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Project Report
Econ 612
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Forecasting CPI for All Urban Consumers: Airline Fares in U.S. City Average

In recent years, some of the worst economic news in the U.S. comes from prices. Consumer price index (CPI) fell dramatically by 1.22 percent in just 2 months from Feb 2020 to Apr 2020 because of the Covid-19 Pandemic. After Fed decided to revitalize the economy through aggressive fiscal and monetary policies, prices skyrocketed. As travel restrictions have been lifted and vaccination rate steadily increases, people's demand for airline travels rises. Meanwhile, a combination of airline companies' slow adjustment to the increasing demand, increasing oil price due to the Ukraine war, and higher operation cost results in soaring in price of flight tickets. Where the price of airline fares go remains mysterious.

In this project, I will employ time series econometric tools to analyze the series of CPI Airline and make forecast for the following year. My methodology of this forecasting project consists of 6 stages: data description, checking for unit root, data transformation, model specification and causality test, model selection, and forecast. For data description, I will specify characteristics of the variable – whether it's collected by levels or percentage change – and describe historical data. For unit root check, I will use Augmented-Dickey Fuller (ADF) test to check whether data is stationary. For data transformation, I will transform original data to the one that econometric theory can apply; original non-stationary data of levels will be changed to growth rates and seasonally not adjusted data will be De-seasoned. For model specification and causality test, Granger or predictive causality test will be used to check causal relationship between different variables in specified models. For model selection, the best predictive model will be selected by Akaike information criterion (AIC). Finally, the last step is to use the best predictive model to forecast the series for the following year, 12 forecasting horizons included.

The original serial data of CPI Air pulled from FRED are measured by levels. Historical times series of CPI Air data shows a general upward trend, but it's not clear if it is a linear or non-linear trend just by visual inspection. But as tempting as it may be to directly work with levels, classical Least Square results will not be applied to the estimates if we just regress levels on time since data may be non-stationary and have a unit root. Therefore, in the next stage, I will check if the series has a unit root. It is worth noticing that, if we compare CPI Air to CPI, we will find that CPI Air data have sharper upward and downward spikes, and thus more volatile. This difference will make forecasting CPI Air more challenging in the later stage.

Since econometric theories need stationary data to be applied to, we first check if the CPI Air data is stationary through ADF test. The result, h = 0 and p-value is large, of ADF test suggests that we fail to reject the null hypothesis that CPI Air has a unit root, and then CPI Air data is non-stationary. So, we need to make transformation of the original data from levels to, for example, growth rate or differenced data.

Before we can engage in working with possible models, we need to conduct data transformation. As mentioned above, since CPI Air data has a unit root, we decide to transform the data from levels to growth rate using the formula:

$$Growth\ rate\ at\ t = \frac{y_t - y_{t-1}}{y_{t-1}}$$

In order to better forecast CPI Air, I also find some leading indicators – variables which reduce the mean squared errors (MSE) of multi-step forecast error. They are Producer Price Index by Commodity: All Commodities (PPI), New Privately-Owned Housing Units Started: Total Units

(Housing Starts), and University of Michigan: Consumer Sentiment (Consumer Sentiment). They are selected based on economic theories as PPI affect the supply-side of airline industry and Housing Starts and Consumer Sentiment are indicators of the demand-side of airline industry. Since some of them are measure by levels and some of them are measured by percentage change, they have different time span, and some of them are seasonally adjusted and the others are not, we need to convert them to the growth rates, De-season the seasonally unadjusted ones, and restrict them to the same time span. After we have done with data transformation, we will specify our models and apply tests to check causal relationship.

In this stage, different models with different leading indicators and CPI Air will be tested to see which leading indicators form a predicative causal relationship with CPI Air and the ones that have causal relationship with CPI Air will be candidate models for our forecast. First and foremost, we need a baseline AR (12) model for CPI Air to compare results from models with leading indicators.

Table 1: Baseline AR (12) Model

Linear Regression Model:
y ~ 1 + cpi_1 + cpi_2 + cpi_3 + cpi_4 + cpi_5 + cpi_6 + cpu_7 + cpi_8 + cpi_9 + cpi_10 + cpi_11 + cpi_12

	Estimate	SE	t-Stat	p-Value
Intercept	0.0020719	0.0012133	1.7077	0.0885
x1	0.55827	0.051396	10.862	3.8e-24
x2	-0.40347	0.058929	-6.8467	3.0062e-11
x3	0.18581	0.062464	2.9746	0.0031187
x4	-0.19325	0.06312	-3.0617	0.002356
x5	0.064736	0.063317	1.0224	0.30723
x6	-0.10595	0.063166	-1.6773	0.094301
x7	0.075549	0.063233	1.1948	0.23291
x8	-0.18589	0.063646	-2.9207	0.003698
x9	0.075413	0.063692	1.184	0.23713
x10	0.00833	0.063262	0.13167	0.89531

x11	0.045292	0.060663	0.74661	0.45575
x12	0.007296	0.055596	0.13123	0.89566

According to table 1, among significant lags of CPI Air which are lags from 1 to 4, lag 2 seems to be the most important as it has the largest estimate coefficient and smallest p-value. This result is crucial in selected best model of forecast. After analyzing the baseline model, we then need to specify possible models by Granger causality test. The Granger causality test concludes that CPI Air has a causal relationship with PPI, and Consumer Sentiment. Now, we have PPI, and Consumer Sentiment as causal leading indicators for CPI Air; and each of the different combinations of them with different lags is a candidate for forecasting model. How to choose one best model from all the candidate models is the problem we are going to solve in the next stage.

In the model selection stage, AIC is used as the criterion for choosing the best forecasting model. To make different models comparable, we will restrict all the variables' sample period by 12 periods from 1990m1 to 2023m2 since we are going to forecast future 12 periods of CPI Air.

Table 2: Baseline AR Model Selection

	AIC
AR(1)	-1812.1
AR(2)	-1839.4
AR(3)	-1834.7
AR(4)	-1835.8
AR(5)	1828.2
AR(6)	-1822.3
AR(7)	-1815.2
AR(8)	-1815.8
AR(9)	-1810.8
AR(10)	-1804.3
AR(11)	-1797.5
AR(12)	- 1790.6

The Table 2 above shows different AIC values associated with baseline AR models with different lags. We choose the model with smallest AIC value, and hence we choose AR(2) for the baseline model. For the combined models, we will use 1, …, 12 lags of CPI Air; 1, …, 6 lags of PPI; and 1, …, 6 lags of Consumer Sentiment.

Table 3: CPI Air(p) – PPI(q) Model Selection

p/q	0	1	2	3	4	5	6
1	-1835.7	-1817.8	-1806.5	-1799.7	-1794.9	-1788.8	-1783.4
2	-1864.2	-1850.1	-1845.3	-1833.5	-1829.3	-1821.2	-1815.8
3	-1859.7	-1845.1	-1839.3	-1833.4	-1829.2	-1821.9	-1816.5
4	-1860.2	-1845.6	-1841.4	-1835.3	-1838.6	-1828.5	-1823.1
5	-1852.7	-1838.1	-1833.8	-1827.7	-1831.0	-1826.5	-1821.1
6	-1847.0	-1832.3	-1828.0	-1821.7	-1825.7	-1820.8	-1821.1
7	-1839.3	-1825.2	-1820.9	-1814.6	-1818.6	-1813.8	-1814.3
8	-1838.4	-1824.1	-1822.0	-1815.3	-1819.3	-1814.5	-1815.5
9	-1834.4	-1819.1	-1817.9	-1810.4	-1814.6	-1809.6	-1810.4
10	-1827.4	-1812.6	-1811.2	-1803.9	-1808.3	-1803.1	-1804.0
11	-1821.9	-1805.9	-1805.0	-1797.2	-1802.0	-1796.3	-1797.3
12	-1815.4	-1799.4	-1797.7	-1790.3	-1794.9	-1789.5	-1790.7

Table 3 shows the AIC values of models using lagged CPI Air and lagged PPI, and the lowest AIC = -1864.2 appears where p = 2 and q = 0. Some insights we get from this table are: lagged values of CPI Air only help make better forecasting model up to lag 2. As a result, for the following models, we only consider p from up to 3 to save time.

Table 4: CPI Air(p) – Consumer Sentiment (s) Model Selection

p/s	0	1	2	3	4	5	6
1	-1810.2	-1810.3	-1805.2	-1802.1	-1797.0	-1789.1	-1783.3
2	-1837.5	-1837.7	-1837.4	-1834.1	-1829.3	-1821.3	-1816.1
3	-1832.8	-1833.3	-1832.8	-1835.0	-1830.1	-1822.1	-1816.8

According to table 4 which shows AIC values of models using lagged CPI Air and lagged Consumer Sentiment, the lowest AIC = -1837.7 appears where p = 2 and s = 1. The AIC values in table 4 confirms our precious finding that lags of CPI Air only help make better forecasting model up to lag 2. Now, let us consider the combined models with lags of CPI Air, PPI, and Consumer Sentiment.

Table 4: CPI Air(p) – PPI(q) – Consumer Sentiment(s) Combined Models

p,q,s	(2,0,0)	(2,1,0)	(2,0,1)
AIC	-1862.4	-1848.1	-1863.0

From table 4, the lowest AIC = -1863.0 value appears where p = 2, q = 0, and s = 1. However, it is still not as small as -1864.2 which is the AIC value of the model with p = 2 and q = 0. After comparing all the AIC values of different candidate models, we can conclude that the model with 2 lags of CPI Air and 0 lag of PPI is the best forecasting model under AIC criterion. The best forecasting model and parameter estimates are shown in table 5 below.

Table 5: Best Forecasting Model (p=2, q=0)

Linear Regression Model:
y ~ 1 + cpi_1 + cpi_2 + ppi_0

	Estimate	SE	t-Stat	p-Value
Intercept	0.00037219	0.0013297	0.2799	0.77971
x1	0.073299	0.057463	1.2756	0.20288
x2	-0.095793	0.057817	-1.6568	0.098374
x3	0.73048	0.11106	6.5775	1.5818e-10

Number of observations: 385, Error degrees of freedom: 381
Root Mean Squared Error: 0.0256
R-squared: 0.11, Adjusted R-Squared: 0.103
F-statistic vs. constant model: 15.7, p-value = 1.22e-09

Our last objective is to make point and interval forecasting using the best forecasting model we selected. First, since the models are based on growth rate data of CPI Air and PPI, we will forecast growth rate of CPI Air, then convert the growth rate data to level data. Specifically, the forecasting method I use in my model is the direct method. The following tables 6 and 7 show point and interval forecast of CPI Air for the next 1 year.

Table 6: Point Forecast of CPI Air from Mar 2023 to Feb 2024

Time	Point Forecast
Mar 2023	299.8877
Apr 2023	297.3694
May 2023	295.4679
June 2023	293.5546
July 2023	291.4096
Aug 2023	289.4336
Sep 2023	289.2228
Oct 2023	286.1442
Nov 2023	283.1512
Dec 2023	282.4329
Jan 2024	283.0411
Feb 2024	283.7461

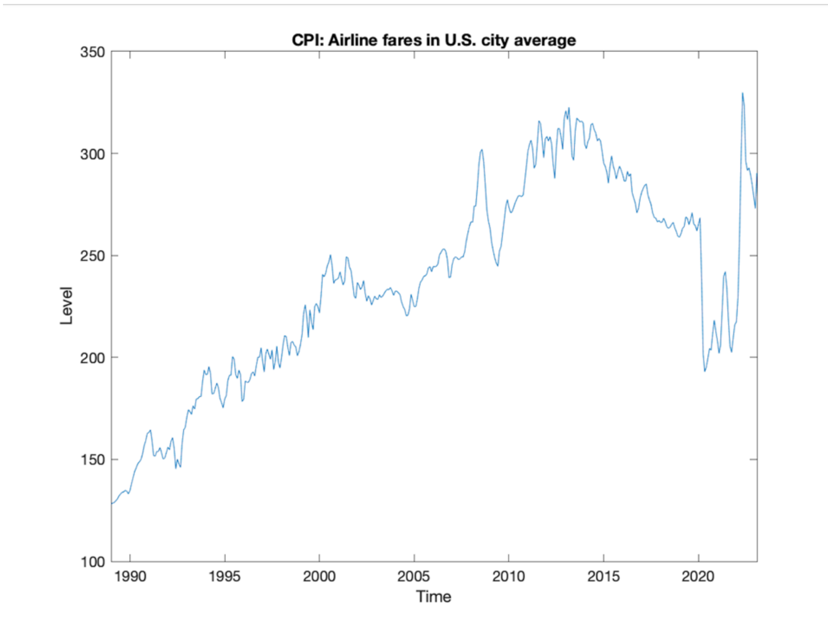
Table 7: Interval Forecast of CPI Air from Mar 2023 to Feb 2024

Time	Lower Forecast interval	Upper Forecast interval
Mar 2023	288.7697	311.0057
Apr 2023	274.1073	321.5737
May 2023	260.7183	333.1687
June 2023	247.9479	345.1731
July 2023	235.5768	357.3509
Aug 2023	223.9134	370.1971
Sep 2023	214.2009	385.7155
Oct 2023	202.7762	398.0768
Nov 2023	192.0012	410.9019
Dec 2023	183.3256	427.3837
Jan 2024	175.8880	446.5638
Feb 2024	168.7849	466.8224

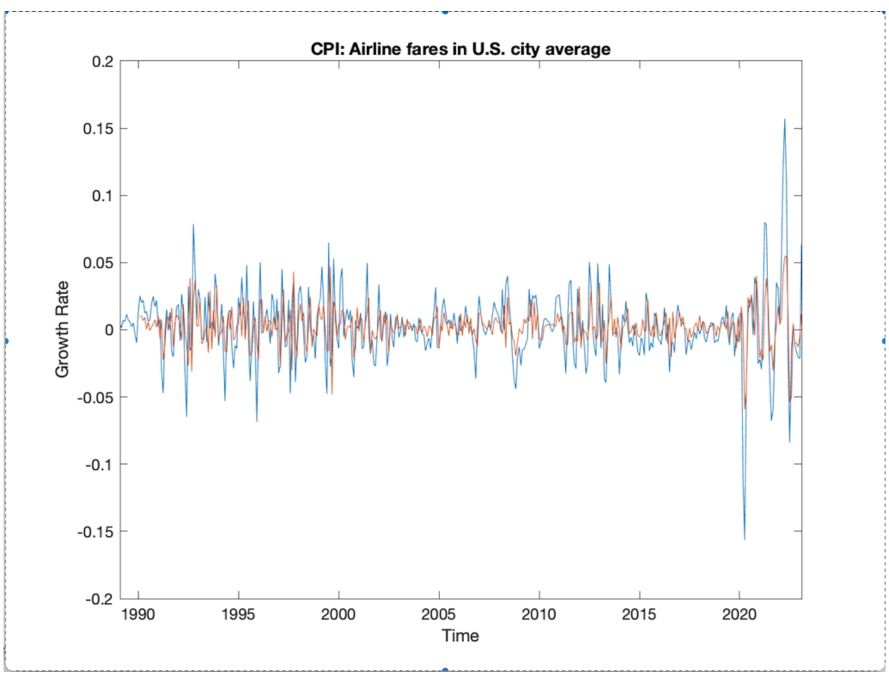
It seems like our model does a decent job in predicting future values of CPI Air. However, there is some worrisome news of our best forecasting model which is its small R-squared value (0.11) even after we incorporate a composite of leading indicators. Though R-squared value is the criterion for model of fit, and not for model's predictive ability, such a small value may imply some potential model flaws, which is worth being paid attention to. One possible reason is that, since CPI Air is one category of the broader CPI, CPI Air is much more fluctuating than CPI as there are many factors that contribute to the change of CPI Air, and it involves more subtilties. More about model evaluations will be discussed in the next part of final project.

Appendix

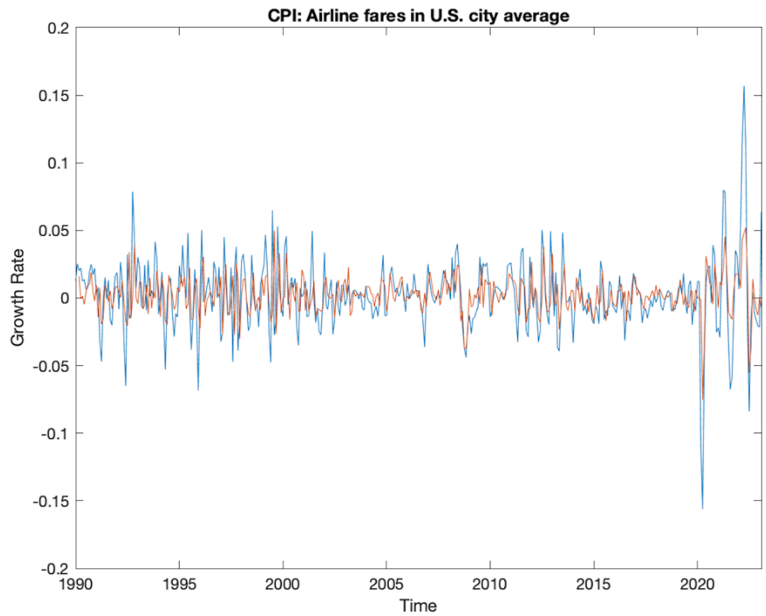
Original times series:



Baseline AR(12) model with predicted values:



Smallest AIC model for CPI Air (p = 2, q = 0):



CPI Air forecast in growth rates:

CPI Air forecast in levels: