avoided because it effectively reduces the model to a Random Walk by setting all coefficients to zero, thus ignoring the predictive content of the regressors. Similarly, $\kappa = 0$ was excluded as it leads to an overfitted model, where the variance of the residuals is fully absorbed by the predictors, undermining out-of-sample forecast accuracy.

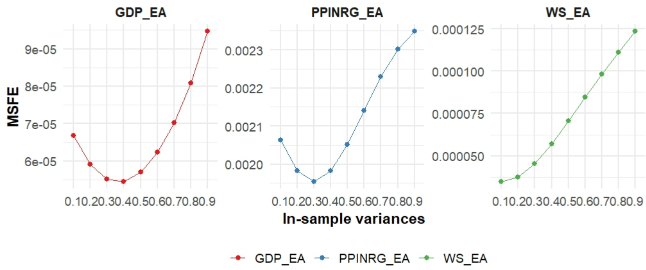

Figure 6: MSFE estimates for Bayesian forecast with Gaussian prior

The results of the Ridge Regression forecasting performance, presented in absolute terms, are shown in figure 6. Estimated MSFEs produced by Ridge Regression exhibits greater smoothness compared to the PCR ones. This smoothness is a desirable feature, as it facilitates a more confident selection of the optimal value for ν and demonstrates better generalization to out-of-sample data. Moreover, these results align well with the theoretical properties of Ridge Regression, since it uses all eigenvalues in decreasing importance instead of truncating after r as the PCR does.

	In-sample residual variance (κ)								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
GDP	0.597	0.527	0.493	0.488	0.511	0.558	0.628	0.723	0.846
WS	0.258	0.277	0.336	0.422	0.522	0.625	0.726	0.822	0.913
PPINRG	0.869	0.835	0.823	0.835	0.864	0.901	0.939	0.970	0.989

Table 2: MSFE ratio for different in-sample residual variances from Bayesian forecast with Gaussian prior

From the MSFE ratio results, it is evident that the Ridge forecast performs well for the target variables GDP and Energy PPI within a range of κ values between 0.2 and 0.5, corresponding to shrinkage parameter ν values ranging from half to five times the cross-sectional dimension of our dataset (Table 19 in the Appendix). These findings are quite close to the evidence presented by De Mol, Giannone, and Reichlin 2008.

Conversely, the Ridge forecasting performance for the third target variable, Wages and Salaries, exhibits a distinctive pattern. The optimal predictive value of ν, which improves upon the Random Walk estimates by approximately 75%, corresponds to the model with the lowest in-sample residual variance ($\kappa = 0.1$), suggesting a tendency toward overfitting. Interestingly, the MSFE of this Ridge forecast is very similar to that of the best PCR model for Wages and Salaries, which selects only one principal component. This behavior may derive from the need for the model to effectively aggregate information—either through dimension reduction, as in principal components, or by selecting a low penalization parameter that permits the inclusion of all predictors, as in Ridge—to adequately capture the dynamics of this target variable.

Bayesian Shrinkage with Double-Exponential prior As underlined by De Mol, Giannone, and Reichlin 2008, with Double-exponential prior, the solution of the maximization of the posterior density amounts to a LASSO regression problem. We perform the LASSO on a pre-specified number of non-zero coefficients ($r = 1, 3, 5, 10, 25, 40, 50$). These values are determined by selecting penalization parameters that yield r non-zero coefficients in the in-sample data. We accomplish this task using the *glmnet* function in R to fit the LASSO model. Our goal is to select the penalization parameter (ν) that results in the desired number of nonzero coefficients in the model. As the rolling window advances, the number of re-estimated nonzero coefficients identified through the penalization parameter may fluctuate slightly with the arrival of new data.

In order to choose the optimal r, we look at the MSFE in Figure 7. For the target variable GDP, the optimal choice of non-zero coefficients is 3, for Producer Energy Price index is 25 and for Wage and Salaries is 5. In particular, for GDP LASSO with three non-zero coefficients achieves an MFSE that is nearly 40 per cent lower than that of the Random Walk. For the other two variables instead, it is never able to outperform the Random Walk. As in the case of PC regression, the target variables GDP and Wage and Salaries are better forecasted with a small number of regressors, while Energy Producer Price Index can afford more regressors without the risk of overfitting.

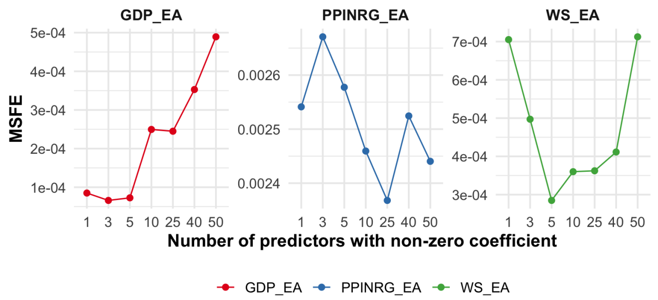

Figure 7: MSFE estimates for Bayesian forecast with double-exponential prior

However, it is worth noting that LASSO solution enforces sparsity directly on the variables themselves, rather than on their principal components. This is an important feature because it means the regression focuses on only a few original variables instead of a few linear combinations of them (De Mol, Giannone, and Reichlin 2008).

	Non-zero coefficients						
	1	**3**	**5**	**10**	**25**	**40**	**50**
GDP	0.761	0.590	0.650	2.232	2.190	3.155	4.375
WS	5.214	3.675	2.106	2.662	2.679	3.042	5.268
PPINRG	1.070	1.125	1.086	1.036	0.997	1.063	1.028

Table 3: MSFE ratio for different non-zero coefficients from Bayesian forecast with double-exponential prior

4.2 FarmSelect

FarmSelect is the econometric model we implement to correct the main drawback of LASSO, that is that, especially in case of high correlation, "it may select redundant models as it ignores correlations among covariates" (Fan, Ke, and Wang 2020). The first procedure to carry out is the lifting step. We estimate the approximate factor model through PCA. In order to choose the number of components explaining the main co-movements, we look at the gap between eigenvalues. It can be easily inferred from Figure 8 that the main gap is between the eigenvalues of the first and the second principal component, therefore we use the first component only to decorrelate regressors.

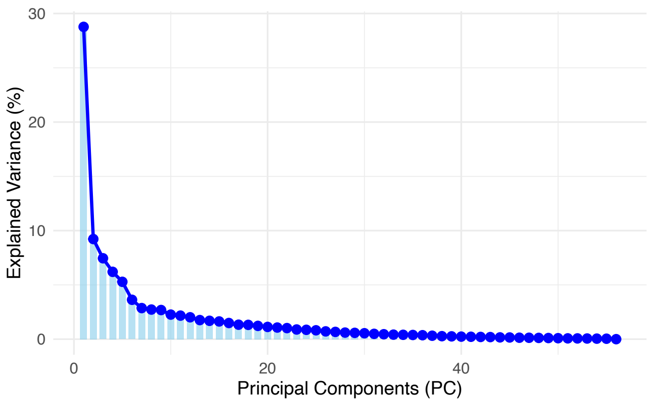

Figure 8: Explained Variance by each principal component

After the lifting step, we perform a LASSO regression implemented according to the same methodology used in Bayesian Shrinkage. Then we examine the MSFE for every penalization parameter in order to choose the best one. As shown in Figure 9, the optimal choice for FarmSelect is 1 non-zero coefficient for GDP, 3 non zero-coefficients for Wage and Salaries, while for Energy Producer Price Index it is better to select 5 of them. Moreover, we can infer graphically that the estimated MSFE presents a greater smoothness with respect to LASSO, and as we mentioned above this is a desirable property.

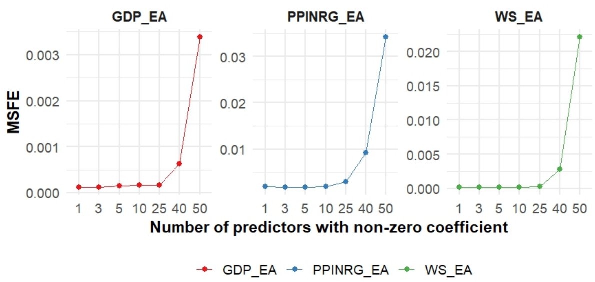

Figure 9: MSFE estimates for FarmSelect model

In order to further compare the performance of FarmSelect with respect to LASSO from Bayesian Shrinkage, we look at their MSFE ratio. It is clear that FarmSelect leads to better results for the variable related to Energy PPI, with the best parameter leading to a MSFE that is 30% lower than the Random Walk (see Table 9). For what concerns Wage and Salaries, there is an improvement with respect to LASSO, even if with the best paramater the MSFE is comparable to the one of the Naive Random Walk, probably because model sparsity is not desirable for the forecast of this target variable. However, when it comes to GDP, FarmSelect works poorly, doing worse of the Random Walk benchmark for every number of non-zero coefficients, and for most parameters also performs worse than LASSO.

	Number of non-zero coefficients						
	1	**3**	**5**	**10**	**25**	**40**	**50**
GDP	1.012	1.036	1.242	1.446	1.437	5.997	35.642
WS	1.009	1.006	1.040	1.176	2.374	20.658	284.564
PPINRG	0.838	0.729	0.698	0.795	1.129	3.328	22.691

Table 4: MFSE ratio for different non-zero coefficients from the Lasso estimate in FarmSelect model

4.3 COVID-19 Counterfactual for Optimal Forecasting Models

In this final section, we compare the performance of the forecasting models we implemented. Simulating a scenario as if we were in 2019, prior to the outbreak of COVID-19, we identify the best model for each target variable based on a comparison of their respective out-of-sample performances. Using these selected models, we estimate forecasts for 2020 [3], propose the most likely policies the European Central Bank (ECB) might have implemented, and discuss their potential effects on each variable of interest.

Our forecasts for 2020 initially indicated modest economic growth. However, the unexpected outbreak

[3]It is worth noting that we are able to construct the counterfactuals for the year 2020 freed from four quarters before (h-step ahead method), hence unaffected by the outbreak of the pandemic.

of COVID-19 overturned all expectations, rendering the envisioned policies ineffective. In response to this unprecedented crisis, the ECB implemented significantly different measures, emphasizing the necessity for central banks to respond flexibly to unforeseen events. A brief discussion about the ECB's COVID-19 response policies for each variable is provided.

4.3.1 Best Model selection

At this stage we further analyse the best model for each econometric methodology used, commenting each variable separately.

GDP The best-performing models for GDP were the Ridge regression model with an in-sample residual variance of 0.4 and the PCR model with one principal component. PCR outperforms the Random Walk model by 40%, while Ridge achieved a 51% improvement. The superior performance of the Ridge model is likely attributed to its ability to effectively forecast some of the peaks observed in the actual data (Figure 10).

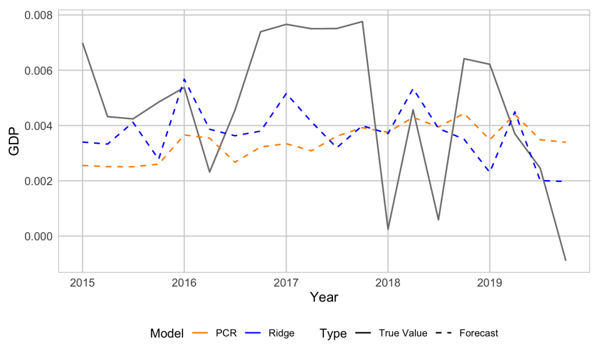

Figure 10: Model forecast comparison for GDP: PCR and Ridge

In Figure 11, we present the best models for both LASSO and FarmSelect, which consist of three and one non-zero coefficient, respectively. Graphically, it can be seen how LASSO is better able to track the different levels of GDP with respect to FarmSelect. GDP may be predicted worse by FarmSelect than by LASSO because the lifting step in FarmSelect removes the part of correlation which turns out to be needed for accurate GDP forecasting. Given the complexity of GDP, which is influenced by a wide range of factors, LASSO's simpler approach retains more key predictors, making it more effective in this context. FarmSelect's stricter criteria for variable selection can exclude relevant information, which negatively impacts its performance despite its theoretical advantages.

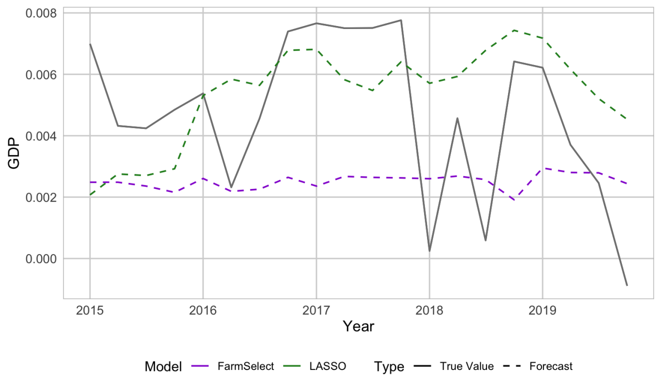

Figure 11: Model forecast comparison for GDP: LASSO and FarmSelect

Consistent with the findings of Fan, Ke, and Wang 2020, the regressors selected by LASSO tend to specify redundant models, as it struggles to account for the high correlation between chosen variables, such as CCONFIX and the other Confidence Indicators (Table 5).

Selected Variables	Frequency	Percentage
CCONFIX_EA	20	100%
KCONFIX_EA	20	100%
ICONFIX_EA	20	100%
RTCONFIX_EA	10	50%
SCONFIX_EA	1	5%

Table 5: Top 5 variables selected by LASSO for GDP forecasts

In contrast, FarmSelect demonstrates the ability to identify separate meaningful covariates for GDP forecasting, such as variables related to households (i.e. HHASS [4]) and Nominal Labor Costs (i.e. ULCCON). Still, this does not translate in a better forecasting performance of FarmSelect with respect to LASSO.

[4]The further we move away from the in-sample data, the more selection of Household Assets in the Long Run (HHASS.LLN)

Selected Variables	Frequency	Percentage
HHASS_EA	15	75%
ULCCON_EA	14	70%
HHASS.LLN_EA	7	35%

Table 6: Main variables selected by FarmSelect for GDP forecasts

The conclusion that can be drawn from the forecasting performance of the GDP variable is that this variable requires model aggregation rather than model selection. This is because many covariates meaningfully contribute to its value, and thus, they must be considered when attempting to forecast this aggregate. For these reasons, the model chosen to compute the counterfactual during the year characterized by the COVID-19 outbreak is Ridge regression. Among the variable aggregation methods, Ridge demonstrates the lowest MSFE and, graphically, shows an ability to detect some of the observed peaks in the data. As a result, Ridge was chosen as the forecast model for 2020.

Wage and Salaries The best-performing models for forecasting the Wage and Salaries variable were the Ridge Regression with an in-sample residual variance of 0.1 and the Principal Component Regression using a single principal component. Both models outperformed the Random Walk, with PCR achieving a 72% improvement and Ridge achieving a 74% improvement.

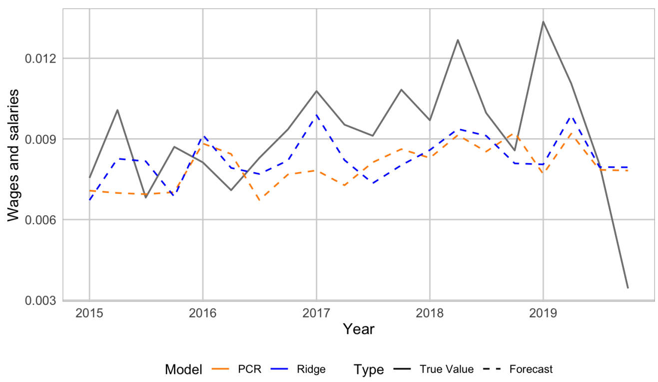

Figure 12: Model forecast comparison for Wage and Salaries: PCR and Ridge

The superior performance of the Ridge Regression model can likely be attributed to its ability to capture most of the peaks observed in the actual data (Figure 12). However, there is a potential concern regarding overfitting, especially given that it was trained such that the lowest in-sample residual variance was achieved and it is the closest to the OLS regression one. As a result, the model's forecasting accuracy might be more reflective of the specific test data rather than its ability to generalize to out-of-sample data or capture the underlying dynamics of Wage and Salaries. In contrast, the PCR model, while still detecting key peaks, is less likely to suffer from such overfitting issues, as it only retains the variance explained by the first PC.

Although the inadequacies in the forecasts of Wages and Salaries through the best LASSO model, which selected five non-zero coefficients, were already evident from the MSFE ratio tables, they are further shown in Figure 13. The forecasted values consistently fall below the average WS values, with a clear downturn in forecasts between 2015 and 2016.

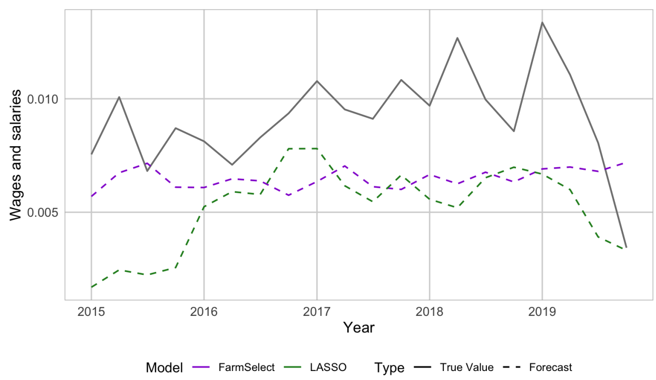

Figure 13: Model forecast comparison for Wage and Salaries: LASSO and FarmSelect

One possible explanation for this anomaly lies in the variables selected by the LASSO model and the coefficients assigned to them (Table 7). In particular, the variable associated with the Construction Confidence Indicator (i.e. KCONFIX) exhibited unusually low values in 2014-15 compared to its average in the in-sample data. By retaining this variable in every forecast and assigning it a large coefficient, the LASSO model may be overemphasizing its impact, leading to biased forecasts.

Moreover, as already commented for GDP, the variable selection is clearly influenced by the high correlation between Confidence Indicators that LASSO is not able to disentangle.

Selected Variables	Frequency	Percentage
ESENTIX_EA	20	100%
KCONFIX_EA	20	100%
RTCONFIX_EA	18	90%
CCONFIX_EA	17	85%
ICONFIX_EA	13	65%

Table 7: Top 5 variables selected by LASSO for Wage and Salaries forecasts

For what concerns FarmSelect model, which retained three non-zero coefficients in the in-sample data, it still shows subpar performance when forecasting out-of-sample data, as shown in Figure 13. However, its variable selection process improved with respect to LASSO, in line with theoretical evidence. Regressors selected by FarmSelect provide more relevant information for predicting Wages and Salaries, as they include both the Quarterly Employment in the Construction Sector (i.e., EMPCON) and household consumption expenditure variables, such as AHFCE and HFCE (Table 8).

Employment in construction is considered an indicator of economic growth, as it often follows periods of economic expansion. Similarly, household consumption expenditure reflects changes in consumer demand, which, in turn, stimulates production in consumer-related industries. This increased production creates the conditions for wage growth, as firms hire more workers and adjust wages to attract and retain labor.

However, despite the improvements, the FarmSelect model still underperforms the Random Walk model, implying that it does not fully capture the underlying dynamics of Wages and Salaries. The likely explanation, supported by the previous analysis, is that the dynamics of Wages and Salaries may require models that aggregate variables, instead of selecting them.

Selected Variables	Frequency	Percentage
EMPCON_EA	20	100%
AHFCE_EA	16	80%
HFCE_EA	12	60%
HHASS.LLN_EA	7	35%
NFCLB_EA	6	30%

Table 8: Top 5 variables selected by FarmSelect for Wage and Salaries forecasts

Summing up, given the overfitting concerns for the selected Ridge regression and the inferior performance of FarmSelect and LASSO models, we will opt for the PCR method with one PC to assess the counterfactuals of Wages and Salaries during the first year of the pandemic crisis.

Energy Producer Price Index The target variable, the Energy Producer Price Index, emerges as the most challenging to forecast using Ridge regression. While Ridge regression achieves a modest improvement over the Random Walk model, reducing the MSFE by approximately 18% with a residual in-sample variance of 0.3, its performance is generally less effective compared to its results for GDP and Wages and Salaries. For these variables, Ridge regression delivers at least a 50% improvement relative to the Random Walk model. For what concerns PCR, the best model for this variable takes 5 principal components, improving forecasts by 38% with respect to the Random Walk. The plot in Figure 14 compares true Energy PPI values with forecasts from PCR and Ridge models. While both models generally follow the trend, PCR shows closer alignment to the true values, particularly in periods of fluctuation. This graphical feature aligns with the observation that PCR outperforms Ridge by over 20% in forecasting accuracy.

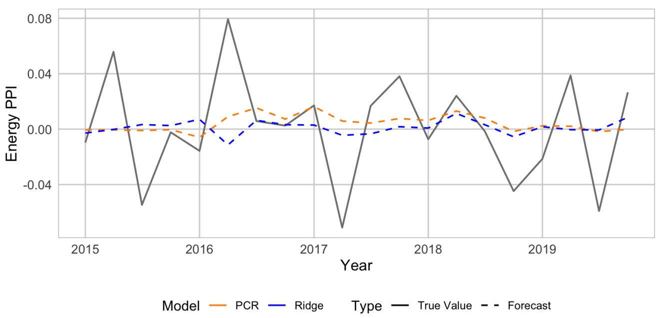

Figure 14: Model forecast comparison for Energy PPI: PCR and Ridge

As it can be seen in Figure 15, for the target variable Energy PPI FarmSelect tends to follow the true values, demonstrating a stronger forecasting capability, while LASSO struggles to capture trends and performs approximately on par with a Random Walk baseline. Notably, with respect to the MSFE ratio, FarmSelect outperforms LASSO by around 30%.

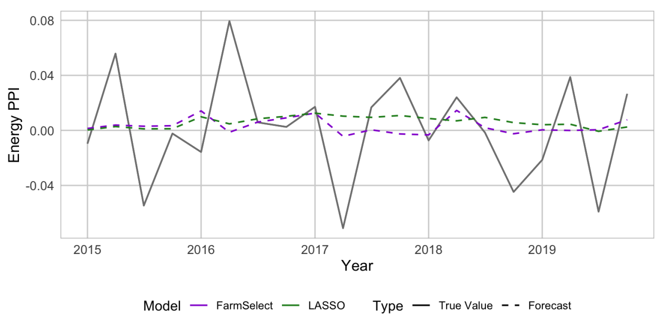

Figure 15: Model forecast comparison for Energy PPI: LASSO and FarmSelect

As shown in Table 9, LASSO shows an high degree of redundancy, as it selects more times Confidence Indicators (CCONFIX, ICONFIX, KCONIFX) and Interest Rates (IRT6M, IRT3M), which are likely to be high correlated and so do not bring new information.

Selected Variables	Frequency	Percentage
CCONFIX_EA	20	100%
ICONFIX_EA	20	100%
IRT3M_EACC	20	100%
IRT6M_EACC	20	100%
KCONFIX_EA	20	100%
RTCONFIX_EA	20	100%
SCONFIX_EA	20	100%

Table 9: Main variables selected by LASSO for Energy PPI forecasts

In contrast, FarmSelect identifies different but still economically meaningful variables, such as the Turnover Index Energy (TRNNRG), Gross Household Saving Rate (GHSR) along with Non-Financial Companies' Liabilities (NFCLB) and Total Economy-Liabilities: Long term loans (TLB.LLN).

Selected Variables	Frequency	Percentage
TLB.LLN_EA	20	100%
TRNNRG_EA	20	100%
GHSR_EA	20	100%
NFCLB.LLN_EA	12	60%
ESC_EA	9	45%

Table 10: Top 5 variables selected by FarmSelect for Energy PPI forecasts

These variables are particularly relevant for disentangling the drivers of the dependent variable. FarmSelect's variable selection is notably precise and allows for straightforward economic interpretation by focusing on model selection rather than aggregation. Although Farm performs 7% worse than PCR in terms of the MSFE ratio, we prefer this type of model for computing counterfactuals during the COVID-19 outbreak due to its greater interpretability.

4.3.2 Policy Comparison

The best predictive model for each target variable, as presented in the previous subsection, generates forecasts for 2020 that differ significantly from the actual outcomes, which were heavily influenced by the exogenous shock caused by the pandemic. Indeed, while our forecasts projected moderate economic growth, COVID-19, on the other hand, inflicted a severe and negative perturbation on the economy. In the following subsections, we speculate on policies that could have been adopted in 2020 based on our forecasts and those that were instead rapidly implemented by the ECB as an answer to COVID-19. Finally, we discuss the effects of the these stabilizing policies on each target variable.

Policies accommodating forecasts Even if forecasts suggest a modest economic growth, as indicated by rising GDP (Figure 16) and Wages and Salaries (Figure 17), the rise in Energy prices (Figure 18) introduces complexity. Although the slight but consistent quarterly increase in GDP suggests an expanding economy, and the rise in Wages and Salaries along the year indicates higher consumer spending, the increasing Energy Prices may point to cost-push inflation. This occurs when rising production costs, such as higher energy prices, lead to an increase in the prices of goods and services. If Energy Producer Price Index increases too rapidly, it could harm consumer confidence and spending, offsetting some of the benefits of economic growth. The ECB's challenge, therefore, would be to balance supporting growth while preventing excessive inflation. However, based on forecasts, the acceleration in price growth was expected to peak in January 2020, followed by a steady growth rate close to zero. n this context, the ECB is likely to adopt a more cautious approach. Specifically, we assume that the ECB would maintain an accommodative monetary stance, given the minimal inflation risks, rather than tightening policy in response to sustained inflationary pressures.

Policies that ECB could implement to accommodate forecasts we provided would concern:

- **Assess Inflation Risks:** Rising energy producer prices and wages might push inflation toward its target. ECB would then need to determine if the inflationary pressures are transitory or persistent and might consider tightening monetary policy, gradually increasing interest rates to curb demand or reducing asset purchases under quantitative easing programs.
- **Support Economic Growth:** If inflation remains within acceptable bounds, the ECB could focus on sustaining the growth by maintaining accommodative policies like low interest rates. This would encourage investment and consumption, supporting GDP growth.
- **Monitor Real Wages:** While rising wages can be a sign of growth, they must outpace inflation for real incomes to improve. If energy prices rise faster than wages, households might face a squeeze in purchasing power, dampening consumption. This could persuade the ECB to adopt expansionary monetary policy, such as Quantitative Easing or the reduction of interest rates to stimulate consumption and investment.

ECB supervisory measures against COVID The unexpected pandemic crises forced ECB to adopt emergency countermeasures. Indeed, during the peak impact of the pandemic around April 2020, the stationary variation of GDP and that of Wages and Salaries experienced a downturn, as again shows in figures 16 and 17. According to Grynberg and Habib 2021, ECB posed measures collectively aimed to address financial risks, support the economy, and stabilize the monetary policy framework during the pandemic. These measures consisted of three key elements:

- **Asset Purchases:** In March 2020, the ECB expanded its asset purchase programme and introduced the Pandemic Emergency Purchase Programme (PEPP) with an initial envelope of €750 billion, later increased to €1,850 billion by December 2020. This aimed to stabilize financial markets, ease monetary policy, and mitigate severe risks to the euro area outlook.
- **Lending Operations:** The ECB revised and enhanced its long-term refinancing operations, including targeted longer-term refinancing operations (TLTRO III) and pandemic emergency longer-term refinancing operations (PELTROs). These measures provided banks with central bank liquidity, supported credit supply, and included lower interest rates, higher borrowing allowances, and expanded collateral eligibility.

- **Euro Liquidity for Non-Euro Areas:**The ECB offered euro liquidity to non-euro area central banks via swap and repo lines to prevent negative spill-back effects on the euro area.

Therefore, what remains is to observe the effects that these policies hand on the economy using our target variables. The outcomes of ECB policies are markedly different from those that would have resulted from the policies envisioned under our forecasts. The COVID-19 crisis led to measures aimed at stabilizing the euro area economy, preventing a sharper contraction, and supporting a gradual recovery, rather than accommodating a growth that never occurred.

GDP: The ECB's asset purchases injected liquidity into the financial system, reducing borrowing costs for governments, businesses, and households. This boosted spending and investment, contributing to GDP stabilization and recovery during the pandemic. Additionally, lending operations ensured that banks could access affordable credit, enabling them to support businesses and households. Finally, by mitigating financial disruptions in non-euro area countries and maintaining trade flows, these measures reduced risks to the euro area economy.

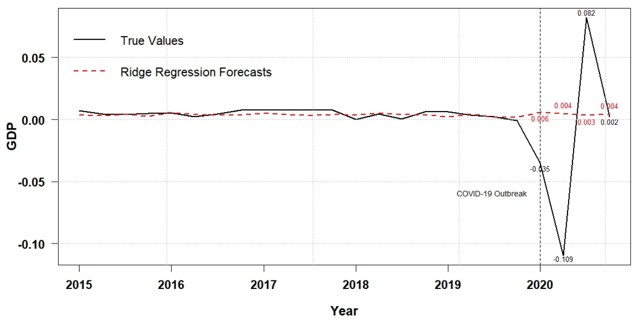

Figure 16: COVID-19 Counterfactual GDP Forecasts

Wages and Salaries: Despite the pandemic's significant disruptions, the policies helped limit job losses and wage cuts, stabilizing incomes in the most affected sectors. Access to credit allowed businesses to continue operating, avoiding widespread bankruptcies and preserving employment levels and wage stability.

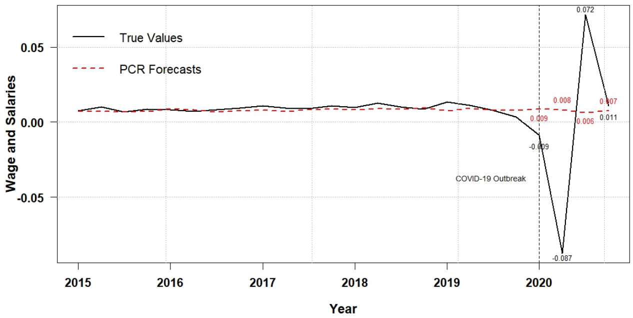

Figure 17: COVID-19 Counterfactual Wage and Salaries Forecasts

Energy Producer Price Index: The measures indirectly stabilized energy prices by supporting demand and economic activity. Lower interest rates and increased liquidity helped stimulate demand, contributing to higher energy prices, that during pandemic slowed their growth. However, global factors, such as oil supply dynamics and shifts in consumption patterns during the pandemic, played a more significant role in driving energy prices.

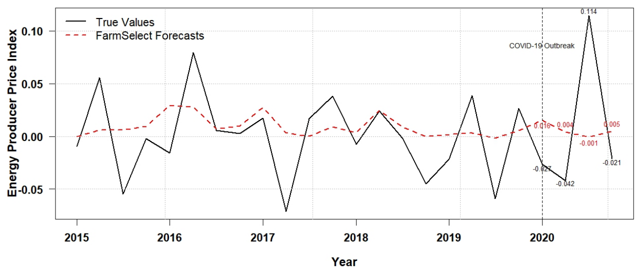

Figure 18: COVID-19 Counterfactual Energy PPI Forecasts

In summary, these policies were tailored to counteract the economic contraction and facilitate recovery. Hence, the goal of ECB was stabilize the economy rather than fostering growth as forecasts could have initially implied.

5 Concluding remarks

In this paper we have compared four methodologies, namely PCR, Ridge, LASSO, and FarmSelect, which allowed us to forecast key macroeconomic indicators in high-dimensional settings.
Our evidence is quite in line with De Mol, Giannone, and Reichlin 2008 and Stock and Watson 2002 for what concerns the performance of Ridge and PCR. Additionally, we found out that for two key macroeconomic indicators, that is Wage and Salaries and GDP, variable aggregation model are the most preferable ones, probably because most of the regressors are informative about the future of the variable to forecast. For what concerns the evidence from paper by Fan, Ke, and Wang 2020, FarmSelect method works particularly well for the variable Energy PPI as it removes the part of collinearity that makes LASSO redundant in the choice of variables, improving consistently the forecasting power. Moreover, for all the target variables, FarmSelect allows to better disentangle the idiosyncratic components underlying them, enabling a more complete economic interpretation of their dynamics.
Nonetheless, some of our findings contrast with our reference papers. First of all, FarmSelect reveals to be the worst model in terms of forecasts for GDP because through the lifting step it likely eliminates the part of high correlation that turns out to be essential to produce accurate forecasts. Secondly, LASSO forecasting power performs subpar for both Energy PPI and Wage and Salaries with respect to PCR and Ridge. The only exception is GDP, for which LASSO is able to select significant predictors to capture GDP trends. Notably, these discrepancies might stem from the specific dimensions of the rolling window used to train the model, where the number of observations was less than half the number of variables.
By selecting the best forecasting method for each variable of interest, we computed COVID-19 counterfactuals and analyzed the hypothetical monetary policies that could have been implemented had the pandemic not occurred. The economic growth we had projected through stabilization policies led by the European Central Bank was never realized. Instead, the pandemic necessitated immediate responses focused on stabilizing and reviving the economy. These included asset purchase programs, lending operations, and support for non-Euro area banks to mitigate the crisis's impact.
The final forecasts struggle to achieve a high level of accuracy, often failing to capture the peaks and troughs of the variables of interest. To address this limitation, we propose exploring alternative methods such as the Three-Pass Regression Filter and Nowcasting, which are better suited to the macroeconomic data employed. These approaches aim to more effectively anticipate changes, enabling the ECB to respond more quickly with appropriate policies.
Additionally, our analysis could be improved by incorporating the Bayesian Information Criterion (BIC) as a complementary tool for selecting the best performing models, particularly for Ridge, LASSO, and FarmSelect methods.
Lastly, a Vector Autoregressive (VAR) analysis could be implemented to estimate variable dependencies more flexibly. This would allow us to capture underlying dynamics and leverage the full extent of the correlations among variables, further enriching the insights derived from the data.

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APPENDIX

Descriptive Analysis: Serial Correlation

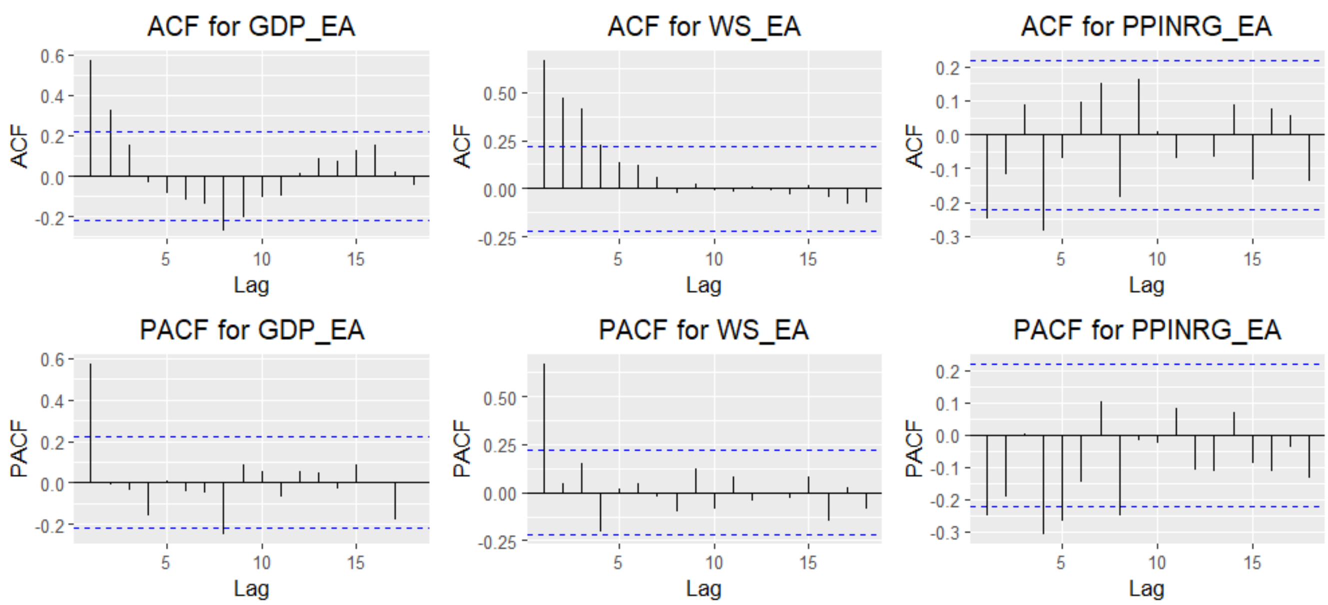

Figure 19: Serial Correlation for target variables

Rescaled ν Ridge Coefficients

	Rescaled ν								
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
GDP	33.57	79.06	146.40	247.34	402.80	656.09	1112.65	2099.94	5281.65
Wage and Salaries	58.08	176.57	397.26	782.17	1415.23	2431.88	4159.79	7623.94	17999.46
Energy PPI	21.14	53.33	105.65	191.39	335.24	590.71	1095.92	2285.83	6281.67

Table 11: Rescaled penalization parameter ν in the Bayesian Shrinkage with Gaussian prior for each level of in-sample residual variance