A Machine Learning Approach to Inflation Forecasting

Alessandro Dodon
MS Quantitative Finance Student at USI Lugano

February 2025

Outline

This presentation covers (very briefly) the following topics:

- Introduction and objective of the study
- The FRED-MD dataset
- Pre-processing for time series
- A simple recursive forecasting setup
- Setting a baseline with AR(1)
- Regularisation methods (Lasso, Ridge)
- Principal Component Regression
- VAR and its challenges with "Big Data"
- Random Forest

Introduction

- Objective: Compare methods from econometrics and ML for forecasting, using "Big Data" and addressing the "curse of dimensionality"
- Baseline: The classic AR(1) model serves as the benchmark for comparison
- Focus: Explore whether advanced techniques (Lasso, Ridge, PCR, VAR, Random Forest) can surpass the benchmark
- Outcome: Surpassing AR(1) is challenging, but careful experimentation yields moderate improvements

Inspired By: De Mol, Giannone, Reichlin (2008), *"Forecasting Using a Large Number of Predictors: Is Bayesian Shrinkage a Valid Alternative to Principal Components?"*, Journal of Econometrics.

Introduction

- This study loosely follows the referenced paper, making simpler assumptions and using simpler techniques (e.g., no Bayesian methods)
- The focus is solely on judging the forecasting accuracy of each method, as done in the paper
- A key downside of ML techniques is that they can act as a "black box" (briefly covered later)
- New and exciting literature is emerging on causal ML, which aims to bridge the gap between interpretability and performance

Introduction

- ML is a very math-heavy topic, but I will focus on the intuition behind each method and their application (this is an introductory discussion)
- Results will be analyzed after each method, with some thoughts on limitations provided at the end
- All my code is in R, and you can find each script in my GitHub repository: InflationForecast
- Some technical issues are not discussed here, but they may be mentioned briefly in the scripts (with `# NOTE:`)

The FRED-MD Dataset

- A gold standard for modern macroeconomics and macroeconometrics
- Contains convenient (US) macroeconomic data from 1960 to today, spanning different sectors
- Uses (also) monthly observations, providing more data
- Offers convenient functions for pre-processing through their R package "fbi"
- Used in Giannone et al.'s paper (older version); this study uses the updated dataset
- Dataset link: FRED-MD Database
- R package link: fbi R Package

Pre-Processing for Time Series

- Unlike traditional methods, ML techniques are not designed specifically for time series data, requiring extensive pre-processing
- Stationarity is crucial and can be handled easily using the `fredmd` function from the "fbi" package
- To double check, I plot each time series before and after and their autocorrelation
- Other essential steps include handling missing values and treating outliers

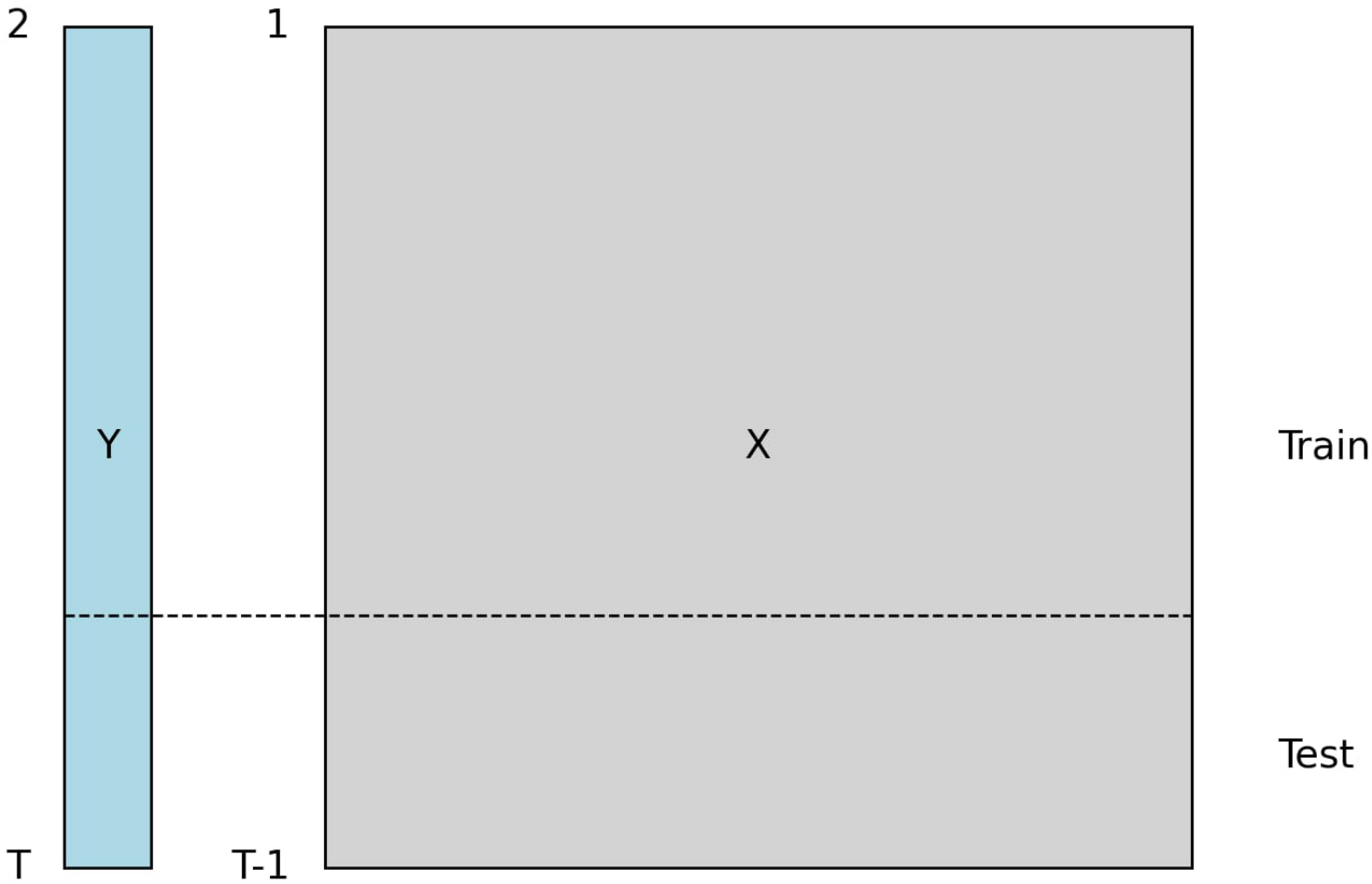
Pre-Processing for Time Series

- I handle missing values and outliers manually in R
- The time series is shortened to cover the period from January 1960 to December 2019
- Time series with too many Na values are removed, leaving 121 variables
- I use a SMA algorithm for the remaining Na vaues
- For outliers, I exclude the COVID-19 period by cutting the data short
- This approach is very approximative and may influence the results

A Simple Recursive Forecasting Setup

- The data is manually lagged, with Y_t as the dependent variable and X_{t-1} as the predictor
- The dataset is split into roughly 70% training and 30% testing
- The (training) data is standardized each time
- The model is trained on the training data for each iteration
- Predictions are made recursively, using X_{test} as input to generate one-month-ahead predictions (no bias since X_{t-1} is in the same information set)
- After each prediction, the test data is added to the training set to update the (recursive) model

A Simple Recursive Forecasting Setup

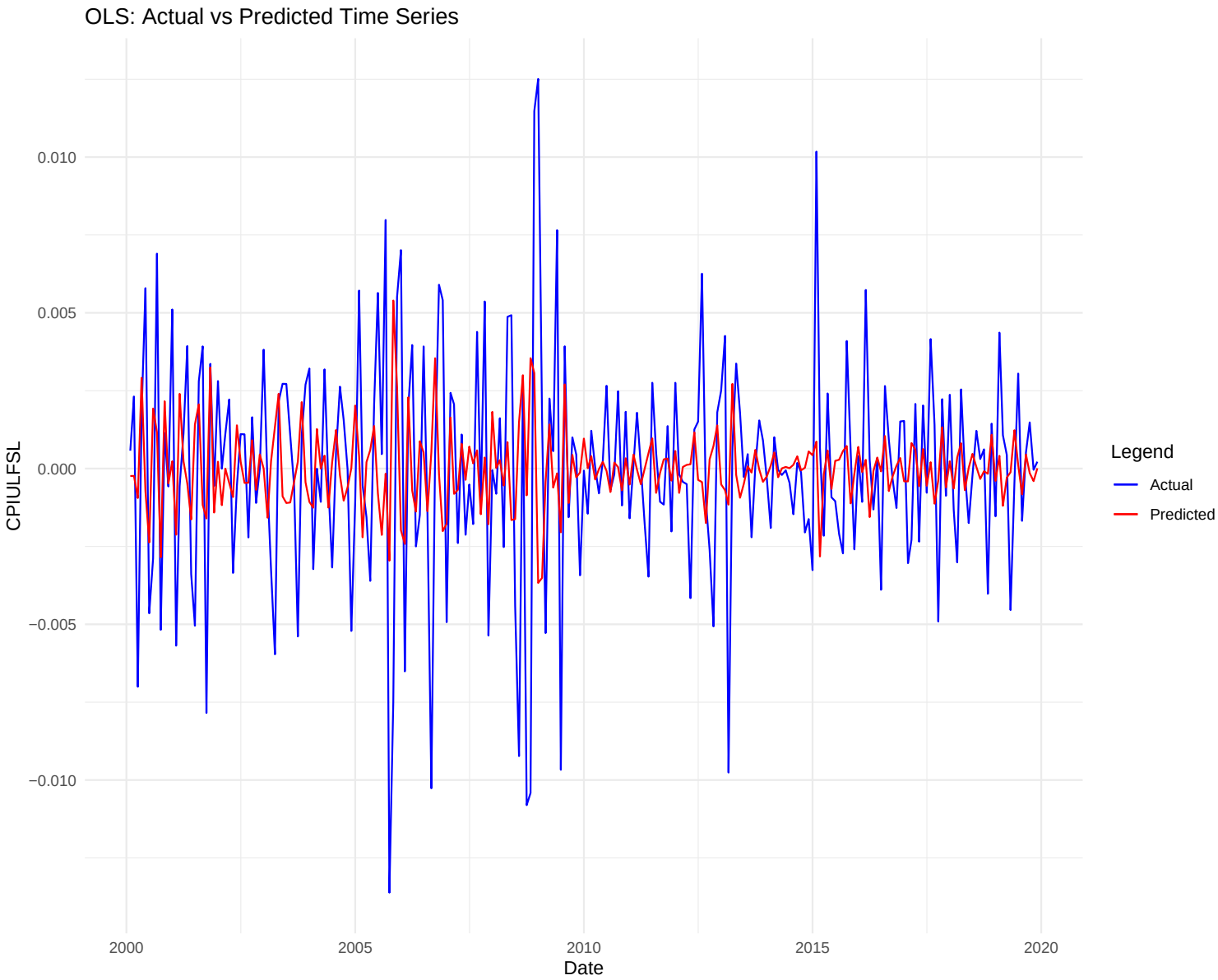


First month of Y and last month of X are excluded

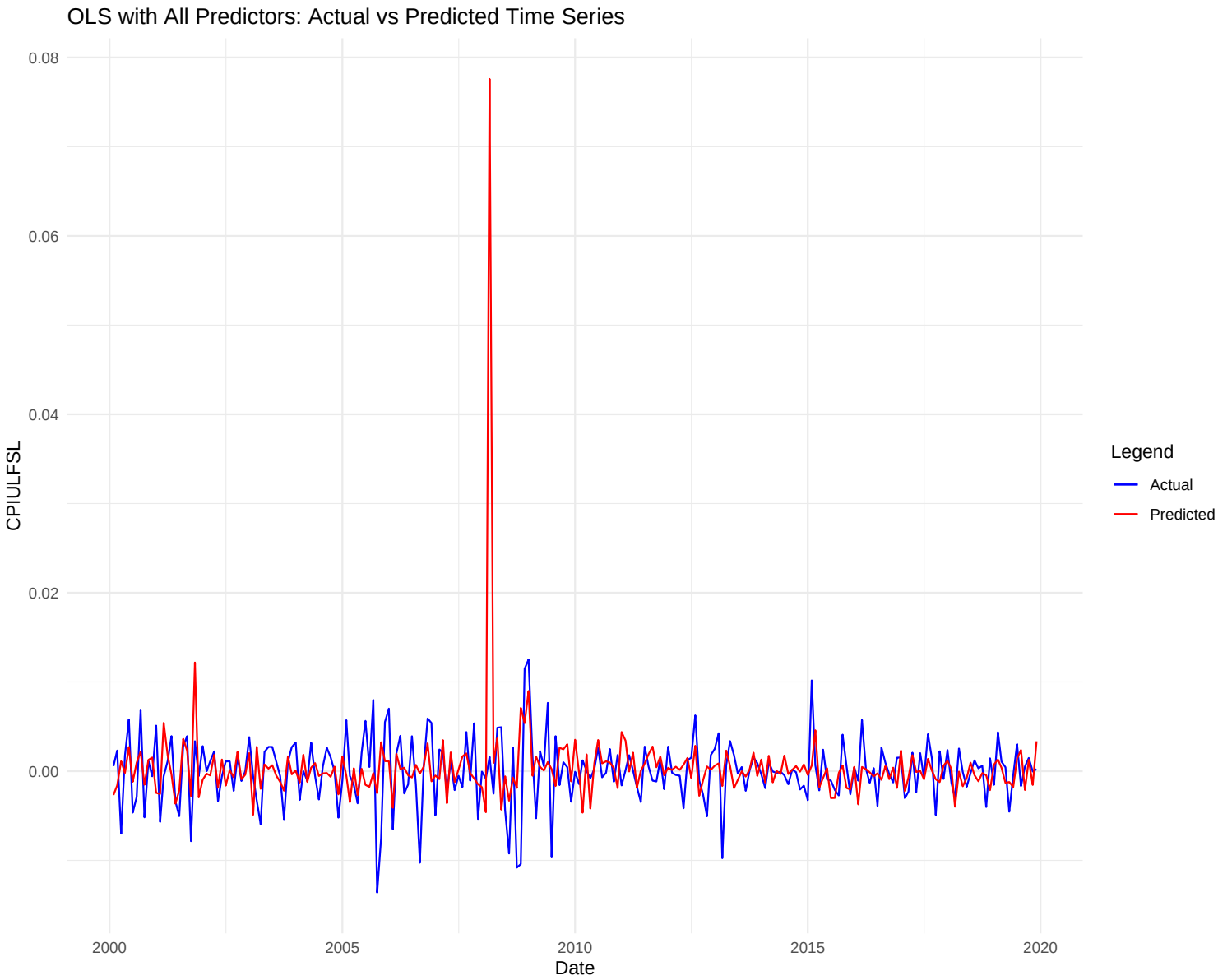
Setting a Baseline with AR(1)

- AR(1) is the simplest model and surprisingly tough to beat
- It requires little to no computational power
- MSE and a plot of actual vs. forecasted values are used to compare models
- This provides an effective baseline to analyze trade-offs (approximatory, as this is an exploratory study)
- E.g., while an advanced neural network may outperform AR(1), it is not guaranteed
- Neural networks also require significantly more time and computational power

AR(1) Results (MSE: 1.351304e-05)



Overfitting Example (OLS with All Regressors)



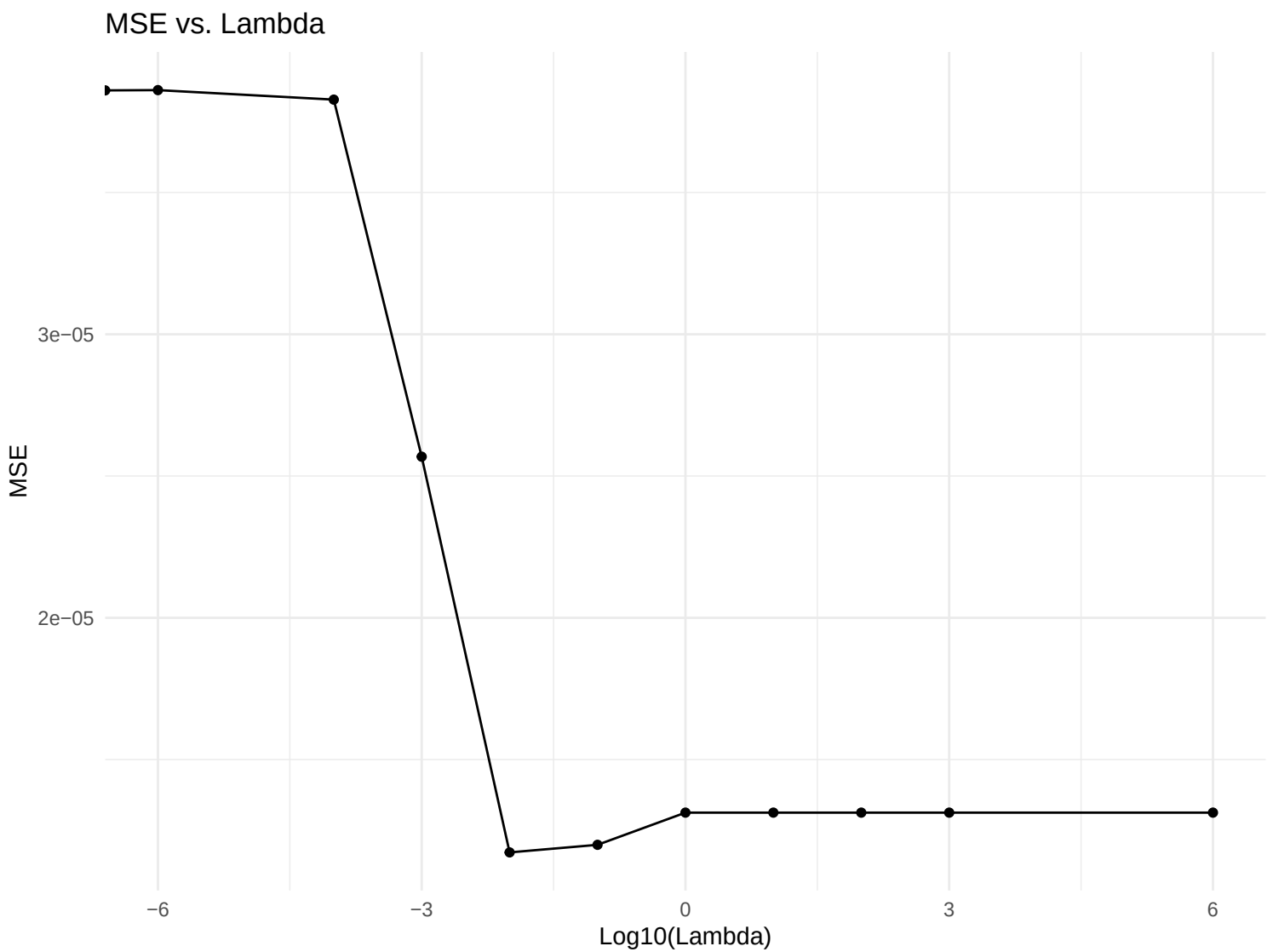
Regularisation Methods (Lasso)

- Lasso minimizes the following objective function:

$$\min_{\beta} \left(\sum_{t=1}^{n} (Y_t - X_t\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right)$$

- Can set some coefficients exactly to zero, effectively performing variable selection
- Requires an appropriate penalty parameter λ, typically selected through cross-validation
- In time series, cross-validation is particularly challenging
- I perform a grid search to find the optimal λ (similar to the approach in the referenced paper)

Lasso Results (Best MSE = 1.172451e-05)



Regularisation Methods (Ridge)

- Ridge minimizes the following objective function:

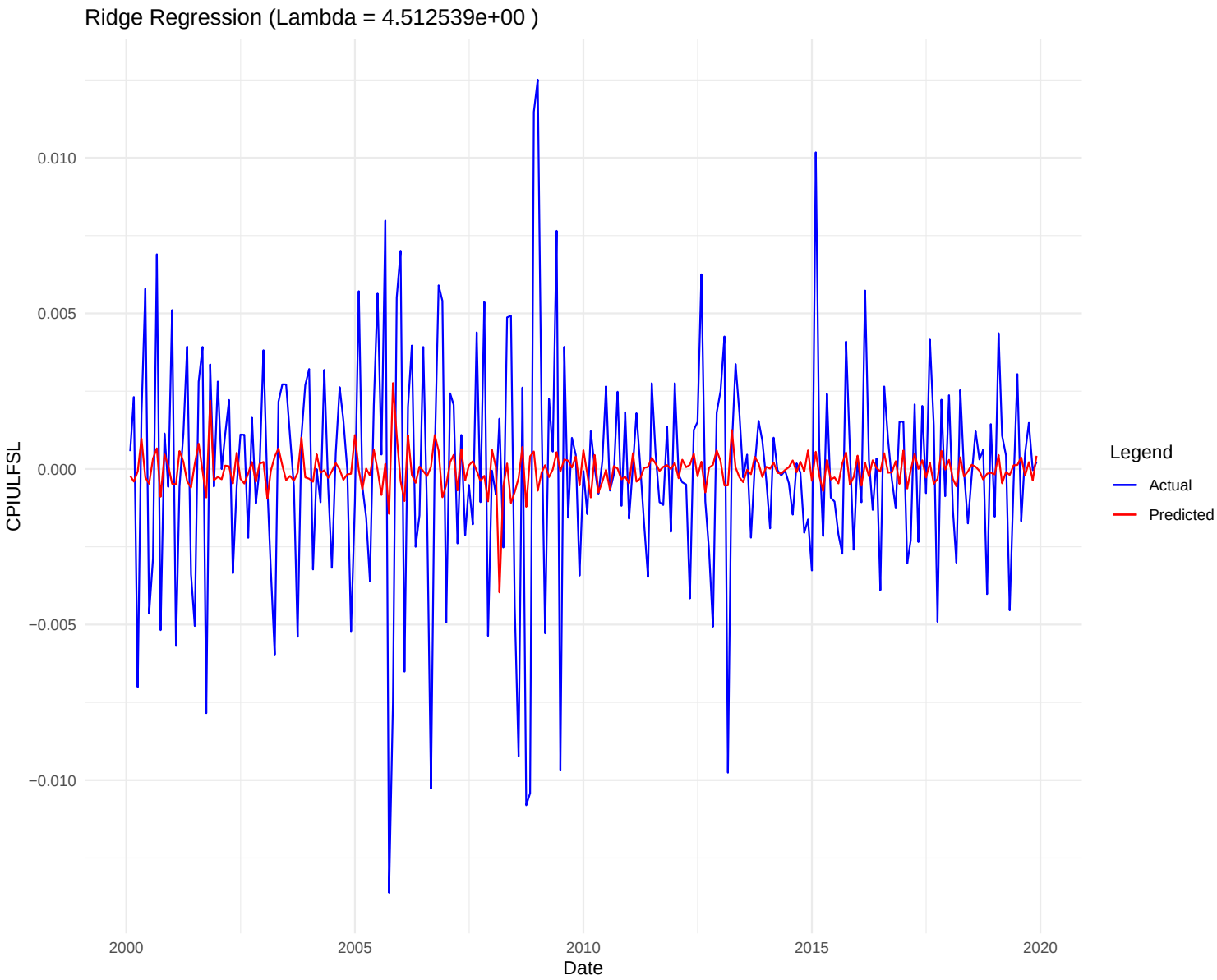
$$\min_{\beta} \left(\sum_{t=1}^{n} (Y_t - X_t\beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right)$$

- Similar to Lasso but shrinks coefficients towards zero instead of setting them exactly to zero
- The optimal λ is (roughly) suggested by the paper as:

$$\lambda \approx \frac{P}{\sqrt{T}}$$

- As $\lambda \to \infty$, heavy penalization reduces coefficients, effectively fitting an intercept
- As $\lambda \to 0$, it resembles OLS with all regressors (overfitting and poor results)

Ridge Results (Optimal λ MSE = 1.257817e-05)



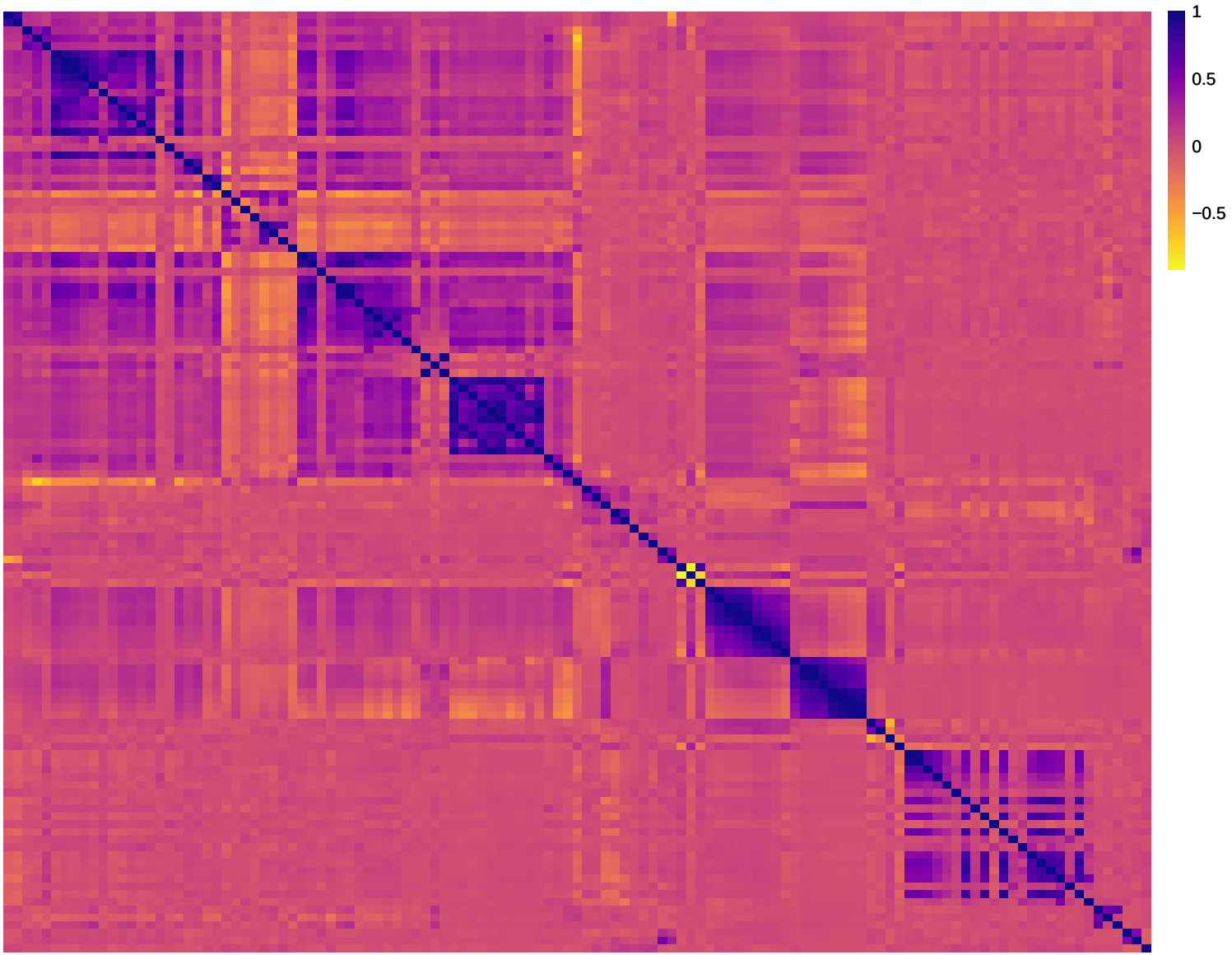
Ridge Results (Rounded Values)

Lambda Value	MSE
1e-06	3.861e-05
1e-04	3.847e-05
1e-03	3.538e-05
1e-02	2.819e-05
1e-01	1.596e-05
0e+00	3.860e-05
1e+00	1.186e-05
1e+01	1.280e-05
1e+02	1.308e-05
1e+03	1.312e-05
1e+06	1.313e-05
Optimal Guess 1	1.264e-05
Optimal Guess 2	1.258e-05

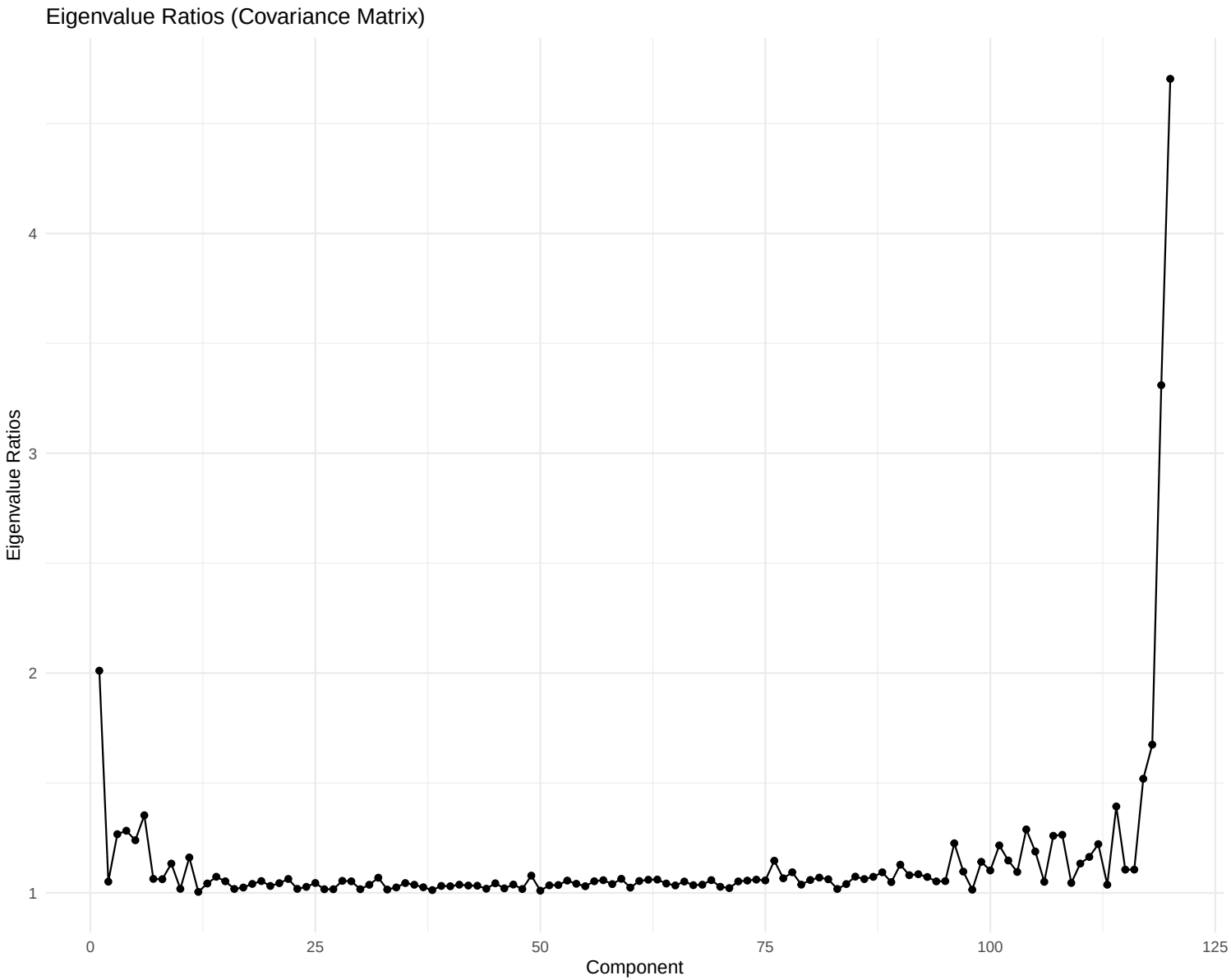
Principal Component Regression (PCR)

- PCA identifies directions (principal components) that maximize variance in the data
- A classic technique for dimensionality reduction, heavily simplifying calculations
- Principal components (PCs) are not interpretable, making PCR "black box"
- PCR is simply linear regression with the principal components (PCs) as regressors
- I use both an empirical approach (trying different PCs) and a formal one (eigenvalue analysis from the covariance matrix)

Covariance Matrix Heatmap of FRED-MD



Explained Variance from Eigenvalues



PCR Results (Rounded Values)

Number of Components	MSE
1	1.323e-05
2	1.311e-05
3	1.340e-05
5	1.351e-05
10	1.307e-05
25	2.002e-05
50	1.219e-05
75	5.756e-05
121 (all regressors)	3.704e-05

The sweet spot for dimensionality reduction lies around 10 or 50 PC's

VAR and its Challenges with "Big Data"

- VAR models capture relationships between multiple time series using the formula:

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \epsilon_t$$

- Variables must be aligned and not lagged (pre-processing is crucial)
- This application focuses on forecasting accuracy, though VAR is versatile
- VAR struggles with many variables due to overparameterization
- Bayesian VAR is popular as it introduces shrinkage to address this issue
- I experiment with a VAR using PCA on X to forecast Y, which is effective (but not interpretable)

VAR Results (Rounded Values)

Number of Components	MSE
2	1.380e-05
3	1.334e-05
5	1.332e-05
10	1.299e-05
15	1.291e-05
20	1.291e-05
25	1.253e-05
30	1.282e-05
35	1.257e-05
40	1.234e-05
45	1.389e-05
50	1.193e-05
60	1.508e-05
75	1.245e-05

Random Forest

- Random Forest averages predictions from multiple decision trees to reduce variance:

$$\hat{y} = \frac{1}{M} \sum_{m=1}^{M} \hat{y}_m$$

- Unlike previous models, Random Forest is non-linear and can capture complex patterns (also scale-invariant)
- Regularisation involves experimenting with the number of trees (M) and maximum nodes per tree
- More trees reduce variance, improving stability but increasing computation time
- Larger trees (more nodes) capture finer details but risk overfitting

Random Forest Results (Rounded Values)

Number of Trees	Max Depth	MSE
10	5	1.304e-05
25	8	1.293e-05
50	10	1.285e-05
75	12	1.256e-05
100	15	1.267e-05
150	18	1.266e-05
200	20	1.245e-05
500	25	1.262e-05

Noticeable improvement with 75 trees, gains stall around 200 trees

Conclusions (1/2)

- ML techniques can yield moderate improvements in forecasting performance with proper regularisation (5–10% on average)
- Basic models, like AR(1), are still surprisingly effective
- The trade-off is clear: ML is effective but requires significantly more time, skills, and computational power
- A major downside is their "black box" nature (uninterpretable), limiting practical use

Conclusions (2/2)

- Another limitation is that macroeconomic data is relatively "small" (not truly "Big Data")
- Interesting observation: there is growing literature on this topic in Economics and Finance, even from as early as 2008!
- Personal consideration: while macro data is not "Big Data," finance deals with truly massive datasets (where ML may excel)
- However, for forecasting, the Efficient Market Hypothesis (EMH) works against you in finance

Potential Future Development

- Bayesian methods are very interesting and effective (as demonstrated in the referenced paper)
- There are many more advanced ML techniques to explore (also specific to time series), but they raise questions
- E.g.: Can we justify their use? Do we have enough data to avoid overfitting?
- E.g.: How do we incorporate domain-specific knowledge into ML? Can it be done?

References

- Stock, J. H., Watson, M. W. (2020), "Introduction to Econometrics" (4th ed.), Pearson Education.
- James, G., Witten, D., Hastie, T., Tibshirani, R. (2023), "An Introduction to Statistical Learning with Applications in R" (2nd ed.), Springer.
- Mullainathan, S., Spiess, J. (2017), "Machine Learning: An Applied Econometric Approach," Journal of Economic Perspectives.
- De Mol, C., Giannone, D., Reichlin, L. (2008), "Forecasting Using a Large Number of Predictors: Is Bayesian Regression a Valid Alternative to Principal Components?" Journal of Econometrics.
- Stock, J. H., Watson, M. W. (2004), "An Empirical Comparison of Methods for Forecasting Using Many Predictors," Unpublished Manuscript.