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ORIGINAL ARTICLE

A comparison of time series and machine learning models for inflation forecasting: empirical evidence from the USA

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Abstract This study compares time series and machine learning models for inflation forecasting. Empirical evidence from the USA between 1984 and 2014 suggests that out of sixteen conditions (four different inflation indicators and four different horizons), machine learning models provide more accurate forecasting results in seven conditions and the time series models are better in nine conditions. Moreover, multivariate models give better results in fourteen conditions, and univariate models are better only in two conditions. This study shows that machine learning model prevails against time series models for the core personal consumption expenditure (core-PCE) inflation forecasting, and the time series model (ARDL) is better for the core consumer price (core-CPI) index inflation forecasting in all horizons.

Keywords Inflation forecasting · Time series models · Machine learning models

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1 Introduction

Inflation, which is the percentage change in the aggregate price level, is one of the most important key indicators of economic activity. It affects the decisions of households, investors, governments, and policy makers. High inflation rates deteriorate economic growth rates, diminish real wages, and increase production costs. Similarly, a low inflationary environment is considered as a negative economic indicator that is associated with decreasing level of the demand in the economy. Therefore, the forecasting of inflation within different time horizons is important. The aim of this study is to compare time series and machine learning models for inflation forecasting in different horizons.

Seminal studies on inflation forecasting are based on the augmented Phillips Curve (PC) models, which rely on economic activity measures. Stock and Watson [47] claim that these multivariate structural models provide better forecasting results compared to univariate time series models. On the other hand, Atkeson and Ohanian [1] gave prominence to the random walk model (the Naïve model) which does not include economic indicators for inflation forecasting. Although the Naïve model is considered as a benchmark in many inflation forecasting studies, Stock and Watson [48] present that multivariate forecasts do not outperform univariate benchmarks on average, at least since 1985 when the policy makers have started to consider future economic developments more. Besides PC and its derivative models, Gordon's [14] triangle model and term structure models are applied as multivariate models.[1]

[1] One can visit Stock and Watson [49] for a comprehensive review of the univariate and multivariate models and the literature since the great moderation.

Finally, Manzan and Zerom [30], which is one of the key papers this study follows, expand the scope of inflation predictability by using macro-indicators for the post-1984 forecast zone.

The machine learning models are rarely used for inflation forecasting. Nevertheless, machine learning models are applied for the forecasting of other macroeconomic variables. For example, Mizrach [33] and Rodriguez et al. [40] utilize the nearest neighbor to forecast exchange rates. Guegan and Rakotomarolahy [15] use the k-nearest neighbors (k-NN) method to forecast income. Chen et al. [7] utilize the support vector machines (SVM) to forecast the stock market return volatility in the USA. SVM or support vector regression (SVR) was firstly applied in financial data forecasting and estimation as an alternative for the Maximum Likelihood Estimation (see [18, 38]. Alamili [3] compares the forecasting results of Artificial Neural Network (ANN) with SVM for the EUR/Dollar exchange rate. Moreover, several empirical studies evaluate the forecasting performance of machine learning and conventional statistical models, for example, Lam [26]; Lee and Chen [27]; Leigh et al. [28]. In addition to ANNs, there are effectively applications of the SVR in different problems of time series prediction and forecasting [10, 11, 21]. The implication of machine learning models (ANN, SVR and k-NN) for different macroeconomic variables motivates us to compare them with time series models for inflation forecasting.

The main contribution of this study is assessment of the forecasting performance of two univariate (AR and Naïve), two multivariate (VAR and ARDL) time series models, and three machine learning models (k-NN, ANN, and SVM) in US inflation rates. Furthermore, this study shows that ARDL as an accurate model for the US core-CPI inflation forecasting and SVR is the suitable model for core-PCE inflation.

The next section describes the data and methodology. Third section evaluates and compares the forecasts according to residual mean square and log-square statistics, and the last section is the conclusion.

2 Data and methodology

2.1 Description of data

In order to forecast inflation, we specify the forecasting variables according to Manzan and Zerom [30]. We used four measures of the monthly price index. These are the Consumer Price Index for all items (CPI), the CPI excluding food and energy (Core-CPI), the Personal Consumption Expenditure deflator (PCE), and the PCE excluding food and energy (Core-PCE). We denote one-month inflation by $Y_t = 1200 \times [log \;\; P_t - log \;\; P_{t-1}]$, where P_t is the level of the price index in month t.

Considering the models as predictors of inflation, we considered six economic activities: the civilian unemployment rate (UNEM), the index of industrial production (IP), real personal consumption expenditure (INC), employees on nonfarm payrolls (WORK), housing starts (HS), and the term spread (SPREAD), defined as the yield on the 5-year Treasury bond minus the 3-month Treasury bill. Thus, we have the vector of $X \in \{$UNEM, IP, WORK, HS, INC, SPREAD$\}$. We utilize the US data (on Y_t and X_t), gathered from the Federal Reserve Bank of Saint Louis database FRED spanning from January 1984 until December 2014. Table 5 in the "Appendix" provides the definitions and sources of the variables. The Augmented Dickey–Fuller and Phillips–Perron unit root tests indicate that WORK, UNEM, IP, and HS series are nonstationary in levels. The nonstationary variables (WORK, UNEM, IP, and HS) are considered in their gap forms[2] to assure the stationarity conditions of the models. Table 1 reports the unit root test of the level and transformed series.

Moreover, the stationarity conditions, regime change, volatility (noise), and distribution of series are important points for forecasting models. For the forecasted inflation series CPI, core-CPI, PCI, and core-CPI are considered in this paper: The break points are November 2008, January 1991, and September 1986, respectively, according to the minimum Dickey–Fuller t- statistics. The standard errors, which present volatility, are 3.10, 2.43, 6.04, and 6.57, respectively.

Skewness statistics indicate asymmetry and a non-normal distribution (Table 2). The descriptive statics present that the core-PCE series has leptokurtic distribution and the highest volatility and the core-CPI has platykurtic distribution and the lowest volatility. According to Yu et al. [51–53], machine learning models may give better results if the data have nonlinearity and noisy-type properties. Therefore, it is expected that the forecasting performance of machine learning is better than time series models for the core-PCE, and for core-CPI and vice versa.

3 Methodology

3.1 Autoregressive model and Naïve model

Traditionally papers written on forecasting economic variables benefit from Autoregressive Model (AR) and Random Walk (Naïve Model) to compare with more

[2] The gap is estimated as the difference between variable and Hodrick–Prescott (1997, HB) filtered trend, and the long-run trend is obtained by HP.

Table 1 Unit root tests of level and transformed series

	Level				Transformed			
	A: intercept		B: intercept with trend		A: intercept		B: intercept with trend	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
CPI	−0.26	−0.23	−2.75	−2.11	−12.02***	−11.60***	−12.56***	−11.73***
Core-CPI	−1.75	−2.75*	−2.07	−1.12	−1.43	−10.92***	−2.44	−12.92***
PCE	3.15	2.35	−1.79	−1.83	−23.69***	−23.42***	−25.07***	−24.30***
Core-PCE	3.91	2.98	−1.34	−1.52	−24.27***	−23.81***	−18.04***	−25.90***
IP	−0.71	−0.68	−2.50	−1.85	−5.99***	−4.43***	−5.99***	−4.42***
UNEM	−2.33	−2.09	−2.32	−2.18	−3.77***	−4.29***	−3.76**	−4.28***
INC	−26.09***	−24.93***	−26.45***	−25.34***	–	–	–	–
WORK	−1.12	−2.01	−2.29	−1.67	−4.55***	−3.69***	−4.54***	−3.69**
HS	−1.40	−1.78	−1.44	−1.89	−8.17***	−12.92***	−8.17***	−12.90***
SPREAD	−3.76***	−3.25**	−3.84**	−3.28*	–	–	–	–

The critical values are gathered from MacKinnon (1996) and are one-sided p values

The level section of all series is in level. On the other hand, in the transformed section, price series are the one-month inflation calculated by Yt = 1200[log Pt − log Pt − 1]. The nonstationary variables (WORK, UNEM, IP, and HS) are considered in gap form

* Indicates the level of significance at 10%

** Indicates the level of significance at 5%

*** Indicates the level of significance at 1%

Table 2 Descriptive statistics

	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Obs.
CPI	2.71	2.75	16.41	−21.44	3.10	−1.48	15.00	371
Core-CPI	2.74	2.74	9.90	−3.27	2.43	0.18	2.78	371
PCE	5.21	5.03	32.78	−24.52	6.04	−0.11	7.78	371
Core-PCE	5.51	5.32	40.45	−29.95	6.57	0.09	9.63	371
IP	0.00	0.06	4.43	−7.08	1.48	−0.93	8.97	372
UNEM	0.00	0.00	1.34	−1.18	0.37	0.50	5.14	372
INC	0.25	0.20	2.40	−2.60	0.48	−0.21	8.97	372
WORK	0.00	−67.97	2084.31	−2205.99	721.04	0.06	4.44	372
HS	0.00	−0.41	449.17	−341.21	97.87	0.32	5.00	372
SPREAD	1.44	1.45	3.61	−0.60	0.87	−0.04	2.23	372

recently developed ones. For instance, Mendez et al. [31] estimate an AR and a Naïve model to forecast output for European Union countries. We estimated the following equation for the AR model.

$$Y_t = \text{Constant} + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_t \quad (1)$$

The lags chosen by BIC criteria for the Autoregressive Model (AR) are as follows: Core-CPI (12), CPI (2), PCE (1), Core-PCE (5). These results are consistent with Berument et al. [5].

The Naïve model, which is also called as random walk model, is one of the common forecasting techniques and represented as follows:

$$Y_t = \alpha_1 Y_{t-1} + \varepsilon_t \quad (2)$$

where the residuals are white noise. If the coefficient is almost one, random walk is also known as efficient market hypothesis, which assumes that the data inherit all the information available in the market. So it assumes that it is not possible to forecast the future values by other economic indicators. It also assumes that the best price prediction is today's price (see also [29]).

3.2 Autoregressive distributed lag model

The autoregressive distributed lag (ARDL) model is an alternative model to test co-integration which enables to employ I(0) or I(1) variables together. It is developed by

Pesaran and Shin [36] and Pesaran et al. [37]. ARDL can be represented as:

$$\begin{aligned}\mathrm{INF}_t &= C + \sum_{k=1}^{l} A_k \mathrm{INF}_{t-k} + \sum_{k=0}^{m} B_k \mathrm{UNEM}_{t-k} + \sum_{k=0}^{o} C_k \mathrm{IP}_{t-k} \\ &+ \sum_{k=0}^{p} D_k \mathrm{WORK}_{t-k} + \sum_{k=0}^{q} E_k \mathrm{HS}_{t-k} + \sum_{k=0}^{r} F_k \mathrm{INC}_{t-k} \\ &+ \sum_{k=0}^{s} G_k \mathrm{SPREAD}_{t-k} + \varepsilon_t\end{aligned} \tag{3}$$

Inflation is estimated by its lags and other explanatory variables (UNEM, IP, WORK, HS, INC, SPREAD), and their lag orders for each variable are determined by ARDL bond test. The F-statistics critical values of bound test are given in Pesaran et al. [37]. The proper model is determined by ARDL bond test and with minimum Schwartz criteria.

3.3 Vector autoregressive regression model

Vector Autoregressive Model (VAR) has become a pervasive tool after the works of Sims [43, 44] and started to be used in inflation forecasting (see [22, 34]. In Eq. (4), Z_t is a vector of the endogenous variables (INF, UNEM, IP, WORK, HS, INC, SPREAD). Our unrestricted VAR(p) model can be represented as:

$$Z_t = C + \sum_{k=1}^{p} A_k Z_{t-k} + \varepsilon_t \tag{4}$$

C is the vector of the intercept term. A_k is the vector of coefficients, ε_t denotes the residuals, p is the lag order and is selected as one by Schwarz criteria.

3.4 k-Nearest neighbor model

The k-NN is a nonparametric method, which is used to predict the dependent variable according to the closest training examples. The predicted outcomes are memory based; therefore, they do not fit a model. If x_0 is an independent variable, there are k number of training points that are closest into distance x_0 point and then classify using majority vote among the k neighbors. The prediction performance is very sensitive to the selected value of k. If $k = 1$, then it is the nearest neighbor (NN) model. Although the k-NN has a simple algorithm, it is successful in a great number of regression problems. It is frequently well if every class contains many potential prototypes, and the decision boundary is very unbalanced [17]. In our experiments, we tried different k values and the best model is with a k value of 3.

3.5 Artificial neural network model

Another type of nonlinear models is Artificial Neural Network (ANN) model that is widely used in financial and economic studies and estimates the following equation as shown in Enders [12] and Mills [32] where $f_i(y_{t-1})$ may take different forms.

$$y_t = a_0 + a_1 y_{t-1} + \sum_{i=1}^{n} \alpha_i f_i(y_{t-1}) + \varepsilon_t \tag{5}$$

Adhiraki and Agrawal [2] use a hybrid method that is a combination of random walk (RW) and ANN and produce smaller RMSE. Hu et al. [19] estimate a PC for USA, Hong Kong, Japan and Taiwan by ANN and claim that it gives better results compared to RW. Hamdi and Aloui [16] provide a literature review of ANN to forecast crude oil prices. Co and Boosarawongse [9] explore relatively good results to forecast Thailand's rice export compared to Box–Jenkins ARIMA and Holt–Winters additive exponential smoothing methods. They claim that ANN is a nonlinear mapping system, not adaptive and renews its system. Feng and Zhang [13] emphasize the self-learning, self-organizing and self-adapting and experience-based properties of ANN and forecast Chinese GDP with a lower error. Kristjanpoller and Minutolo [23] improve the gold price forecasting performance of traditional GARCH by a hybrid ANN-GARCH specification. Laboissiere et al. [24] obtain a smaller forecasting error with multilayer perceptron compared to others like GARCH-Dynamic ANN with for Brazilian stock market. Singhal and Swarup [45] provide that ANN gives better results to forecast electricity prices. Panda and Narasimhan [35] explore superior forecasting performance of ANN compared to AR and RW for Indian Rupee/US dollar exchange rate. Lin and Yeh [25] suggest that ANN provides arbitrary function approximation and not relies on restrictive parametric assumptions and apply it to Taiwan options pricing. In our implementation of ANN, different values are tested and the best model has a learning rate 0.3 and momentum value 0.2 and one hidden layer with three neurons. Besides, we tried different activation functions as explained by Karlik and Olgac [20] and find the best one, which gives better results, i.e., high correlation coefficient and low mean absolute error.

3.6 Support vector regression model

Support vector regression (SVR) model is one of the machine learning techniques used in financial and economic time series forecasting. For example, Ye et al. [50] explore better results for to forecast Chinese inflation using SVR-type model compared to OLS. Sermpinis et al. [41] claim that GA-SVR improves forecasting of inflation and unemployment compared to RW and ARMA models. Sermpinis et al. [42] also apply SVR to exchange rates. One can refer to Chen and Hayi [8] and Anandhi and Chezian [4] for the details of SVR. While estimating SVR, many kernels are tried and the best one is the RBF kernel function and it is used in our experiments (see [46].

4 Empirical results

This paper compares the forecasting performance of widely used time series models with machine learning alternatives for the US inflation forecasts in different horizons. We apply two univariate (AR and Naïve) and two multivariate (VAR and ARDL) time series models and three machine learning models (ANN, k-NN and SVR) for the data spanning (machine learning) January, 1984 to December, 2013. In addition, we examine a simulated out-of-sample forecasting performance (testing data) for the year 2014. We employ seven different models (AR, Naïve, VAR, ARDL, ANN, k-NN, and SVR) to forecast four different inflation indicators, namely, CPI, Core-CPI, PCE, and Core-PCE in four different horizons (3 months, 6 months, 9 months and 12 months). In total, we assessed 112 different results.

We evaluate the forecasting performance by root-mean-square error (RMSE) at each forecast horizon.

$$\mathrm{RMSE} = \sqrt{\frac{1}{h}\sum_{i=1}^{h}(Y_i - \hat{Y}_i)^2} \tag{6}$$

where Y is observed, and $\hat{Y}$ is forecasted values for h horizon. Table 3 presents the RMSE for the results of all models for 3-month, 6-month, 9-month, and 12-month horizons. The lowest RMSE value shows the most precise forecast result. Therefore, k-NN gives the best forecasting performance for CPI with a RMSE value of 0.38 in the 3-month horizon. The overall scene presents that the forecasting performances of ARDL and SVR are superior to the other models. In other words, multivariate models perform better than univariate models. On the other hand, the VAR gives the most deviant forecast result with a 15.89 RMSE value for the 3-month horizon. In addition, the forecasting performance of VAR is the worst for all inflation series and horizons.

Following RMSE measure, we also provide goodness of fit statistic shown by R^2 (Eq. 8) for the results of all models for 12-month horizon which is obtained by regressing Y_t on $\hat{Y}_t$ as given by:

$$Y_i = \alpha_1 \hat{Y}_i + \varepsilon_i. \tag{7}$$

Since R is a type of correlation coefficient, its square R^2 usually lies between 0 and 1. (See [6, 39], p. 15). If R^2 is close to one, then the model fits the data better compared to the case where this coefficient is near zero.

$$R^2 = \frac{\hat{\beta}_1^2\left(\sum \hat{Y}_i^2\right)}{\sum Y_i^2 - \left(\sum Y_i\right)/n} = \frac{\sum (Y_i - \hat{Y}_i)^2 - \sum (\hat{\varepsilon}_i)^2}{\sum (Y_i - \hat{Y}_i)^2} \tag{8}$$

Table 4 shows these coefficients of determination statistics, and these R^2 values support the RMSE results for all the variables. According to Table 3 and 4, the best model for

Table 3 Pseudo out-of-sample forecasting RMSE results for 2014

Horizon	Root-mean-squared forecast errors							
	Inflation	AR	Naïv 12	ARDL	VAR	ANN	k-NN	SVR
Horizon 3	CPI	1.33	2.30	1.10	12.48	1.01	0.38*	0.97
	Core-CPI	0.84*	0.94	0.98	12.65	1.29	1.82	1.42
	PCE	5.39	6.12	0.81*	14.96	1.47	3.89	1.03
	Core-PCE	6.93	7.26	2.10	15.89	2.35	5.05	1.32*
Horizon 6	CPI	1.06	2.49	1.29	11.25	0.99	1.19	0.89*
	Core-CPI	1.18	1.28	1.08*	10.05	1.53	2.28	1.29
	PCE	4.11	4.71	0.62*	13.36	1.05	2.77	0.77
	Core-PCE	4.94	5.52	2.13	13.79	1.89	3.67	1.77*
Horizon 9	CPI	1.69	2.13	1.58	10.05	1.67	1.38*	1.61
	Core-CPI	1.20	1.18	1.08*	8.68	1.90	2.00	1.49
	PCE	3.67	4.36	1.20*	12.53	1.72	2.52	1.41
	Core-PCE	4.25	5.16	2.27	13.00	1.96	3.31	1.73*
Horizon 12	CPI	3.10	2.62	2.56*	8.89	2.66	2.72	3.11
	Core-CPI	1.25	1.18*	1.20	7.70	2.60	2.26	2.19
	PCE	3.82	3.98	1.85*	11.56	2.64	2.77	2.29
	Core-PCE	3.77	4.77	2.29	12.28	1.92	3.01	1.66*

* Indicates the lowest RMSE value which is the most precise forecast result

Table 4 Coefficients of determination (R^2) of models

Horizon	R^2 results of regression between actual and forecasted values							
	Inflation	AR	Naïve	ARDL	VAR	ANN	k-NN	SVR
Horizon 12	CPI	0.09	0.01	0.23*	0.08	0.11	0.17	0.09
	Core-CPI	0.75	0.78*	0.77	0.36	0.26	0.40	0.40
	PCE	0.53	0.39	0.91*	0.61	0.69	0.85	0.87
	Core-PCE	0.61	0.48	0.90	0.62	0.74	0.92*	0.92*

* Indicates the highest *R*-squared value which is the best goodness of fit

CPI is ANN, the best model for core-CPI and PCE are ARDL and the best model for core-PCE is SVR for the medium-term inflation forecasting. We plot forecast results of each inflation series to examine the forecasting performance of each model. This paper compares different time series and machine learning models for inflation forecasting. The aim is here to find the best model for different inflation forecasting measures. Hence, as it can be seen clearly from these tables, one can check which method is suitable for forecasting inflation values.

Figure 1 shows the forecasting results of CPI inflation for the 12-month horizon. When we compare the forecasting performance of CPI inflation based on RMSE results, the most precise model is the k-NN in 3-month and 9-month horizons, the SVR in the 6-month horizon, and the ARDL in the 12-month horizon. Therefore, forecasting performances of machine learning methods are comparable

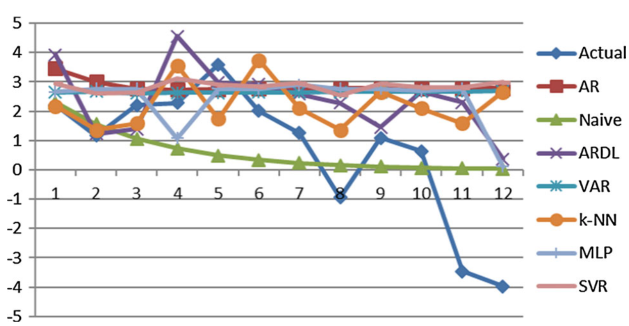

Fig. 1 Forecasted and actual values for CPI inflation in 2014, $h = 12$

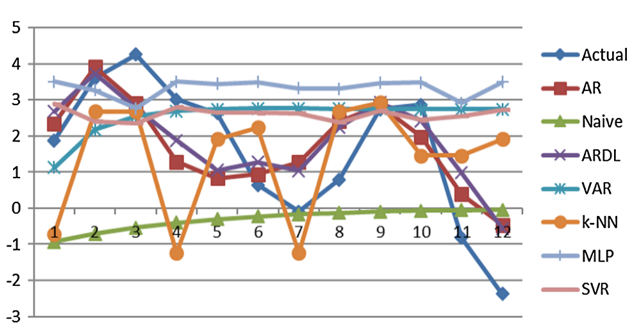

Fig. 2 Forecasted and actual values for Core-CPI-inflation in 2014, $h = 12$

with other models, but multivariate models are better in all horizons for CPI inflation and the most appropriate model is k-NN in the 3-month horizon.

Figure 2 shows the forecasting results of core-CPI inflation in the 12-month horizon. The most precise model is the AR in the 3-month horizon, ARDL in 6-month and 9-month horizons, and Naïve in the 12-month horizon. As a result, the average forecasting performance of ARDL model is better, but the best forecasting result is obtained by AR in the 3-month horizon for core-CPI inflation.

Figure 3 reveals the forecasting results of PCE-inflation for the 12-month horizon. The forecasting performance of ARDL is most precise for 3-month, 6-month, and 12-month horizons, and SVR is best for the 9-month horizon. Moreover, multivariate models have the finest results in all horizons.

Figure 4 shows the forecasting results of core-PCE inflation for the 12-month horizon. SVR clearly outperforms in all horizons.

When we compare the forecasting performances of all models for core and non-core versions CPI and PCE deflator as measures of inflation, we obtain the following results:

1. We observe that, for the CPI inflation forecasting, multivariate models give the most precise results in all horizons. Moreover, the k-NN and ANN machine learning models may be apply for the CPI inflation forecasting.
2. For the core-CPI and PCE forecasting, the ARDL is the best fitting time series model.
3. For the core-PCE forecasting, the SVR is the best model. In other words, out of sixteen conditions (four different inflation indicator and four different horizons), machine learning models provide more accurate forecasting results in seven conditions (SVR in 5 conditions and k-NN in 2 conditions) and the time series models are better in nine conditions (ARDL in 7 conditions, AR in 1 condition, Naïve 12 in 1 condition). Moreover, multivariate models give better results in fourteen conditions, and univariate models are better only in two conditions.

Consequently, the forecasting performances of the multivariate models are more accurate than univariate

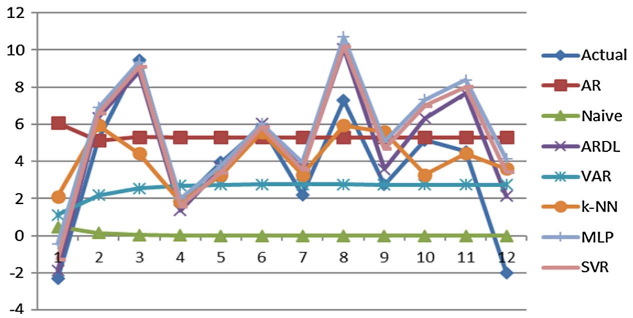

Fig. 3 Forecasted and actual values for PCE-inflation in 2014, $h = 12$

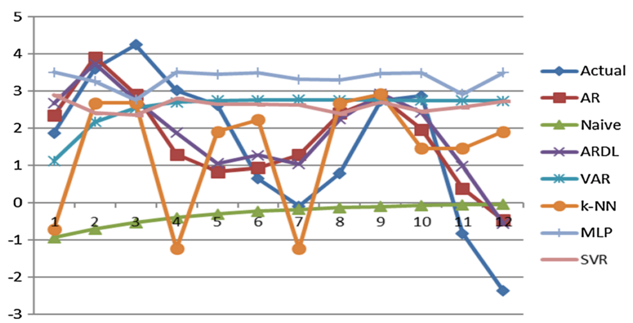

Fig. 4 Forecasted and actual values for Core-PCE-inflation in 2014, $h = 12$

models. Machine learning models prevail against time series models for the core-PCE, which has the highest volatility, and the time series models are better for the core-CPI inflation forecasting.

5 Conclusion

This study presents a comparison of univariate and multivariate time series models as well as machine learning models to forecast inflation (core and non-core versions CPI and PCE deflators). The empirical results demonstrate that (a) SVR outperforms the other models in forecasting core-PCE inflation. (b) The ARDL provides the lowest prediction error and the highest prediction accuracy for forecasting core-CPI inflation. (c) The machine learning models work better with more volatile and irregular series. According to the results, it can be concluded that there is no single best model to forecast inflation.

Acknowledgement We would like to thank Osman Topac for his helpful comments.

Appendix

See Table 5.

Table 5 Data sources

Variable	Definition	Code	Source
CPI	Consumer price index for all urban consumers: all items, index 1982–1984 = 100, monthly, seasonally adjusted	CPIAUCSL	FRED
Core-CPI	1-Consumer price index for all items excluding food and energy, monthly, not seasonally adjusted, index 2010 = 100	USACPICORMINMEI	FRED
PCE	Personal consumption expenditures, billions of dollars, monthly, seasonally adjusted annual rate	PCE	FRED
Core-PCE	Real personal consumption expenditures, percent change from preceding period, monthly, seasonally adjusted	DPCERL1M225NBEA	FRED
IP	Industrial production index, index 2007 = 100, monthly, seasonally adjusted	INDPRO	FRED
UNEM	Civilian unemployment rate, percent, monthly, seasonally adjusted	UNRATE	FRED
INC	Real personal consumption expenditures, percent change from preceding period, monthly, seasonally adjusted	DPCERL1M225NBEA	FRED
WORK	All employees: total nonfarm, thousands of persons, monthly, seasonally adjusted	PAYEMS	FRED
HS	Housing starts: total: new privately owned housing units started, thousands of units, monthly, seasonally adjusted annual rate	HOUST	FRED
SPREAD	The yield on the 5-year treasury bond minus the 3-month Treasury bill 5-year treasury constant maturity rate, percent, monthly, not seasonally adjusted	GS5, TB3MS	FRED and author's own calculations
	3-month treasury bill: secondary market rate, percent, monthly, not seasonally adjusted		

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