The Analysis of Inflation in the United States Under Global Crises Based on Personal Consumption Expenditures Price Index Data From 2019

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Abstract

With the high inflation under global crises, namely the pandemic and the Ukraine war, forecasting inflation is crucial to policy and decision-making. In light of the dramatic changes in commodity prices, this paper aims to build plausible Autoregressive-Integrated-Moving-Average (ARIMA) models for price indexes in the United States for forecasting inflation rates. This paper is based upon four price index time series: Personal Consumption Expenditures Price Indexes (PCEPI), core PCEPI, Consumer Price Index (CPI), and core CPI, while the latter two are used as robustness checks. Each time series contains 47 monthly observations ranging from January 2019 to November 2022. Models are selected based on interpretability and accuracy, which is measured by Akaike and Bayesian information criterion values. ARIMA(1,2,2) and ARIMA(0,2,2) are selected as best-performing models according to these criteria. It is predicted that the inflation and core inflation rates are likely to decrease in the next six months, as a result of continuously decreasing difference between the forecasted upgoing price indexes and that in the previous year. Yet the inflation is likely to remain at a high level compared to the 2% target, with inflation rate above 3.6% and core inflation around 5%. Based on these predictions, raising interest rates, reducing money supply, and improving social welfare are suggested.

Keywords: inflation, forecast, price index, global crises, time series

1. Introduction

Globally, with the prevailing pandemic and tumultuous political issues, there is a mutual upward trend in inflation across nations, with significant surge in consumer good and energy prices. The conflict between Ukraine and Russia has caused the global commodity prices to rise dramatically, primarily due to supply chain disruptions in the oil, gas, and wheat sectors (Caldara et al., 2022, A). Consequently, the inflation rate in the United States, as measured by Personal Consumption Expenditures Price Indexes (PCEPI), has risen above 6% since

December 2021, which is far higher than the pre-pandemic steady state of around 2%, as reported by the Federal Reserve Economic Data (FRED). High inflation rates lower economic growth, decreases stability, and adversely affect people's lives through the erosion of the real value of money and increased living costs. Responding to this soaring inflation, the Federal Reserve has opted to raise the interest rates to over 4.5%, aligning with similar measures taken by many other countries, in the hope of alleviating the high inflationary pressures.

In light of these, forecasting inflation rate is crucial to policymakers and decision-making, which are considered as the practical and economic significance of this paper. Predicting the inflation can also help with financial planning for both corporations and individuals. Individuals can mitigate risks and make better choices by considering the impact of future inflation on expenses, mortgage rates, unemployment, and other factors. It can also help corporations to estimate future expenditures, purchasing and storing raw materials, optimizing prices, and adapting investment decisions according to expected stock values (Ang et al., 2007).

This paper aims to predict short-term inflation rates based on analysis of price indexes time series data including PCEPI and core-PCEPI, which are widely considered as the key indicators for inflation rate in the US. After selecting the models according to model selection criteria, predictions of inflation rates in the next two quarters will be provided. One significance of this paper is that instead of using Consumer Price Index (CPI) or economic models such as the Philips curve, which are commonly used in past papers, it considers the relationship between PCEPI and the inflation in light of the dramatic price changes (Stock & Watson, 1999), (Ang et al., 2007). Additionally, it compares the forecasting results generated from PCEPI to that from CPI based on Autoregressive-Integrated-Moving-Average (ARIMA) models. This paper also considers interpretations of the fitted models and their forecasts under the effects of global crises. All of the above give some importance of this research.

This paper extends the research on inflation rate forecasting by exploring price indexes and the economic interpretations of the parameters in ARIMA models. Based on the time series patterns, model selection criteria, and models interpretations, this paper offers a comprehensive discussion of the application of ARIMA models in inflation analysis. The forecast results indicate that while inflation is expected to decrease, it will still remain at a relatively high level. These findings provide valuable economic insights, such as the potential need to raise interest rates, reduce the money supply in the market, and allocate additional subsidies to social welfare programs to mitigate the adverse effects of high inflation on low-income and volatile households.

The remaining sections of this paper are organized as follows. It begins with a review of relevant research and theories to provide a contextual framework, before moving to data description, selection and transformations. Model fitting and model selection for both PCEPI and core-PCEPI time series will be in the fourth and fifth sections respectively. After that, predictions of the two indexes in the upcoming six months will be generated using the selected models, and the forecasted inflation rates will be presented. A robustness check will then be conducted to check the reliability of the results using CPI and core-CPI data. Finally, it will sum up with discussions and conclusions.

2. Literature Review

Forecasting inflation has been a significant topic of discussion over the years. Researchers have dedicated substantial effort to find accurate methods for predicting inflation. And the recent shocks from pandemic and Ukraine war increase the volatility to global Gross Domestic Product (GDP) and inflation rates, making analysing and forecasting even more crucial.

Some researchers suggest that the geopolitical issues reduce GDP growth, boost inflation, with a greater probability of economic risks, based on analyses across countries and over the last century (Caldara et al., 2022, A), (Caldara et al., 2022, B). And other researchers indicate that both the covid pandemic and the Ukraine war are increasing the uncertainty in economy and business, with the Ukraine war acting as the most influential factor (Anayi et al., 2022).

ARIMA have gained widespread popularity because of their outstanding performance in capturing the patterns across time. And thanks to the famous Box-Jenkins methodology which has played a pivotal role in the development and refinement of ARIMA models, they have become one of the most powerful forecasting methods (Box et al., 2008).

The applications of ARIMA models in inflation forecasting started early. In the 1990s, some researchers proposed ARIMA models for the US inflation rate, in which the forecast was based on aggregated economic indicators, including unemployment, commodity prices, exchange rates and so on. They also pointed out that the Philips curve, which connects the future inflation with economic features, could provide better forecasts during 1970 and 1996 (Stock & Watson, 1999). However, it is important to note that these results may not be directly applicable to the current economic landscape. Later in their research about the difficulty in forecasting US inflation, they pointed out that a low-order autoregression described the inflation process well in the 1970s, but a decade later this approximation became less accurate, even with changes to the coefficients (Stock & Watson, 2007). These findings indicate that the choice of models and parameters is likely to vary over time, which motivated this paper to investigate the best-performing models for current time series data.

With the progressions in academic research, some innovations based on ARIMA models were developed. A hybrid model combining ARIMA with artificial neural network (ANN) to capture both the linear and non-linear patterns in real-life time series was proposed (Zhang, 2003). It is suggested that the prediction accuracy of ARIMA models could be improved by some hybrid models. In more recent studies about inflation forecasting, researchers incorporated ARIMA model with Generalized AutoRegressive Conditional Heteroskedasticity

(GARCH) as an extension when forecasting Pakistan's inflation, in which they applied ARIMA model to the conditional mean but GARCH model to the conditional variance (Qasim et al., 2021). In another research focusing on the inflation rate in Indonesia, researchers compared the performance of ARIMA and ANN models in forecasting inflation, and suggested that the ANN models performed better than the ARIMA models (Estiko & S., 2019). However, the applicability of ANN models to a relatively small dataset with less than 100 data points remains dubious.

In most cases, analysts attempt to forecast inflation based on its driving factors. For example, a study focusing on inflation forecasting in the based its analysis on exchange rate movements, noting that exchange rates played a dominant role in influencing UK inflation, particularly during the Brexit period, especially around the Brexit times (Nasir, 2020). And in the research forecasting the inflation rates in Pakistan, the analyses and predictions were based on CPI, which is considered as another indicator of inflation (Qasim et al., 2021). Interestingly, another research suggested that the inflation forecast based on surveys tend to be more accurate, by comparing inflation forecasts based on surveys, ARIMA models with CPI, and economic theories with GDP growth and unemployment rates (Ang et al., 2007). However, considering the current situations with the conflict and pandemic, it is reasonable to suggest that the prices in global commodities, such as food and energy prices, are the key factors that drive the inflation in the US. Therefore, in this paper, the PCEPI and core-PCEPI are regarded as the key indicators of inflation rates, and ARIMA models will be utilised to fit the price indexes and generate predictions.

3. Data Description and Visualization

In this paper, the Personal Consumption Expenditures Price Index (PCEPI) and core-PCEPI (PCEPI excluding food and energy) data between Jan 2019 and Nov 2022 in the US are the key time series for analyses. Being preferred and widely used by researchers and governments, both PCEPI and core-PCEPI capture and represent the level of inflation, encompassing a wide range of consumer expenses. It is suggested that PCEPI may provide more accurate forecasts of inflation rate compared to Consumer Price Index (CPI) (Caldara et al., 2022, A; U.S. Bureau of Labor Statistics, 2011). Comparing to PCEPI, core PCEPI excludes energy and food, and is less volatile. Short-term forecast of inflation in the US will be provided based on both indexes, and a robustness check will be conducted using CPI and core-CPI data. All the data in this paper are collected from FRED.

The two time series data are seasonally adjusted to eliminate the seasonal patterns. Both the PCEPI and core-PCEPI time series consist of 47 observations, as shown in Figure 1. The (core-)inflation rate is calculated by the percentage change of the year-on-year (core-)PCEPI.

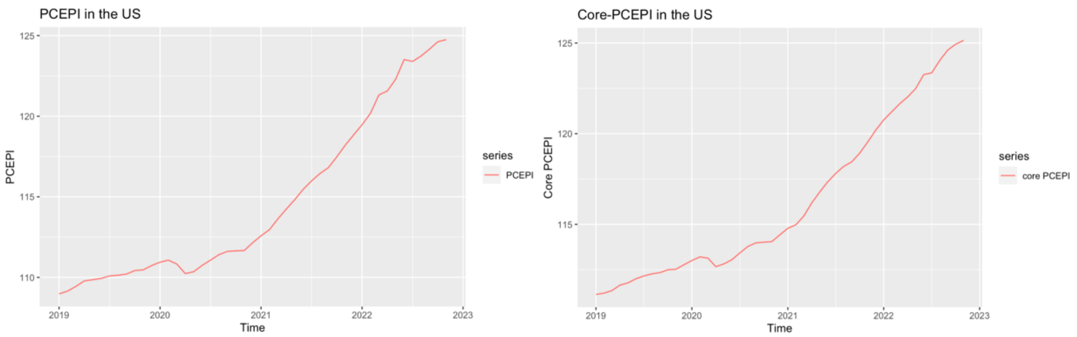

Figure 1: PCEPI and core-PCEPI from 01/2019 to 11/2022

Data: PCEPI and core PCEPI data from the U.S. Bureau of Economic Analysis between 01/2019 to 11/2022.

In this paper, log transformations are applied to stabilize variance in the two time series, and the transformed data are plotted in Figure 2.

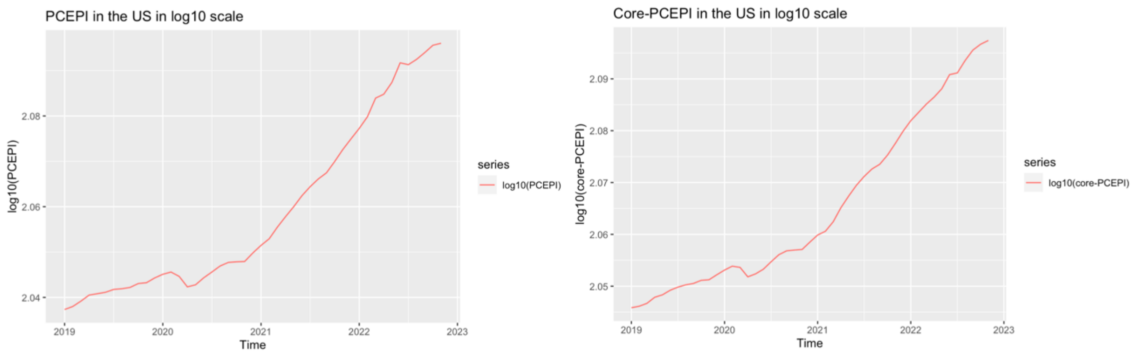

Figure 2: Log_{10}(PCEPI) and log_{10}(core-PCEPI) from 01/2019 to 11/2022

After consideration, it is decided to fit the models using the entire time series in both the PCEPI and core-PCEPI cases, instead of dividing them into training and test sets. Although in many cases the time series data are separated into training set and test sets, commonly 80% and 20%, there are important information in the last 20% of the time series data regarding recent trend, economic shocks and fluctuations, which are crucial in making accurate forecasts. Isolating the last part of the time series would lead to loss of important up-to-date information, yet randomly selecting data as training or tests would lead to a loss of time series patterns and a complexity in data structure. So, in the following analyses, the entire time series are used for model fittings.

4. Model Fitting

Considerable amount of previous research highlighted the wide application of ARIMA models, especially on economics and financial time series analysis. Building on the foundation laid by previous researchers, this paper proposes ARIMA models with different parameters for fitting and forecasting the PCEPI and core-PCEPI data.

ARIMA stands for Auto-Regressive Integrated Moving Average with parameters p, q, and d. Lags of the stationary series, p, are called "autoregressive" (AR) terms. Lags of the forecast errors, q, are called "moving average" (MA) terms. While the I, which represents "integrated", describes the orders of differencing(d) required to stationarise the series. ARIMA has the forecast equation:

$$\widehat{y_t} = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \#(1)$$

where ϕ denotes the autogressive coefficients, and θ denotes moving average coefficients. On the other hand, y_t represents the actual value at t^{th} time period, while e_t represents the error sequence which is assumed to be white noise that has a mean of zero and a constant variance.

According to the plot of $log_{10}(PCEPI)$ and $log_{10}(corePCEPI)$ (Figure2), it is evident that both data do not exhibit stationary patterns. So the analysis started with taking differences to make the data stationary using Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The result of first order differencing is not satisfactory as the test statistics of KPSS reject the null hypothesis that the data being stationary, as shown in Figure 2. Although for most of the cases, taking first order difference could stationarise the inflation data, taking second order differences to further stationarise the time series is required. This decision is motivated by the significant changes in the price index observed in recent years compared to earlier periods. Likewise, similar approaches are conducted for core-PCEPI. Since core-PCEPI and PCEPI have generally identical trend overall, it is reasonable to use second-order differencing to stationarise both time series.

4.1 Fitting $log_{10}(PCEPI)$ Data

Having decided the order of differences to stationarise both series, this paper starts with analyzing and fitting the differentiated $log_{10}(PCEPI)$ time series. In order to propose a reasonable ARIMA model for $log_{10}(PCEPI)$, it is important to refer to the autocorrelation and partial autocorrelation plots to find feasible values for p and q (Box et al., 2008).

Based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots in Figure 4, values 2 and 1 for parameters p and q are selected respectively, as there are corresponding significant decays at the second lag and the first lag in the ACF and PACF plots.

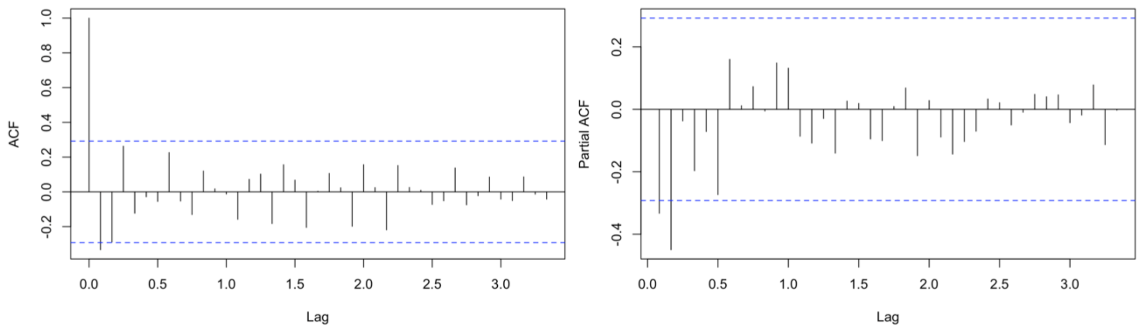

Figure 3: ACF and PACF for log10(PCEPI) data

Hence ARIMA model with parameters 2,2,1 is proposed, and the estimated $log_{10}(PCEPI)$, denoted as $\widehat{y_t}$, can be expressed as:

$$\frac{d^2}{dt^2}\widehat{y_t} = \mu + \phi_1 \frac{d^2}{dt^2}(y_{t-1}) + \phi_2 \frac{d^2}{dt^2}(y_{t-2}) - \theta_1 e_{t-1}$$

which indicates that our predicted $\widehat{y_t}$ will be based on the historical value of y_{t-1} and y_{t-2}, while considering the forecast error at lag one.

The model is economically reasonable, because the second-order differenced PCEPI series is influenced by historically differenced price index in the previous two months and forecast errors from one month prior. The performance of ARIMA(2,2,1) is quite satisfactory, which is supported by the residuals check on the left in Figure 5.

(2)

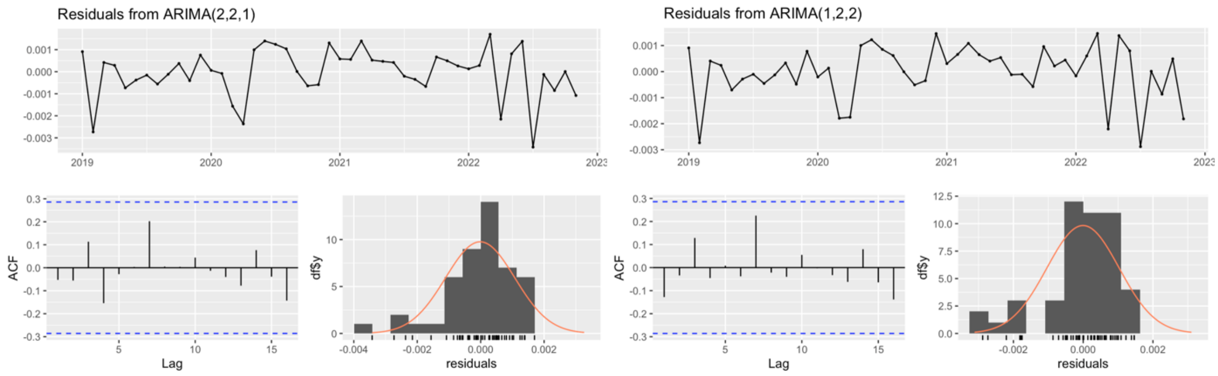

Figure 4: Residuals checks for ARIMA(2,2,1) and ARIMA(1,2,2)

With a relatively decent forecast performance by ARIMA(2,2,1), this paper moves on to check whether this is the best-performing model. . However, upon employing the auto.arima() function, an alternative model, ARIMA(1,2,2), was identified as the best fitting model, which has forecasting function as follow and fitting coefficients in Table 1.

$$\frac{d^2}{dt^2}\widehat{y_t} = \mu + \phi_1 \frac{d^2}{dt^2}(y_{t-1}) - \theta_1 e_{t-1} - \theta_2 e_{t-2}\#(3)$$

Table 1. Coefficients for ARIMA(1,2,2)

ARIMA(1,2,2)	$\boldsymbol{\phi_1}$	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$
Coefficients	-0.5750	0.1956	-0.7275
Standard errors	0.1563	0.1366	0.1143

This model is plausible in light of the recent events such as covid shock and Ukraine war. ARIMA(1,2,2) model mainly considers data from the last time period and errors from the last two periods. Given the significant fluctuations in inflation, forecasts based on historical values are expected to carry larger uncertainties. Consequently, the choice of ARIMA(1,2,2) is recommended as it places greater emphasis on the moving average terms compared to the ARIMA(2,2,1) model, thereby accounting for the potential volatility in inflation more effectively.

4.2 Fitting $\boldsymbol{log_{10}}$(core$\boldsymbol{PCEPI}$) Data

Following similar processes in analyzing $log_{10}(PCEPI)$ data, reasonable p and q values can be identified after stabilizing the data through second-order differencing. From the ACF and PACF plots in Figure 6, values for p and q are selected to be 5 and 2, because there is a significant decay at the second lag in the ACF plot, and we take the fifth spike as the significant lag in the PACF plots.

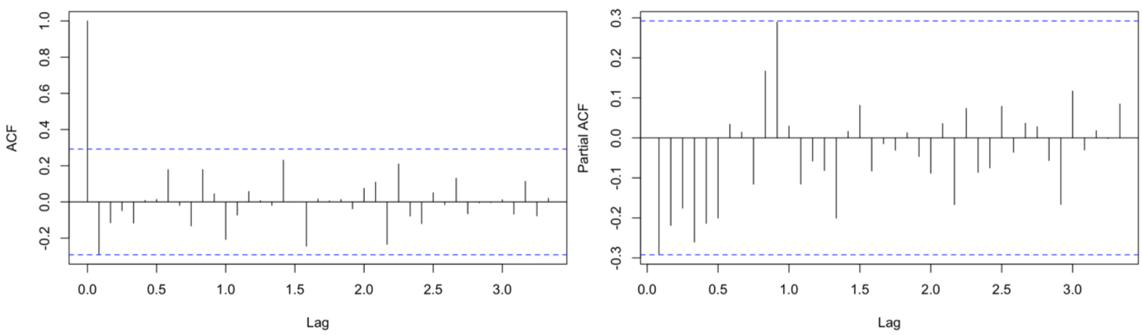

Figure 5: ACF and PACF for log_{10}(core-PCEPI) data

Based on the selection of values for parameters p and q, it is plausible to consider ARIMA(1,2,2) as a potentially well-performing model. The interpretation of this model is that t utilizes the second-order differences of the core-PCEPI data from the previous month, while taking into account the errors in fitting the data from the past two months. The forecasting function is:

$$\frac{d^2}{dt^2}\widehat{y_t} = \mu + \phi_1 \frac{d^2}{dt^2} y_{t-1} - \theta_1 e_{t-1} - \theta_2 e_{t-2} \#(4)$$

ARIMA(1,2,2) has a p-value of 0.78 from the residuals test. From the ACF plot in Figure 7, it is clear that there are no significant spikes. These all suggest that ARIMA(1,2,2) is a feasible model. However, this choice of parameters are identical to the best model for PCEPI, which exhibits a slight different trend to core-PCEPI. This suggests that there might be better models for core-PCEPI.

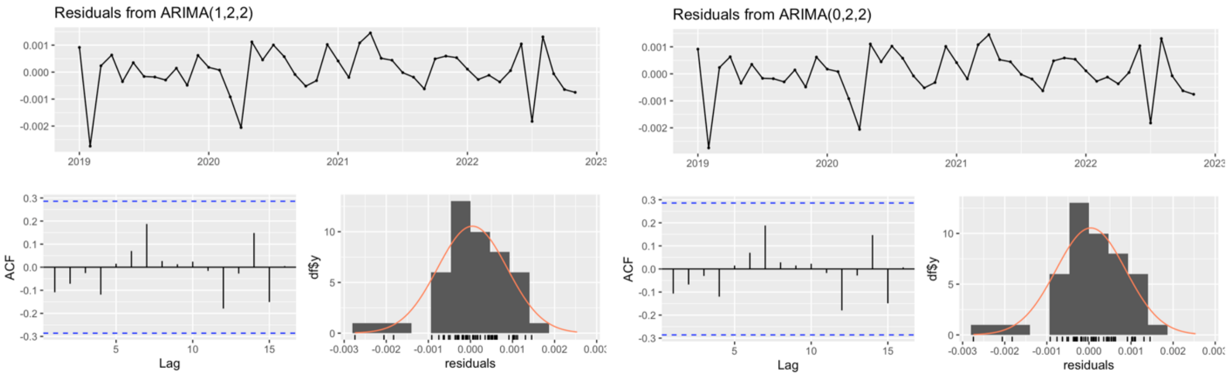

Figure 6: Residuals tests for ARIMA(1,2,2) and ARIMA(0,2,2)

By using auto.arima() function in R, model ARIMA(0,2,2) appears to perform better, with zero lag in the autoregressive part compared to the previous ARIMA(1,2,2) model. This selection of parameters also agrees with the autocorrelation plots, and seems to be more sensible as we are estimating the second-order differenced value at time t based on the error terms from the last two months only, which is plausibly true because the unstable food and energy prices were removed, making core-PCEPI steadier. The corresponding forecasting function of ARIMA(0,2,2) is as follows, with coefficients in Table 2.

$$\frac{d^2}{dt^2}\widehat{y_t} = \mu - \theta_1 e_{t-1} - \theta_2 e_{t-2} \#(5)$$

Table 2: Coefficients for ARIMA(0,2,2)

ARIMA(3,2,2)	$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$
Coefficients	-0.5354	-0.2212
Standard errors	0.1442	0.1362

The test of residuals of ARIMA(0,2,2) model shown in Figure 7 suggests that the residuals follows a white noise process and thus it is another feasible fitting method.

5. Model Selection

5.1 Model Accuracy Measures

Given the various proposed feasible models for both $log_{10}(PCEPI)$ and $log_{10}(\text{core}PCEPI)$ time series, the best-fitting models are selected based on several different criteria measuring the accuracy of each fitted models. Five model selection criteria described below are used.

Mean absolute percentage error (MAPE) and root mean square error (RMSE) are considered as important criteria for model performance. RMSE is the root-mean-square error and is scale dependent. For the PCEPI time series, there are multiple spikes where the index value increases more than expected, which might cause RMSE to have a poor measurement.

More commonly used accuracy measures for ARIMA models are Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and corrected AIC (AICc). Given various possible models for the data, AIC estimates the quality of each model, relative to others. Thus, AIC provides a robust measurement for model selection. Comparing to AIC, AICc adds a penalty term, and it is commonly used for model selection when there are relatively less samples. Furthermore, BIC penalize models for using more parameters, whereas AIC prefer the model which fits the high-dimensional data most sufficiently. In most cases, AIC, AICc, and BIC agree on model preferences, and are used to cross-examine the performance of a model. Give the above, this paper will take AIC, AICc, and BIC as decisive criteria.

5.2 Model Performance

5.2.1 For PCEPI

Table 3. Accuracy measures of models for log_{10}(PCEPI)

	AIC	BIC	AICc	RMSE	MAPE
ARIMA(2,2,1)	-483.68	-476.46	-485.10	0.001081	0.038835
ARIMA(1,2,2)	**-488.32**	**-481.09**	**-487.32**	0.001025	0.037373

From Table 3 it is evident that the ARIMA(1,2,2) model exhibits superior performance compared to the other models, as indicated by its lower AIC, BIC, and AICc values. At the same time, it also has smaller RMSE and MAPE values, further supporting its higher accuracy. Thus it can be concluded that the ARIMA(1,2,2) model outperforms the other model.

5.2.2 For Core-PCEPI

Table 4: Accuracy measures of models for log_{10}(core-PCEPI)

	AIC	BIC	AICc	RMSE	MAPE
ARIMA(1,2,2)	-514.67	-507.45	-516.08	0.0008222	0.029400
ARIMA(0,2,2)	**-516.67**	**-511.25**	**-516.08**	0.0008222	0.029430

From Table 4, it suggests that the ARIMA(0,2,2) model performs better in terms of model selection criteria. Thus these suggest that the ARIMA(0,2,2) has better performance.

6. Results

Using the selected models, forecasts of two price indexes in the next the six-months are generated, as plotted in Figure 8.

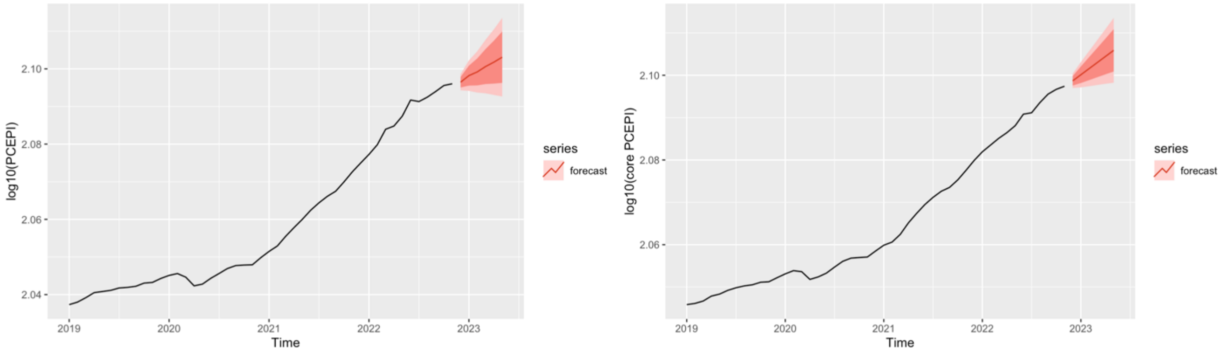

Figure 7: Forecasted log_{10}(PCEPI) and log_{10}(core-PCEPI) with prediction intervals

As we can see from Figure 8, core-PCEPI has smaller prediction intervals than PCEPI. This discrepancy can be attributed to the rising prices of food and energy around the globe. Since PCEPI contains those within its calculation, it is more volatile towards price changes in food and energy. Given the current geopolitical conflict, the unstable of food and energy markets lead to greater price fluctuations. As a result, the prediction intervals for PCEPI are wider, indicating larger uncertainties in forecasting.

Inflation rates based on both PCEPI and core PCEPI can be calculated after converting the predicted log-scale values back into the original scale using the following formulas:

$$10^{log_{10}PCEPI} = PCEPI\#(6)$$

$$10^{log_{10}core\ PCEPI} = core\ PCEPI\#(7)$$

Using these formulas above, the point forecasts and prediction intervals for both PCEPI and core-PCEPI are shown in Table 5 and Table 6.

Table 5: Forecasted values and prediction intervals of PCEPI

Month	Point forecast	95% upper PI	95% lower PI
Dec 2022	124.8652	125.4782	124.2553
Jan 2023	125.3711	126.5452	124.2080
Feb 2023	125.6552	127.2484	124.0819
Mar 2023	126.0688	128.1498	124.0217
Apr 2023	126.4095	128.9722	123.8977
May 2023	126.7939	129.8792	123.7819

Table 6: Forecasted values and prediction intervals of core-PCEPI

Month	Point forecast	95% upper PI	95% lower PI
Dec 2022	125.5108	125.9986	125.0248
Jan 2023	125.9283	126.7976	125.0649
Feb 2023	126.3471	127.5597	125.1461
Mar 2023	126.7674	128.3218	125.2318
Apr 2023	127.1891	129.0941	125.3121
May 2023	127.6121	129.8807	125.3832

Although PCEPI and core PCEPI are key indicators of inflation, they do not directly represent the inflation rates. Thus the corresponding inflation and core-inflation rates are calculated using the following formula:

$$Inflation\ rate\ at\ month\ t: \quad r_t = \frac{Y_t - Y_{t-12}}{Y_{t-12}} \#(8)$$

where Y_t is the PCEPI (or core-PCEPI) at month t.

Table 7: Forecasted inflation and core-inflation

Month	Inflation (PCEPI)	Core-inflation (Core-PCEPI)
Dec 2022	5.069%	4.424%
Jan 2023	4.940%	4.279%
Feb 2023	4.558%	4.243%
Mar 2023	3.913%	4.206%
Apr 2023	3.987%	4.228%
May 2023	3.674%	4.183%

According to the forecasted inflation rates in Table 7, both the inflation and core-inflation rates are expected to decrease in the forecasted period, but the former is likely to decrease faster than the later. And at around March 2023, the inflation rate is predicted to drop below the core-inflation rate. These predictions are consistent with the observed trends in crude oil and food prices. Following the initial surge in prices when the Ukraine war began in early 2022, crude oil and food prices have been relatively stable. This stability, combined with a decrease in year-on-year price differences, supports the forecasted decrease in both inflation rates. Although both inflation rates will drop, they will still remain at a relative high level compared to the 2% target, hovering around 4%. These trends are clearly visible in Figure 9.

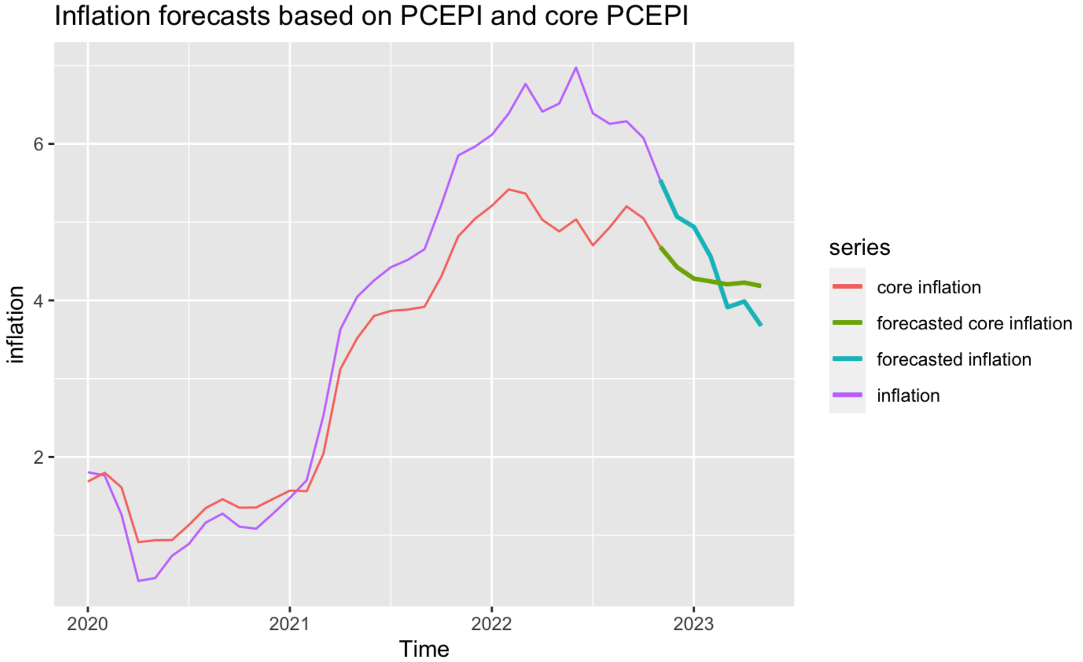

Figure 8: Forecasted inflation and core inflation in the next 6 months

7. Robustness Check

To assess the robustness of the forecasting results, similar processes are applied to CPI and core-CPI data in the US during the same time period (Figure 10). CPI is the city average Consumer Price Index for All Urban Consumers on all items, and core-CPI is chosen as the CPI less food and energy. Compared to PCEPI, CPI is produced by the Bureau of Labor Statistics(BLS), and measures the change in the "out-of-pocket expenditures of all urban households", which is also different from PCEPI which focus the expenditures on goods and services, according to U.S. Bureau of Labor Statistics.

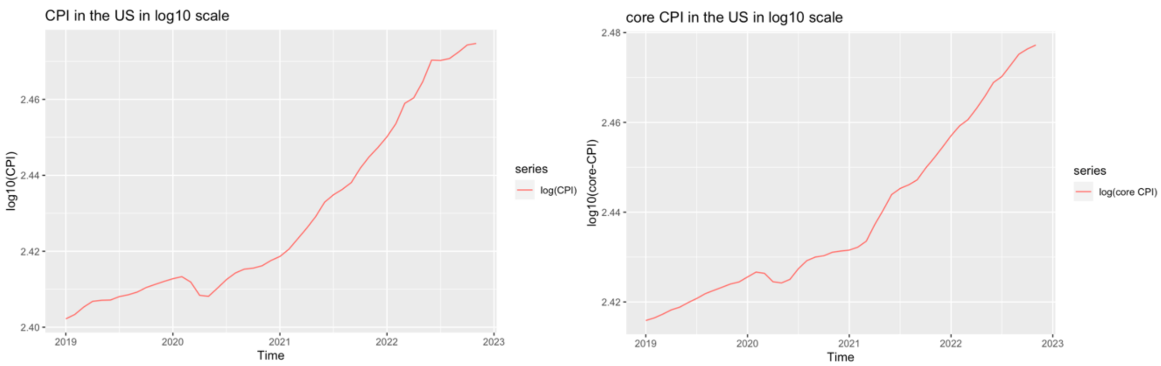

Figure 9: Log10(CPI) and log10(core-CPI) data from 01/2019 to 11/2022

Source: log scale of CPI and core CPI data from the US Bureau of Labor Statistics between 01/2019 to 11/2022

After log-transformation, similar to PCEPI and core-PCEPI data, second-order differences are required to stationarise both time series. After that, ARIMA(2,2,3) and ARIMA(3,2,4) are proposed for $log_{10}(CPI)$ and $log_{10}(\text{core}CPI)$ according to Figure 11 and Figure 12. ARIMA(0,2,3) is recommended by the auto.arima() function for both series, with smaller parameters.

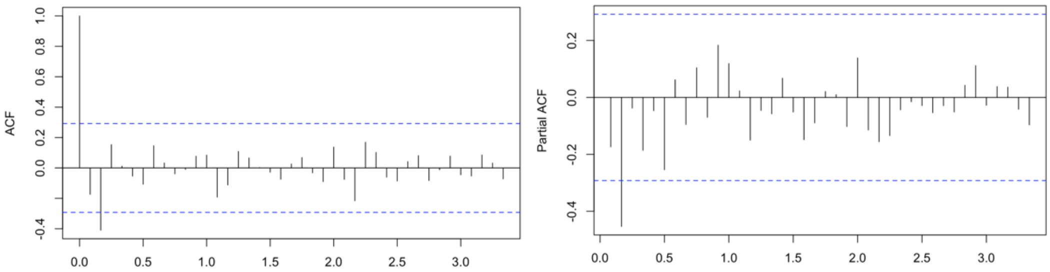

Figure 10: ACF and PACF of second-order differentiated log_{10}(CPI)

Figure 11: ACF and PACF of second-order differentiated log_{10}(core-CPI)

By comparing the AIC, BIC, and AICc values among these models, ARIMA(0,2,3) is selected for fitting CPI an core-CPI. And following similar processes, the forecasts of CPI and core-CPI are plotted in Figure 13, and their corresponding inflation rates are calculated in Table 8 and plotted in Figure 14.

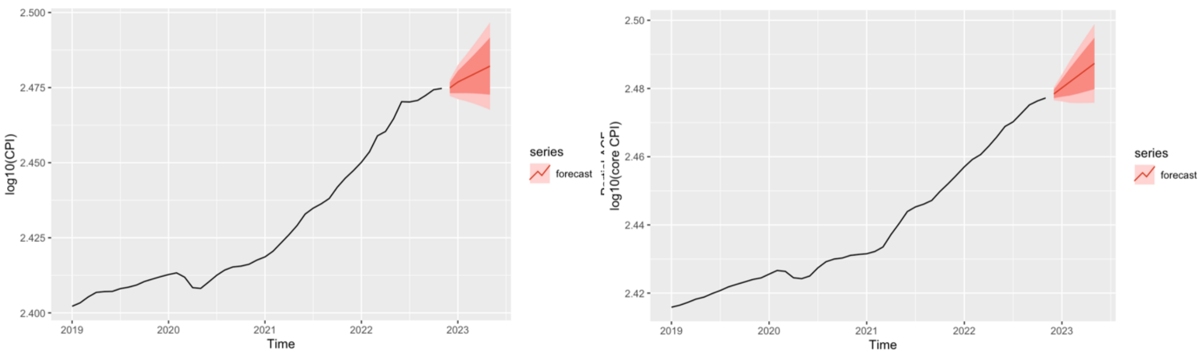

Figure 12: Forecasted log_{10}(CPI) and log_{10}(core-CPI) with prediction intervals

Table 8. Forecasted inflation and core-inflation based on CPI and core-CPI

Month	Inflation (CPI)	Core-inflation(Core-CPI)
Dec 2022	6.547%	5.750%
Jan 2023	6.339%	5.568%
Feb 2023	5.820%	5.454%
Mar 2023	4.843%	5.498%
Apr 2023	4.816%	5.346%
May 2023	4.122%	5.099%

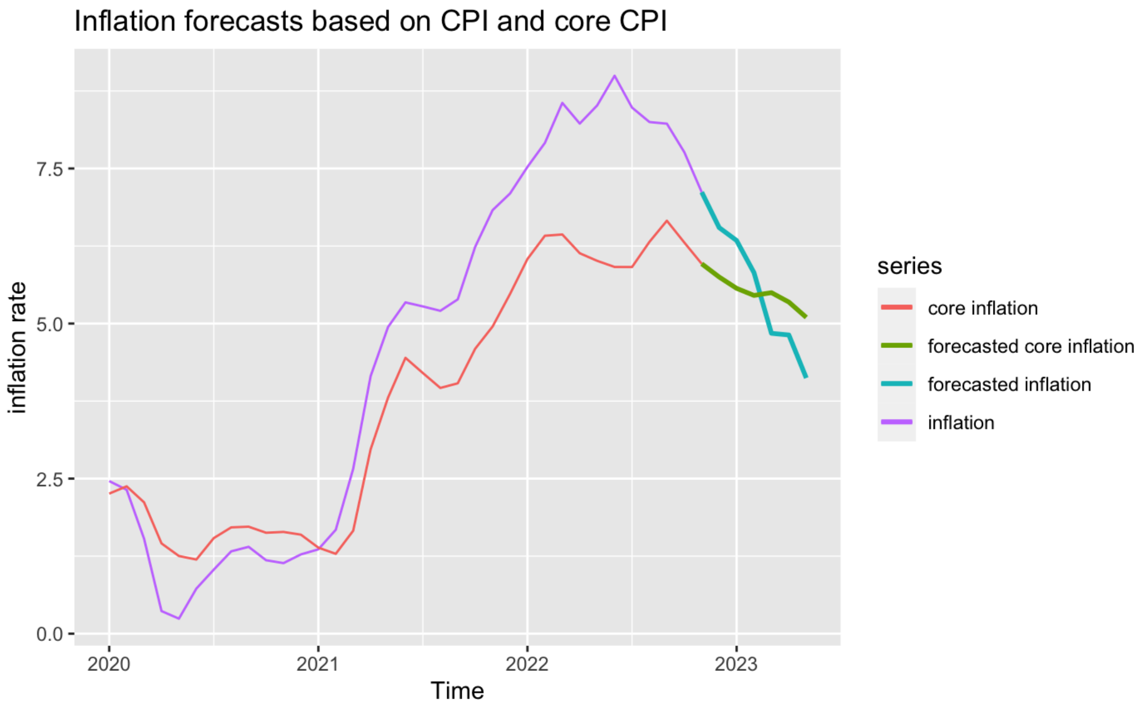

Figure 14: Forecasted inflation and core-inflation based on CPI and core-CPI

By comparing the predicted trends of inflation rates in Figure 9 and Figure 14, it can be observed that the forecasted 6-months inflation rates (blue lines) based on PCEPI and CPI are generally similar. Their decreasing trend agree on each other, with similar scale of decrease. At the meantime, the core inflation rates based on core-PCEPI and core-CPI (green lines) also agree on similar trends. Both of them are predicted to decrease with a slight increase in early 2023, although the one based on core-CPI tends to have larger fluctuation. All in all, the outcomes from this robustness check using (core-)CPI data do not go against the previous results using (core-)PCEPI, providing additional support for the reliability of the methods and forecasts presented in this paper.

8. Discussion

The analyses and forecasts in this paper are conducted under the assumption that the economy conditions will be generally stable in the prediction period, however the actual inflation may be affected by unpredictable policies or shocks in geopolitical issues. These external factors may introduce additional variability and uncertainty into the inflation dynamics, potentially impacting the performance of the selected models. The parameters of the best-fit models are likely to change according to the variation of time series patterns, which is supported by the fact that the best-performing models for inflation data vary considerably in previous research (Stock & Watson, 2007), (Qasim et al., 2021).

In this paper, pre-pandemic price index data are not included as they exhibit a different trend compared to the ones from January 2019 to November 2022, which is shorter than some of the sampling periods in previous research. For example, 684 monthly inflation data ranging from 1962 to 2019 are considered in the study of Pakistan (Qasim et al., 2021). Including a longer sample period and more observations can contribute to a better model fitting and might enable the use of machine learning, yet the price indexes and inflation trends are likely to vary across time due to crises and policies, and observations before 1980 have a risk of being outdated.

Some researchers proposed hybrid methods combining ARIMA with other models, such as refitting the residuals by ARIMA or machine learning models in order to give a better forecast (Zhang, 2003), (Estiko & S., 2019). Yet refitting the residuals would cost a huge loss of the level of model interpretability, and some neural network models such as ANN require a larger amount of data points, which is not applicable in this paper. Future research could focus on comparing the performance of those hybrid models when analyzing inflation data with larger datasets.

9. Conclusion

Motivated by increasing inflation across the globe, this paper studies up-to-date time series data of PCEPI and core-PCEPI in the US, covering the period from 2019 to the present. To provide a 6-mongths forecast for inflation, the time series are pre-processed through log-transformation, and various economically reasonable ARIMA models are proposed and examined to fit $log_{10}(\text{PCE}PI)$ and $log_{10}(\text{coreP}CEPI)$ based on analyses of the trend and fluctuations of the time series. Then by comparing the level of accuracy considering AIC and BIC as key criteria, ARIMA(1,2,2) and ARIMA(0,2,2) are selected as the best-fitting models for PCEPI and core PCEPI time series respectively. Inflation forecasts are then generated based on the predicted values of both indexes for the next 6 months. For both the inflation and core-inflation derived from PCEPI and core-PCEPI, a decreasing trend is predicted. It is predicted that the inflation will drop from 5.53% in Nov 2022 to around 3.7% in May 2023. A slower decrease from 6.08% in Nov 2022 to around 5% in May 2023 is predicted for core inflation. To ensure the robustness of the results, a thorough robustness check is conducted using CPI and core-CPI time series data. The findings from this check align with the results obtained from PCEPI, further supporting the reliability and validity of this research.

Overall, the short-term inflation forecasts provided in this paper offer valuable insights into the potential effects of geopolitical issues and the pandemic. These forecasts can assist policymakers and decision-makers in making informed decisions and formulating effective strategies for the future.

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