Forecasting US Inflation in the Post-Global Financial Crisis Era: An Application of Machine Learning Methods*

Joshua Bailey†

Yale University

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Abstract

Inflation forecasting has long been a central task of empirical macroeconomics. The complexity of the macroeconomy, limits on data, and computational power have also made it a consistently challenging one. Recent advances in the quality of macroeconomic data and the increasing popularity of machine learning techniques are helping to make this challenge more tractable. I employ two such techniques – the Random Forest (RF) and regularised Lasso regression – to forecast inflation over two periods, the post-GFC period, 2015-2020, and the 2020-2022 inflation shock period. Comparing their performance to the workhorse univariate autoregressive (AR) model, I find that both methods perform better in forecasting inflation in the initial post-GFC period. Since the start of Covid, the AR model retains its advantage, performing slightly better than the RF. While performing relatively less well in post-Covid forecasting, the Lasso offers valuable insights into the features that drive inflation, with the model conforming to the theoretical findings that monetary policy and labour markets substantially determine inflation outcomes.

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*Econon 566 - Final project

†Yale University, `e-mail:` joshua.bailey@yale.edu

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1 Introduction and Literature Review: Machine Learning and Inflation Forecasting

1.1 Inflation Forecasting and Machine Learning: A Brief Review

Inflation forecasting has long been a central interest of empirical macroeconomics.[1]. Central banks, financial institutions, large corporates, and households all have a strong interest in accurate, timely forecasts of inflation. At the birth of modern macroeconomics, theorists like Tinter and Tinbergen (1940) established the foundations of the discipline, before the advent of large Keynesian macroeconomic models with many equations, solved simultaneously, provided the basis of modern macro forecasting (Ekeblad and Klein 1952). These models evolved into the vector autoregressive (VAR) models that are the workhorse tools of forecasting today (Sims, Goldfeld, and Sachs 1982).

This general approach to empirical macroeconomic forecasting famously came under attack, first by Friedman (1968), who argued that the standard Phillips curve relationship (Phillips 1958) did not represent a static policy trade-off between unemployment and inflation, and that the underlying relationship was much more dynamic and subject to change in the face of shocks. Friedman's critique was formalised by Lucas (1976) with a formal model. Lucas ushered in the 'rational expectations' revolutions to macroeconomics and brought with it a dynamic understanding of the Phillips curve.

Many view the Lucas critique as a fundamental for macroeconomic forecasting. If underlying relationships have the dynamics described by Lucas, what is the point in modelling the historic relationship $Y \sim X$. The response is two-fold. At one level, Lucas' argument is just a call for models to be more dynamic. It should be obvious that response elasticities are not likely to be constant, while other factors in a model evolve over time. Better empirical models need to be sensitive to changing conditions and complex underlying relationships between variables.

More fundamentally, challenges in isolating causal factors in econometric modelling does not obviate the need for policymakers to engage in such analysis. Consider the argument made in Kleinberg et al. (2015). In their paper, they set

1. See, for instance, Gordon (1990) and Stock and Mark W Watson (1999).

out a toy problem faced by a policymaker:

> *"Let Y be an outcome variable (such as rain) which depends in an unknown way on a set of variables X_0 and X. A policy-maker must decide on X_0 (e.g., an umbrella or rain-dance) in order to maximise a (known) payoff function $\pi(X_0, Y)$. Our decision of X_0 depends on the derivative:*
>
> $$\frac{d\pi(X_0, Y)}{dX_0} = \frac{\partial \pi}{\partial X_0} \underbrace{(Y)}_{\text{prediction}} + \frac{\partial \pi}{\partial Y} \underbrace{\frac{\partial Y}{\partial X_0}}_{\text{causation}} \text{"}$$

The policymaker has to solve for both terms, $\frac{\partial Y}{\partial X_0}$ and $\frac{\partial \pi}{\partial X_0}$. To do this, the term, $\frac{\partial \pi}{\partial X_0}$, must be evaluated at Y, which needs to be estimated through prediction. In the language of their hypothetical, the rain dance choice is a purely causal question – because rain dances have no effect on the payoffs – but umbrellas are a pure prediction problem because umbrellas have no effect on rain.

In the realm of macroeconomic policymaking, particularly in forecasting inflation, the dichotomy between causality and prediction—akin to the umbrella and rain dance analogy—proves highly instructive. For instance, consider a central bank tasked with maintaining price stability, confronting decisions akin to whether to engage in a rain dance or merely prepare an umbrella. The 'rain dance' in this scenario is analogous to a central bank's decision to adjust interest rates or implement quantitative easing, grounded in the causal belief that such actions will directly influence inflation rates. This causal inference demands a robust understanding of economic dynamics, including how monetary policy adjustments lead to changes in consumer behaviour, investment, and ultimately, price levels. Here, the policy's efficacy hinges on accurately discerning and manipulating the causal levers of the economy.

The 'umbrella' approach is exemplified by predictive tasks, such as using economic indicators to forecast inflation trends. Here, the central bank, much like an individual deciding whether to carry an umbrella based on weather predictions, utilises models to predict future inflation rates based on current data. This predictive inference does not require understanding or establishing the causality between observed data and future states but focuses on accurately forecasting outcomes to inform policy decisions. Beyond a central bank, financial firms or households have various responses at their disposal if they predict higher inflation that do not depend on having a causal effect on inflation, e.g., increase savings, cut back on expenditure, and pay down debts. In practice, effective macroeconomic management often necessitates a blend of both approaches. While predictive models, enhanced by machine learning algorithms, provide high-accuracy forecasts to anticipate economic conditions, understanding the causal impact of policy instruments is crucial for crafting interventions that achieve desired economic objectives. This integration of causal and predictive insights enables policymakers to not only react to economic developments but also to strategically influence future economic outcomes, balancing immediate actions with long-term planning.[2] Central banks themselves have recognised the importance of improving inflation prediction accuracy as a research goal unto itself (Chakraborty and Joseph 2017; Smalter Hall 2018).

Despite its importance, it has been, as Stock and Mark W Watson (2010) noted, " exceedingly difficult to improve systematically upon simple univariate forecasting models, such as the Atkeson and Ohanian (2001) random walk model [...] or the time-varying unobserved components model in James H. Stock and Mark W. Watson (2007)." Machine learning offers the potential to substantially improve these efforts. The complex relationships that govern the macroeconomy lend themselves to the techniques offered by machine learning. To take just two advantages, machine learning methods can handle larger datasets and handle the nonlinear relationships inherent in the working of the macroeconomy. This sub-set of the literature also has a long history. Stock and M. w. Watson (2023) recount early efforts of theirs in the late 1990s to look at the use of neural networks to forecast inflation. Nakamura (2005) also exploited a simple neural network to forecast inflation, comparing it to a univariate autoregression model and finding that the neural network improved forecasting performance.

While these early models often showed incremental improvements on existing methods, they were limited to the availability of good data and computational

2. This leaves aside the body of machine learning literature that focuses on causal relationships as well. The point being made here is that, *even if* a model is only purely predictive, it is still an important tool for governments, households, and firms.

power. As a result of recent advances in these areas, there has been a significant growth in research examining the application of machine learning to a range of areas of economics (Athey 2019).

In the field of inflation forecasting, Kleinberg et al. (2015) explored the benefits and limitations of using ML approaches for economic forecasting. They advocated for ML as a disciplined, non-parametric approach to predicting economic outcomes. Mullainathan and Spiess (2017) illustrated how regression trees can enhance predictions of house prices, summarising their findings by asserting that, "machine learning offers a potent tool to discern, with unprecedented clarity, the messages conveyed by the data." Thus, ML can serve as a valuable adjunct to traditional model-based methods. Chakraborty and Joseph (2017) evaluated the performance of ten econometric and ML models in predicting inflation in the United Kingdom post-Global Financial Crisis, identifying random forests as the superior model in their test samples. Subsequently, Medeiros et al. (2021) assessed various ML techniques for forecasting inflation in the United States, also highlighting the superiority of random forests over competing methods. These results echo broader findings by Fernández-Delgado et al. (2014), who evaluated 179 classifier models across 121 datasets and found random forests to excel as the top performer. Furthermore, Goulet Coulombe (2024) makes an initial effort to integrate random forest methodology with a macroeconomic model. The increasing focus on random forests informs the focus of this paper (Kohlscheen 2021).

1.2 Paper Overview

The selection of the models in this paper reflects the realities faced by macroeconomic forecasters. If an omniscient planner had access to both perfect data and boundless computational prowess, the approach to forecasting inflation would transcend traditional methodologies. Such a planner would have access to non-traditional data like real-time biometric economic indicators from individuals reflecting their spending propensity and stress levels linked to financial stability, detailed satellite imagery tracking raw material movements globally, and predictive logistics data foreseeing supply chain disruptions before they occur. Futuristic data like genetic algorithms predicting entrepreneurial success and the economic impact of unpatented innovations could also feed into this vast informational nexus.

Leveraging infinite computational power, the planner would integrate these vast datasets into a hybrid model combining traditional econometric methods with cutting-edge machine learning techniques. Structural economic models would be used to ensure the incorporation of well-established economic theories, while deep learning networks would manage the sheer scale and complexity of the data, capturing subtle nonlinearities and interactions that traditional models might miss. This model would not only continuously update in real-time as new data becomes available, but also simulate countless economic scenarios to predict the impacts of potential economic shocks or policy interventions. This ultimate model would serve as more than a forecasting tool; it would be an economic oracle, capable of advising policymakers on the optimal interventions to avoid inflationary pressures or deflationary spirals before they materialise.

In the absence of such a system, forecasting needs to make use of macroeconomic data as it exists today. That is to say, data that is often untimely and subject to substantial revision. While there are increasingly novel datasets, like satellite imagery, most macroeconomists, especially those with significantly policymaking responsibility, have not seen fit to integrate them into their forecasting systems as yet. There are, however, as this paper will now explore, an increasingly powerful array of machine learning tools (and improving time series macro data) that are finally allowing us to improve the accuracy of macroeconomic forecasting.

Having situated the paper in the literature on inflation forecasting in the section above, §1.1, I now move to the substantive section of the paper. The goal of this paper is to compare methods for forecasting US inflation. Specifically, I employ a series of models to forecast inflation one month ahead, specifically, the month-over-month log change in US CPI. In §2.1 I formally introduce the models estimated in the paper, an autoregressive (AR) model, a Random Forest (RF) and a Least Absolute Shrinkage and Selection Operator (Lasso) model. I then discuss the data used in the paper, the FRED-MD macroeconomic dataset, in §2.2. In §3, I then present and analyse the results from the models.

2 Methods and Data: Forecasting Inflation with Machine Learning Models

The forecasting approach employed in this study adopts an expanding window approach to predict inflation, focusing on a period from January 2015 to January 2024. This methodology allows for the incremental inclusion of new data as it becomes available, thus expanding the training dataset over time and improving the model's adaptability to new economic conditions. The target variable for this analysis is the Consumer Price Index for All Urban Consumers (CPIAUCSL), a common measure of inflation. The CPI data undergoes various transformations to stabilise its variance and improve the predictive performance of the models (set out in §2.2). These transformations address non-stationarity in the time series data. Several forecasting models are utilised:

- **Random Walk (RW):** This model serves as a naive benchmark, assuming that the best prediction for the next period is the value observed in the current period. It is useful for its simplicity and often performs surprisingly well in financial time series prediction, as noted above in §1.1.

- **Autoregressive (AR):** This model capitalises on the premise that past values have a linear influence on future values up to 'n lags'. It is well-suited for time series data where lagged dependencies are pronounced.

- **Random Forest (RF):** A non-linear model that handles complex interactions between features. It is particularly good at capturing non-linear effects that linear models like AR might miss.

- **Lasso Regression:** Ideal for datasets with many predictors, Lasso helps in feature selection by shrinking the coefficients of less important variables to zero. This is especially valuable in econometric modeling where the researcher is interested in identifying a parsimonious model.

The combination of these models provides a robust framework for understanding and forecasting inflation. In addition to the transformed FRED-MD variables, the models employ principal component analysis (PCA) to reduce dimensionality and focus on the most informative aspects of the data, to further enhance the model's effectiveness. Economic datasets often contain a large number of interrelated variables, which can lead to model complexity and computational inefficiency. PCA helps to reduce the dimensionality of the dataset by transforming the original variables into a smaller number of principal components. This makes the dataset more manageable while preserving as much of the critical information as possible. In economic data, predictors can be highly correlated, which complicates the estimation process and can make the model unstable and difficult to interpret. PCA mitigates this by creating principal components that are orthogonal, thus eliminating multicollinearity among them. This stabilisation of the data structure allows for more reliable predictions and interpretations from the models used in the analysis.

The performance of all models is assessed by comparing its forecast accuracy against actual observed values, using error statistics, root mean squared error (RMSE), mean absolute error (MAE), and median absolute deviation (MAD), which are defined as follows:

$$\begin{aligned}
\mathrm{RMSE}_{m,h} &= \sqrt{\frac{1}{T-T_0+1}\sum_{t=T_0}^{T}\widehat{e}_{t,m,h}^{2}}, \\
\mathrm{MAE}_{m,h} &= \frac{1}{T-T_0+1}\sum_{t=T_0}^{T}\left|\widehat{e}_{t,m,h}\right|, \\
\mathrm{MAD}_{m,h} &= \text{median }\left[\left|\widehat{e}_{t,m,h}-\text{median}\left(\widehat{e}_{t,m,h}\right)\right|\right],
\end{aligned} \tag{1}$$

where $\widehat{e}_{t,m,h} = \pi_t - \widehat{\pi}_{t,m,h}$ and $\widehat{\pi}_{t,m,h}$ is the inflation forecast for month t, produced by a model m with data up to $t-h$. The first two measures are typical of the forecasting literature. MAD is less common but is useful in capturing the dispersion of predictions, as well as absolute error.

2.1 Models

2.1.1 Random Walk Model

The first benchmark model used is the RW model, which assumes that the best predictor of tomorrow's value is today's value. Formally, the RW model for one-step-ahead forecasts is defined as:

$$\widehat{y}_{t+h|t} = y_t \tag{2}$$

for $h = 1, \ldots, 12$, where y_t is the last observed value at time t. For accumulated forecasts over h months, the forecast is set as:

$$\widehat{y}_{t+1:t+h|t} = y_{t-(h-1):t} \tag{3}$$

where $y_{t-(h-1):t}$ represents the accumulated values of the target variable over the previous h months. This model provides a baseline for assessing the predictive power of more complex models.

2.1.2 Autoregressive Model

The AR model is a key benchmark in time series forecasting. It utilises historical values of the target variable to predict future values, assuming dependencies only on its own past values. Formally, the AR model is specified as:

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_t \tag{4}$$

where:

- y_t represents the value of the target variable at time t,
- p denotes the number of lags used, indicating the dependency of the forecast on p past observations,
- $\beta_0, \beta_1, \ldots, \beta_p$ are coefficients estimated from the data, and
- ϵ_t is the error term, typically assumed to be independently and identically distributed with a mean of zero and constant variance.

The parameters are estimated using ordinary least squares (OLS), with the dependent variable being the current value of the target series, and the independent variables are the lagged values of the series. For a model with $n\_lags = p$, the predictor matrix X is constructed as:

$$X = \begin{bmatrix} y_1 & y_2 & \cdots & y_p \\ y_2 & y_3 & \cdots & y_{p+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_{T-p} & y_{T-p+1} & \cdots & y_{T-1} \end{bmatrix}, \tag{5}$$

where T is the total number of observations in the training dataset. Forecasts are generated by applying the estimated model to the lagged values present in the test dataset. This produces a series of one-step-ahead forecasts, facilitating direct comparison between forecasted and actual values.

2.1.3 Random Forest Model

In the field of inflation forecasting, RFs offer a robust method that effectively captures the complex, nonlinear interactions among macroeconomic indicators. Conceptually, an RF model consists of numerous decision trees, each partitioning the feature space into segments that yield constant predictions within each segment—typically, the mean of the target values for regression tasks. The model starts with a root node containing the entire dataset and iteratively divides it into smaller nodes by optimising a loss function, usually the mean squared error, which minimises the variance within each node (Breiman 2001).

However, individual decision trees, while detailed, are prone to overfitting—fitting noise rather than signal—and can vary drastically with slight changes in input data. To counteract this, RFs deploy a combination of bootstrapping (sampling random subsets of the training data) and feature bagging (using random subsets of features), to construct each tree. This strategy reduces overfitting by decorrelating the trees' predictions, enhancing the model's generalisation capabilities to unseen data.

For macroeconomic forecasting, and specifically for predicting inflation trends, RFs are useful because they assess the importance of various predictors, facilitating the identification of the most influential economic indicators. Additionally, the out-of-bag error estimation provides a reliable internal validation mechanism, allowing performance assessment without a separate validation dataset—a significant advantage in fields where data availability may be restricted. The robustness of RFs to overfitting and their capability to handle extensive feature sets without performance degradation make them particularly suited for modeling the intricate dynamics of economic systems, where traditional linear models might fall short.

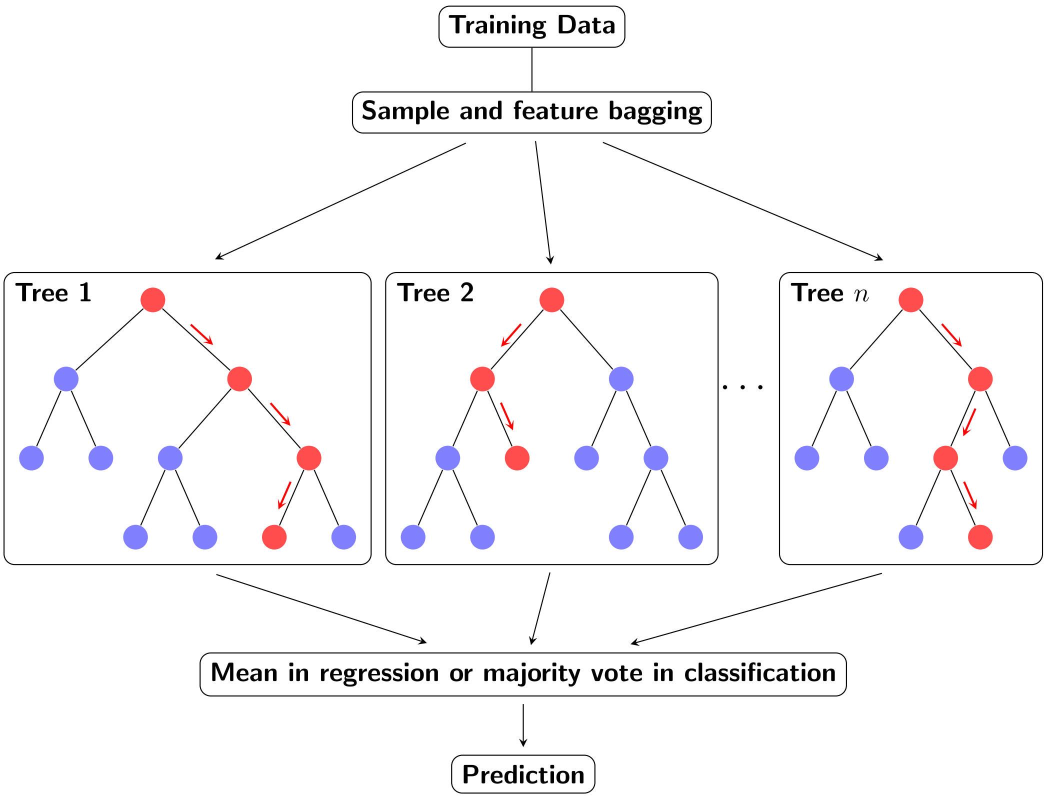

Figure 1: A visual representation of a Random Forest model showing sample and feature bagging, decision trees, and the averaging process.[4]

This paper follows the Random Forest method set out in Medeiros et al. (2021), which is based on the original ideas proposed in Breiman (2001). This approach constructs a multitude of regression trees on bootstrapped subsets of the data, each tree making local predictions by recursively partitioning the covariate space. A regression tree approximates an unknown nonlinear function by dividing the covariate space into distinct regions, within which the response variable is predicted with a constant estimated from the data. Using an example that draws

4. This diagram is based on conceptual material from "RFs and Decision Trees from Scratch in Python" by Towards Data Science, available at https://towardsdatascience.com/random-forests-and-decision-trees-from-scratch-in-python-3e4fa5ae4249. Adaptations and modifications were made to the TikZ code originally found on TeX StackExchange at https://tex.stackexchange.com/questions/503883/illustrating-the-random-forest-algorithm-in-tikz.

from Hastie, Tibshirani, and Friedman (2009), given the explanatory variables X_1 and X_2, the partition might first split on $X_1 = s_1$, and subsequent splits on $X_2 = s_2$ and $X_1 = s_3$, leading to several distinct regions. Within each region R_k, the model predicts the dependent variable Y with a constant value c_k, calculated as the average of Y values within that region. Each tree is thus a series of binary decisions leading to terminal nodes, where each node corresponds to a region in the input space. The RF model aggregates several such trees to form a robust predictor. This process is visualised in the tree diagram contained in Figure 2.1.3. Each tree is built on a different bootstrap sample of the dataset, allowing for variations in the structure and splits of each tree. This process helps in reducing the variance of the model without substantially increasing the bias.

Formally, the model for a given dependent variable π_{t+h} and a vector of predictors $\boldsymbol{x}_t$ can be described by:

$$\widehat{\pi}_{t+h} = \frac{1}{B}\sum_{b=1}^{B}\left[\sum_{k=1}^{K_b}\widehat{c}_{k,b}\mathbf{I}_{k,b}\left(\boldsymbol{x}_t;\widehat{\boldsymbol{\theta}}_{k,b}\right)\right]$$

where:

- B is the number of bootstrap samples,
- K_b is the number of terminal nodes (regions) in the b-th tree,
- $\widehat{c}_{k,b}$ is the predicted value for region k in bootstrap sample b,
- $\mathbf{I}_{k,b}$ is an indicator function that is 1 if $\boldsymbol{x}_t$ falls into region k of the b-th tree and 0 otherwise, and
- $\widehat{\boldsymbol{\theta}}_{k,b}$ are the parameters defining the splits that lead to the k-th region in the b-th sample.

The dataset is prepared by including lagged values of the target variable and applying PCA to reduce dimensionality, forming a comprehensive set of predictors. The RF model utilises these predictors to generate forecasts for each observation in the test dataset. The final forecast for π_{t+h} is the average of the forecasts from all trees in the forest, applied to the original data.

Discussion of the Random Forest Model

The performance of the RF model depends on the appropriate tuning of its hyperparameters, which are selected to optimise the model's accuracy and computational efficiency while ensuring its robustness to overfitting. These parameters are set based on empirical evidence and theoretical considerations, aimed at achieving optimal predictive performance.

Number of Trees: The number of trees, specified by the hyperparameter `n_estimators`, is set to 500. This choice is designed to provide a high level of accuracy while also ensuring that the model's performance stabilises, as increasing the number of trees beyond this point typically yields diminishing returns in terms of error reduction (Medeiros et al. 2021). A larger number of trees enhances the ensemble's ability to generalise, thereby mitigating variance without unduly increasing bias. Choosing a smaller number of trees could lead to increased model variance and potentially underfitting, while an excessively large number might not only waste computational resources but also not yield proportional gains in performance.

Maximum Features per Split: The hyperparameter `max_features` is set to one-third of the total number of features available. This parameter controls the number of features considered when determining the best split at each node of the trees. By restricting the number of features, this setting helps in maintaining a diversity among the trees, preventing the model from fitting too closely to the training data. It strikes a balance between exploring new attribute combinations and retaining prediction accuracy, which is crucial in handling complex economic data structures. Setting `max_features` too high could increase the correlation between the trees, reducing the benefit of bagging by making the ensemble too similar to a single decision tree, whereas setting it too low might not capture sufficient information and could increase bias.

Minimum Samples per Leaf: Set at a minimum of five, the `min_samples_leaf` parameter ensures that each terminal node (leaf) in the tree structures contains no fewer than five data points. This setting helps in preventing the trees from growing overly complex and sensitive to specific samples in the training data, thus enhancing the model's generalisability and robustness against noise and outliers commonly present in economic time series data. A lower threshold might allow the model to capture more detailed information but at the risk of overfitting, while a higher threshold might simplify the model excessively, potentially ignoring valuable information in smaller subsets of data.

2.1.4 Lasso Model

The Least Absolute Shrinkage and Selection Operator (Lasso) was introduced by Tibshirani (1996) as a modification of the linear regression that incorporates a penalty on the sum of the absolute values of the model coefficients. The method is particularly useful for cases where the number of predictors exceeds the number of observations or when a data set exhibits multicollinearity. The Lasso approach encourages simple, sparse models (i.e., models with fewer parameters).

Formally, the Lasso solution is defined by the following optimisation problem:

$$\min_{\beta} \left\{ \frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}, \tag{6}$$

where y_i is the dependent variable, x_{ij} is the j^{th} predictor of the i^{th} observation, β_j is the coefficient for the j^{th} predictor, β_0 is the intercept, λ is a non-negative regularisation parameter, and n is the number of observations. The penalty term $\lambda \sum_{j=1}^{p} |\beta_j|$ imposes a constraint on the coefficients that causes some of them to shrink towards zero. This regularisation can significantly reduce the variance of the estimates, at the expense of introducing some bias, hence trading off variance against bias.

In this implementation, the Lasso model is fitted using the `LassoCV` class from the `scikit-learn` library, which performs Lasso regression with built-in cross-validation to find the optimal value of λ. The parameters used in the model fitting included a 5-fold cross-validation (`cv=5`) and a maximum number of iterations set to 10,000,000 (`max_iter=10000000`) to ensure convergence, given the large size of the data set.

To assess the importance and relevance of different predictors in the model, I also compute statistics on the model coefficients. The number of non-zero coefficients (indicative of the model's sparsity), the number of zero coefficients, and the absolute values of the coefficients (indicative of the strength of each predictor) are recorded and analysed in §3.2.

While Lasso can significantly reduce the risk of overfitting by introducing bias through its regularisation term, the choice of λ and the resulting sparsity of the model can have a profound impact on its interpretability and predictive performance. The application of Lasso in inflation forecasting must be done with careful consideration of these trade-offs, particularly in the context of economic data that may exhibit non-standard patterns or noise. This issue is discussed further in §3.2.

2.2 Data: FRED-MD

FRED-MD is a large macroeconomic database designed for the empirical analysis of "big data" (McCracken and Ng 2016). The dataset has become a popular resource for modelling US macro variables, due to the number of variables, the length of the time series, and the regularity of updates.

The dataset is of monthly observations, updated on a monthly basis. Each monthly release is referred to as a vintage. A different CSV file is released for each month. The data is publicly accessible.[5] The sample spans from March, 1959 to the present, providing us with a relatively rich data set of macroeconomic time series with $x = 127$ variables and $t = 780$ observations. These variables are grouped under eight headings of macroeconomic indicators: output and income, labour market, consumption and orders, orders and inventory, money and credit, interest rates and exchange rates, prices, and stock market.

As the focus of this paper in inflation forecasting, the dependent variable of interest throughout the analysis is `CPIAUCSL`. I use the data from January 2015 to January 2024 as the forecasting window throughout the paper. The time series of `CPIAUCSL` is shown below in Figure 2.

5. The latest vintage, as of the time of publication, is available at: https://files.stlouisfed.org/files/htdocs/fred-md/monthly/2024-04.csv. The historical vintages can be accessed directly at https://s3.amazonaws.com/files.research.stlouisfed.org/fred-md/Historical_FRED-MD.zip

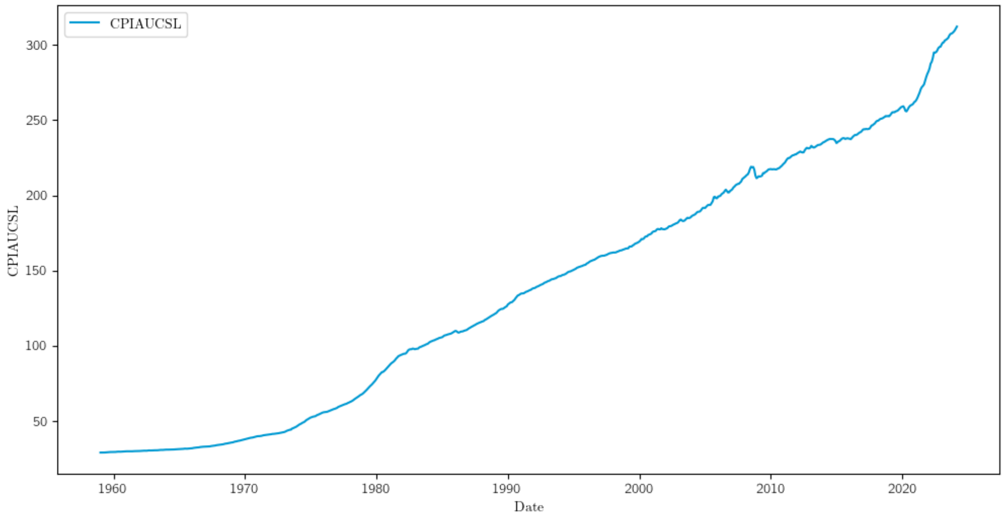

Figure 2: CPI, all items, 1960-2024.

A full list of the variables available in FRED-MD is included in the Appendix, in Table 7. The data is not stationary by default, but the first row of the data contains the relevant transformations needed to prepare the data. The codes are as follows:

1. no transformation,
2. first order difference,
3. second order difference,
4. logarithm,
5. first order logarithmic difference,
6. second order logarithmic difference, and
7. percentage change.

In the model, the dataset is divided into two subsets: training data (`train_data`) and test data (`test_data`). The training data is used to estimate the parameters of the model, while the test data is used to evaluate the model's forecasting ability.

3 Analysis and Results: How do Machine Learning Methods Perform at Forecasting Inflation?

3.1 Overall Results — Forecasting Inflation

The results of the forecasting exercise are shown in Figure 2, which includes the one-month ahead forecasts for each model, RF, AR, and Lasso respectively, as well as the out-turn CPI series. A simple visual inspection reveals a number of points. In general, we see that all three models reasonably track the out-turn series. The Lasso overreacts to the negative Covid shock and slightly underreacts to the following inflation during 2021/22.

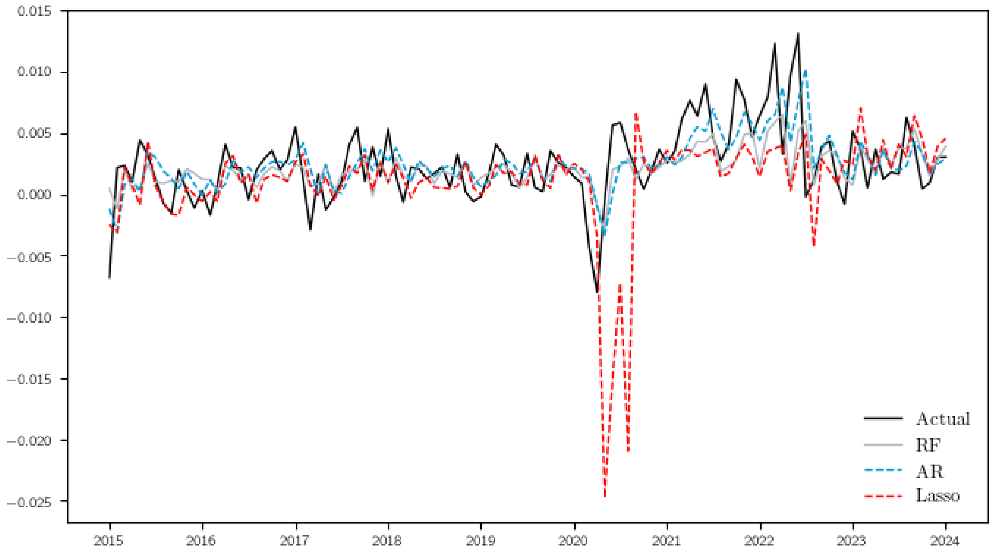

Figure 3: CPI change, actual and forecasts, 1960-2024.

In assessing the efficacy of various inflation forecasting models over distinct periods characterised by differing economic conditions, I rely on three measures of forecasting error per Equation 1: RMSE, MAE, and the MAD. The MAE over the whole forecast period for each model is shown in Figure 1.

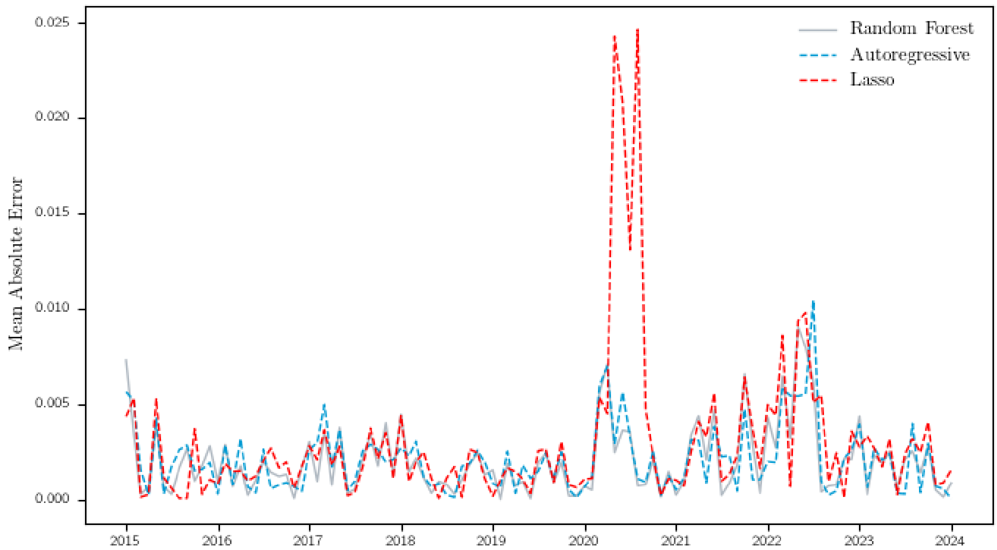

Figure 4: Mean Absolute Error of CPI Forecasts, by Model.

Taking the relevant periods in turn, I turn first to the pre-Covid period, January 2015–January 2020. The errors for this period are shown in Table 1. The models exhibit notably lower error metrics, reflecting the predictable nature of inflation trends absent significant shocks. Consistent with the finding in the literature, the RF model shows superior performance with the lowest RMSE of 0.002114 and MAE of 0.001641, suggesting its effective capture of underlying economic patterns during stable times. The Lasso model also performs well, closely following the RF with an RMSE of 0.002156 and MAE of 0.001725. Importantly, both models manage to beat the standard AR model, a feat that many inflation forecasts struggle with, as discussed in §1.1. Table 2 shows the percentage difference in forecast errors between the RF and other models. The RF is 4.28% and 8.79% better in RMSE and MAE terms, respectively, than the AR model.

Table 1: Forecast Errors — Pre-Covid: January 2015–January 2020

	RW	AR	RF	Lasso
RMSE	0.002580	0.002209	0.002114	0.002156
MAE	0.002098	0.001799	0.001641	0.001725
MAD	0.001837	0.001671	0.001334	0.001424

Table 2: Percentage Difference in Forecast Errors — Pre-Covid

Error Type	RF-AR	RF-RW	RF-Lasso
RMSE	-4.28%	-18.04%	-1.95%
MAE	-8.79%	-21.79%	-4.90%
MAD	-20.16%	-27.40%	-6.37%

The advent of the Covid-19 pandemic saw a series of cascading shocks to inflation. Broadly speaking, the initial pandemic period saw a large negative shock to inflation as households were told to stay at home and firms closed. This was then followed by a period of rolling supply shocks, first in the form of supply chain disruptions resulting from prolonged Covid lockdowns in global manufacturing hubs, like China, and then the energy and food supply shocks caused by Russia's invasion of Ukraine in February 2022. This presents a challenge to any inflation forecasting model, as underlying relationships between variables can change quickly, in a way that can have nonlinear and chaotic effects on prices.

Figure 5 shows a close-up of Figure 1 for the period following the initial Covid shock (July 2020 onwards). The forecast errors for just this period are displayed in Table 3. During this period of upheaval, the AR model adjusts best to these conditions, exhibiting the lowest RMSE (0.003068) and MAE (0.002276) among the models, which points to its strength in adapting to more volatile economic environments. The Lasso model, however, struggles considerably during this period, with the highest RMSE and MAE (0.005705 and 0.003826, respectively). This is discussed further below in §3.2.

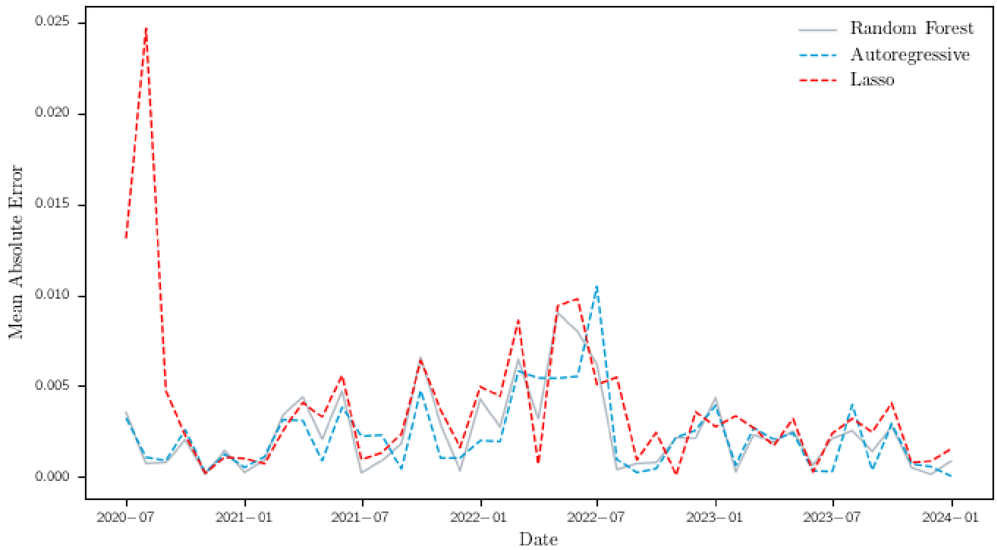

Figure 5: Mean Absolute Error of CPI Forecasts, by Model, Since Covid.

Table 3: Forecast Errors — Recent Shocks: July 2020–January 2024

	RW	AR	RF	Lasso
RMSE	0.003629	0.003068	0.003284	0.005705
MAE	0.002697	0.002276	0.002462	0.003826
MAD	0.002148	0.001940	0.001994	0.002642

Looking at the whole period (January 2015–January 2024), Table 4 shows that the AR model exhibits a slightly superior performance with the lowest RMSE (0.002750) compared to the RF's RMSE of 0.002766, suggesting its robustness over varied economic cycles. However, it is notable that the RF model shows a better MAE (0.002058) than the AR model (0.002102), indicating its consistency in minimising larger errors across predictions. The Lasso model again shows the least favourable performance (RMSE of 0.005026 and MAE of 0.002984), reinforcing the challenges it faces in periods marked by significant economic disruptions.

Table 4: Forecast Errors — Whole Period: January 2015–January 2024

	RW	AR	RF	Lasso
RMSE	0.003177	0.002750	0.002766	0.005026
MAE	0.002437	0.002102	0.002058	0.002984
MAD	0.001970	0.001758	0.001606	0.001792

Table 5: Percentage Difference in Forecast Errors — Whole Series

Error Type	RF-AR	RF-RW	RF-Lasso
RMSE	0.57%	-12.95%	-44.97%
MAE	-2.10%	-15.53%	-31.01%
MAD	-8.67%	-18.48%	-10.39%

The relative performance of the forecasting models over different periods can be attributed to their inherent methodological differences and how these interact with the underlying economic dynamics. The RF model's strong performance in periods of economic stability is likely due to its ability to capture complex interactions between multiple economic indicators without prior assumptions about their relationships. RF, being ensemble methods, build multiple decision trees and aggregate their predictions, thereby reducing the model's variance without a substantial increase in bias. This characteristic makes them robust to overfitting, particularly useful in handling high-dimensional data common in economic datasets. However, during periods of sudden economic shocks, the RF model may not react as swiftly to structural breaks or non-linear shifts as models specifically designed to handle time-series data, like AR models.

By comparison, the AR model avoids having to capture these step-changes by just following patterns from previous time points as inputs to predict future values, inherently accounting for time-based trends and cycles. This temporal sensitivity makes AR models particularly effective in rapidly changing environments, where past values contain predictive signals about future conditions. Their ability to quickly incorporate new information as it becomes available helps explain their superior performance during economic upheavals, such as those induced by the Covid-19 pandemic.

Lasso's performance, particularly the challenge it faced during periods of economic shocks, may be explained by the model's linear nature and its regularisation process, which tends to shrink the coefficients of less important variables towards zero. While this characteristic is beneficial for reducing complexity and avoiding overfitting by eliminating weakly contributing variables, it can also lead to underfitting in scenarios where relationships between variables become non-linear or where sudden changes in economic conditions alter these relationships fundamentally. Lasso's limitations in handling non-linear interactions can severely restrict its effectiveness under dramatic economic shifts.

Some researchers have argued that Lasso, and more broadly other regularisation techniques, can't beat normal factor models because the factor models are already, in effect, regularised models, with the relevant features included (Goulet Coulombe et al. 2022). One other explanation is that the Lasso model here does not allow for any nonlinearities, despite the fact that we know they play an important role in understanding macroeconomic dynamics (Forbes, Gagnon, and Collins 2022).

Incorporating nonlinearities into a large Lasso model is however computationally intensive, and I have not sought to address this issue comprehensively in this paper. By way of illustration, I did not have the computational resources to successfully solve a Lasso model with full nonlinearities. To make such a model tractable, I ran a demonstration model that incorporated 2nd degree polynomials and further dimensionality reduction through PCA. This included a feature selection process that generates polynomial and interaction terms up to the second degree. The tentative results are included for reference in the Appendix at Table 8. It indicates that the performance of the Lasso can be improved, while remaining tractable, by introducing nonlinearities in a constrained way.

3.2 Feature Importance — Unpacking the Lasso

While Lasso's forecasting performance was less impressive during the post-Covid shock period, it offers distinct advantages, especially when it comes to understanding the importance of different features. Unlike methods such as RF, which is a non-linear model that can handle complex interactions between features but does not inherently provide straightforward interpretability regarding the importance of each feature, Lasso imposes sparsity on the coefficient estimates. This property of Lasso is crucial in high-dimensional datasets where the number of predictors can be large compared to the number of observations.

The Lasso achieves this by penalising the sum of the absolute values of the regression coefficients, as encapsulated in the regularisation term $\lambda \sum_{j=1}^{p} |\beta_j|$. This penalty term not only helps in avoiding overfitting but also shrinks the less important feature's coefficients exactly to zero, thus performing feature selection automatically. This aspect of Lasso is particularly beneficial in inflation forecasting, where economists are often interested in identifying which variables (such as interest rates, unemployment figures, or manufacturing indexes) most significantly impact inflation. The Lasso method, therefore, not only simplifies the model but also enhances its interpretability by clearly delineating which features are most predictive of inflation, enabling policymakers and economists to focus on these key indicators.

Table 6 contains the average number of zero coefficients, the average number of non-zero coefficients, and the top 10 predictors with the highest average absolute values of their coefficients, indicating the strength and importance of each in the model's forecasting ability, across all iterations of the Lasso model.

A high number of zero coefficients (421.30 on average) indicates that the Lasso model found a substantial number of the predictors to be irrelevant or redundant when forecasting inflation. This is indicative of a sparse model, where only a small subset of the available predictors is used, reducing the risk of overfitting and improving model interpretability. Relatedly, there was an average of 34.81 non-zero coefficients, suggesting that while the model simplifies by eliminating many predictors, it still relies on a core set of features to make forecasts. These features are deemed by the model to have substantial influences on the movements in inflation.

The feature list is interesting because it shows a series of variables theory tells us are important in determining inflation also determine it empirically. The Federal Funds Rate ('FEDFUNDS'), used as both the 1-month and 4-month lagged predictors, stands out with coefficient values of 0.000179 and 0.000265, respectively.[6] This underscores the importance of interest rate changes in forecasting inflation trends. The reserves of depository institutions ('NONBORRES'), which we can think of as forming part of the credit and banking channels of monetary policy, and average weekly hours ('AWHMAN'), as the Phillips curve term (Phillips 1958), also emerge as significant predictors, with coefficients across multiple lags. Other variables theory tells us are important in the transmission of monetary policy were also significant in determining inflation. Treasury spreads

6. Note, the values are displayed as absolute values. The actual 'FEDFUNDS' coefficient was negative, as we would expect.

and yields, as reflected by 'TB3SMFFM', 'GS5', and 'GS10', play a significant role, highlighting the impact of short and long-term interest rate movements on inflationary expectations. The coefficients associated with these features suggest that shifts in the yield curve contain important information for forecasting inflation.

Table 6: Lasso Model Summary Statistics and Top 10 Most Important Features

Statistic	Value	
Average Number of Zero Coefficients	421.30	
Average Number of Non-Zero Coefficients	34.81	
Top 10 Most Important Features		
Feature	Coefficient	Lag
FEDFUNDS	0.000265	4
NONBORRES	0.000206	4
AWHMAN	0.000179	1
FEDFUNDS	0.000179	1
NONBORRES	0.000146	3
BAAFFM	0.000128	2
TB3SMFFM	0.000119	4
GS5	0.000118	1
GS10	0.000092	4
AWHMAN	0.000085	4

4 Concluding Remarks

In this paper, I have shown that modern machine learning techniques, like RFs, can substantially improve the accuracy of inflation forecasting over traditional AR models. Even though the traditional model reasserted itself over the post-Covid period, the broader literature finds that RF models continue to perform well in a variety of settings. Kohlscheen (2021) for instance, finds that an RF model predicts inflation across 20 advanced countries between 2000 and 2021 and finds that it outperforms the benchmark AR and OLS models over the three-month forecasting horizon. The Lasso model also generated an important result, by showing over a nearly 10-year period that – as we would expect from theory – monetary policy and labour market variables substantially explain the path of inflation.

RF models, due to their ability to handle large datasets with underlying nonlinearities, are a particularly promising area for further study in macroeconomic forecasting. One recent innovation, not explored in this paper due to time limitations, is the 'Macro Random Forest' developed by Goulet Coulombe (2024). The MRF framework refines this approach by focusing on modelling time-varying economic coefficients (β_t), rather than directly predicting the output variable (y_t). The interpretability of MRF is a significant advantage, especially during shocks. The Generalised Time-Varying Parameters (GTVPs) it produces serve as a flexible tool, accommodating various forms of nonlinearities such as thresholds, structural breaks, or smooth transitions. This adaptability ensures that the model can dynamically adjust its parameters in response to shock-induced changes in economic relationships. Models like the MRF are promising avenues for further research and show the continued potential of machine learning tools to improve inflation forecasting going forward.

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5 Appendix

Table 7: Appendix: Full FredMD variable list

Group 1: Output and Income

	id	tcode	fred	description	gsi	gsi:description
1	1	5	RPI	Real Personal Income	$\mathrm{M}_1$4386177	PI
2	2	5	W875RX1	Real personal income ex transfer receipts	$\mathrm{M}_1$45256755	PI less transfers
3	6	5	INDPRO	IP Index	$\mathrm{M}_1$16460980	IP: total
4	7	5	IPFPNSS	IP: Final Products and Nonindustrial Supplies	$\mathrm{M}_1$16460981	IP: products
5	8	5	IPFINAL	IP: Final Products (Market Group)	$\mathrm{M}_1$16461268	IP: final prod
6	9	5	IPCONGD	IP: Consumer Goods	$\mathrm{M}_1$16460982	IP: cons gds
7	10	5	IPDCONGD	IP: Durable Consumer Goods	$\mathrm{M}_1$16460983	IP: cons dble
8	11	5	IPNCONGD	IP: Nondurable Consumer Goods	$\mathrm{M}_1$16460988	IP: cons nondble
9	12	5	IPBUSEQ	IP: Business Equipment	$\mathrm{M}_1$16460995	IP: bus eqpt
10	13	5	IPMAT	IP: Materials	$\mathrm{M}_1$16461002	IP: matls
11	14	5	IPDMAT	IP: Durable Materials	$\mathrm{M}_1$16461004	IP: dble matls
12	15	5	IPNMAT	IP: Nondurable Materials	$\mathrm{M}_1$16461008	IP: nondble matls
13	16	5	IPMANSICS	IP: Manufacturing (SIC)	$\mathrm{M}_1$16461013	IP: mfg
14	17	5	IPB51222s	IP: Residential Utilities	$\mathrm{M}_1$16461276	IP: res util
15	18	5	IPFUELS	IP: Fuels	$\mathrm{M}_1$16461275	IP: fuels
16	19	1	NAPMPI	ISM Manufacturing: Production Index	$\mathrm{M}_1$10157212	NAPM prodn
17	20	2	CUMFNS	Capacity Utilization: Manufacturing	$\mathrm{M}_1$16461602	Cap util

Group 2: Labor Market

	id	tcode	fred	description	gsi	gsi:description
1	21*	2	HWI	Help-Wanted Index for United States		Help wanted index
2	22*	2	HWIURATIO	Ratio of Help Wanted/No. Unemployed	M_110156531	Help wanted/unemp
3	23	5	CLF16OV	Civilian Labor Force	M_110156467	Emp CPS total
4	24	5	CE16OV	Civilian Employment	M_110156498	Emp CPS nonag
5	25	2	UNRATE	Civilian Unemployment Rate	M_110156541	U : all
6	26	2	UEMPMEAN	Average Duration of Unemployment (Weeks)	M_110156528	U : mean duration
7	27	5	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	M_110156527	U < 5 wks
8	28	5	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	M_110156523	U 5-14 wks
9	29	5	UEMP15OV	Civilians Unemployed - 15 Weeks & Over	M_110156524	U 15+ wks
10	30	5	UEMP15T26	Civilians Unemployed for 15-26 Weeks	M_110156525	U 15-26 wks
11	31	5	UEMP27OV	Civilians Unemployed for 27 Weeks and Over	M_110156526	U27+ wks
12	32*	5	CLAIMSx	Initial Claims	M_15186204	UI claims
13	33	5	PAYEMS	All Employees: Total nonfarm	M_123109146	Emp: total
14	34	5	USGOOD	All Employees: Goods-Producing Industries	M_123109172	Emp: gds prod
15	35	5	CES1021000001	All Employees: Mining and Logging: Mining	M_123109244	Emp: mining
16	36	5	USCONS	All Employees: Construction	M_123109331	Emp: const
17	37	5	MANEMP	All Employees: Manufacturing	M_123109542	Emp: mfg
18	38	5	DMANEMP	All Employees: Durable goods	M_123109573	Emp: dble gds
19	39	5	NDMANEMP	All Employees: Nondurable goods	M_123110741	Emp: nondbles
20	40	5	SRVPRD	All Employees: Service-Providing Industries	M_123109193	Emp: services
21	41	5	USTPU	All Employees: Trade, Transportation & Utilities	M_123111543	Emp: TTU
22	42	5	USWTRADE	All Employees: Wholesale Trade	M_123111563	Emp: wholesale
23	43	5	USTRADE	All Employees: Retail Trade	M_123111867	Emp: retail

24	44	5	USFIRE	All Employees: Financial Activities	M_123112777	Emp: FIRE
25	45	5	USGOVT	All Employees: Government	M_123114411	Emp: Govt
26	46	1	CES0600000007	Avg Weekly Hours : Goods-Producing	M_140687274	Avg hrs
27	47	2	AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	M_123109554	Overtime: mfg
28	48	1	AWHMAN	Avg Weekly Hours : Manufacturing	M_14386098	Avg hrs: mfg
29	49	1	NAPMEI	ISM Manufacturing: Employment Index	M_110157206	NAPM empl
30	127	6	CES0600000008	Avg Hourly Earnings : Goods-Producing	M_123109182	AHE: goods
31	128	6	CES2000000008	Avg Hourly Earnings : Construction	M_123109341	AHE: const
32	129	6	CES3000000008	Avg Hourly Earnings : Manufacturing	M_123109552	AHE: mfg

Group 3: Consumption and Orders

	id	tcode	fred	description	gsi	gsi:description
1	50	4	HOUST	Housing Starts: Total New Privately Owned	$M_1$10155536	Starts: nonfarm
2	51	4	HOUSTNE	Housing Starts, Northeast	$M_1$10155538	Starts: NE
3	52	4	HOUSTMW	Housing Starts, Midwest	$M_1$10155537	Starts: MW
4	53	4	HOUSTS	Housing Starts, South	$M_1$10155543	Starts: South
5	54	4	HOUSTW	Housing Starts, West	$M_1$10155544	Starts: West
6	55	4	PERMIT	New Private Housing Permits (SAAR)	$M_1$10155532	BP: total
7	56	4	PERMITNE	New Private Housing Permits, Northeast (SAAR)	$M_1$10155531	BP: NE
8	57	4	PERMITMW	New Private Housing Permits, Midwest (SAAR)	$M_1$10155530	BP: MW
9	58	4	PERMITS	New Private Housing Permits, South (SAAR)	$M_1$10155533	BP: South
10	59	4	PERMITW	New Private Housing Permits, West (SAAR)	$M_1$10155534	BP: West

Group 4: Orders and Inventories

	id	tcode	fred	description	gsi	gsi:description
1	3	5	DPCERA3M086SBEA	Real personal consumption expenditures	$M_1$23008274	Real Consumption
2	4*	5	CMRMTSPLx	Real Manu. and Trade Industries Sales	$M_1$10156998	M&T sales
3	5*	5	RETAILx	Retail and Food Services Sales	$M_1$30439509	Retail sales
4	60	1	NAPM	ISM : PMI Composite Index	$M_1$10157208	PMI
5	61	1	NAPMNOI	ISM : New Orders Index	$M_1$10157210	NAPM new ordrs
6	62	1	NAPMSDI	ISM : Supplier Deliveries Index	$M_1$10157205	NAPM vendor del
7	63	1	NAPMII	ISM : Inventories Index	$M_1$10157211	NAPM Invent
8	64	5	ACOGNO	New Orders for Consumer Goods	$M_1$4385863	Orders: cons gds
9	65*	5	AMDMNOx	New Orders for Durable Goods	$M_1$4386110	Orders: dble gds
10	66*	5	ANDENOx	New Orders for Nondefense Capital Goods	$M_1 78554409 Orders : capgds$	
11	67*	5	AMDMUOx	Unfilled Orders for Durable Goods	$M_1$4385946	Unf orders: dble
12	68*	5	BUSINVx	Total Business Inventories	$M_1$5192014	M&T invent
13	69*	2	ISRATIOx	Total Business: Inventories to Sales Ratio	$M_1$5191529	M&T invent/sales
14	130*	2	UMCSENTx	Consumer Sentiment Index	hhsntn	Consumer expect

Group 5: Money and Credit

	id	tcode	fred	description	gsi	gsi:description
1	70	6	M1SL	M1 Money Stock	$M_1$10154984	M1
2	71	6	M2SL	M2 Money Stock	$M_1$10154985	M2
3	72	5	M2REAL	Real M2 Money Stock	$M_1$10154985	M2 (real)
4	73	6	AMBSL	St. Louis Adjusted Monetary Base	$M_1$10154995	MB

5	74	6	TOTRESNS	Total Reserves of Depository Institutions	$M_1$10155011	Reserves tot
6	75	7	NONBORRES	Reserves Of Depository Institutions	$M_1$10155009	Reserves nonbor
7	76	6	BUSLOANS	Commercial and Industrial Loans	BUSLOANS	C&I loan plus
8	77	6	REALLN	Real Estate Loans at All Commercial Banks	BUSLOANS	DC&I loans
9	78	6	NONREVSL	Total Nonrevolving Credit	$M_1$10154564	Cons credit
10	79*	2	CONSPI	Nonrevolving consumer credit to Personal Income	$M_1$10154569	Inst cred/PI
11	131	6	MZMSL	MZM Money Stock	N.A.	N.A.
12	132	6	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	N.A.	N.A.
13	133	6	DTCTHFNM	Total Consumer Loans and Leases Outstanding	N.A.	N.A.
14	134	6	INVEST	Securities in Bank Credit at All Commercial Banks	N.A.	N.A.

Group 6: Interest rate and Exchange Rates

	id	tcode	fred	description	gsi	gsi:description
1	84	2	FEDFUNDS	Effective Federal Funds Rate	$M_1$10155157	Fed Funds
2	85*	2	CP3Mx	3-Month AA Financial Commercial Paper Rate	CPF3M	Comm paper
3	86	2	TB3MS	3-Month Treasury Bill:	$M_1$10155165	3 mo T-bill
4	87	2	TB6MS	6-Month Treasury Bill:	$M_1$10155166	6mo T-bill
5	88	2	GS1	1-Year Treasury Rate	$M_1$10155168	1 yr T-bond
6	89	2	GS5	5-Year Treasury Rate	$M_1$10155174	5 yr T-bond
7	90	2	GS10	10-Year Treasury Rate	$M_1$10155169	10 yr T-bond
8	91	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield		Aaa bond
9	92	2	BAA	Moody's Seasoned Baa Corporate Bond Yield		Baa bond
10	93*	1	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS		CP-FF spread
11	94	1	TB3SMFFM	3-Month Treasury C Minus FEDFUNDS		3 mo-FF spread
12	95	1	TB6SMFFM	6-Month Treasury C Minus FEDFUNDS		6mo – FF spread

13	96	1	T1YFFM	1-Year Treasury C Minus FEDFUNDS		1 yr-FF spread
14	97	1	T5YFFM	5-Year Treasury C Minus FEDFUNDS		5 yr-FF spread
15	98	1	T10YFFM	10-Year Treasury C Minus FEDFUNDS		10 yr-FF spread
16	99	1	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS		Aaa-FF spread
17	100	1	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS		Baa-FF spread
18	101	5	TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies		Ex rate: avg
19	102*	5	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	$M_1$10154768	Ex rate: Switz
20	103*	5	EXJPUSx	Japan / U.S. Foreign Exchange Rate	$M_1$10154755	Ex rate: Japan
21	104*	5	EXUSUKx	U.S. / U.K. Foreign Exchange Rate	$M_1$10154772	Ex rate: UK
22	105*	5	EXCAUSx	Canada / U.S. Foreign Exchange Rate	$M_1$10154744	EX rate: Canada

Group 7: Prices

	id	tcode	fred	description	gsi	gsi:description
1	106	6	PPIFGS	PPI: Finished Goods	M110157517	PPI: fin gds
2	107	6	PPIFCG	PPI: Finished Consumer Goods	M110157508	PPI: cons gds
3	108	6	PPIITM	PPI: Intermediate Materials	$M_1$10157527	PPI: int matls
4	109	6	PPICRM	PPI: Crude Materials	$M_1$10157500	PPI: crude matls
5	110*	6	OILPRICEx	Crude Oil, spliced WTI and Cushing	$M_1$10157273	Spot market price
6	111	6	PPICMM	PPI: Metals and metal products:	$M_1$10157335	PPI: nonferrous
7	112	1	NAPMPRI	ISM Manufacturing: Prices Index	$M_1$10157204	NAPM com price
8	113	6	CPIAUCSL	CPI : All Items	$M_1$10157323	CPI-U: all
9	114	6	CPIAPPSL	CPI : Apparel	$M_1$10157299	CPI-U: apparel
10	115	6	CPITRNSL	CPI : Transportation	$M_1$10157302	CPI-U: transp
11	116	6	CPIMEDSL	CPI : Medical Care	$M_1$10157304	CPI-U: medical
12	117	6	CUSR0000SAC	CPI : Commodities	CPI-U: comm.	

13	118	6	CUUR0000SAD	CPI : Durables	$M_1$10157315	CPI-U: dbles
14	119	6	CUSR0000SAS	CPI : Services	CPI-U: services	
15	120	6	CPIULFSL	CPI : All Items Less Food	$M_1$10157328	CPI-U: ex food
16	121	6	CUUR0000SA0L2	CPI : All items less shelter	CPI-U: ex shelter	
17	122	6	CUSR0000SA0L5	CPI : All items less medical care	$M_1$10157330	CPI-U: ex med
18	123	6	PCEPI	Personal Cons. Expend: Chain Index	gmdc	PCE defl
19	124	6	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	gmdcd	PCE defl: dlbes
20	125	6	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	gmdcn	PCE defl: nondble
21	126	6	DSERRG3M086SBEA	Personal Cons. Exp: Services	gmdcs	PCE defl: service

Group 8: Stock Market

	id	tcode	fred	description	gsi	gsi:description
1	80*	5	S&P 500	S&P's Common Stock Price Index: Composite	$M_1$10155044	S&P 500
2	81*	5	S&P: indust	S&P's Common Stock Price Index: Industrials	$M_1$10155047	S&P: indust
3	82*	2	S&P div yield	S&P's Composite Common Stock: Dividend Yield	S&P div yield	
4	83*	5	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	S&P PE ratio	

Table 8: Appendix: Lasso vs Reduced Polynomial Lasso – Errors Comparison

	Lasso	Reduced Poly Lasso
RMSE	0.005705	0.003450
MAE	0.003826	0.002557
MAD	0.002642	0.002182