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# Analysis of the Seasonality of China's CPI based on X-12-ARIMA

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## Abstract

**CPI is a price fluctuation indicator that reflects the price of products and service. It can be used to analyze the dynamics of market prices. Therefore, it is an important reference for economic activities and monetary policy. In the past ten years, although China's consumer price index has been relatively stable, the fluctuations during the year have been relatively large. This paper predicts that the stable seasonality of CPI monthly series in China has been significant in the past ten years, while the seasonality of movement is not significant, that is, the seasonality of CPI in China is stable and identifiable, and the results predicted by X-12-ARIMA multiplication model are also consistent.**

## Keywords

**Seasonality, Consumer Price Index, X-12-ARIMA.**

## 1. INTRODUCTION

CPI (Consumer Price Index) is an indicator of price fluctuation that reflects the price of products and services. It is used as an important indicator for observing inflation levels. CPI can be used to analyze dynamics of market prices, so it is an important reference indicator for economic activities, government monetary policy and employment policy. In addition, CPI is an important factor affecting economic stability and an important reference indicator for the financial industry to analyze economic fundamentals. If the consumer price index rises too much, it indicates that inflation has become a factor of economic instability, and the country will have the risk of tightening monetary and fiscal policies, thus causing uncertainty in the economic outlook.

After the world economic crisis in 2008, with the rapid economic development, China's economy has strengthened its self-regulation ability. The annual growth rate of China's CPI is relatively stable in range of 2% to 5%. It reflects the development of China's market economy in the direction of good development since the government proposed and implemented economic transformation and upgrading and industrial structure reform.

Although the annual growth rate of China's CPI tends to be stable. However, the fluctuation of CPI during the year is still large and cannot be ignored. Fig.1 shows that in the past five years, China's CPI year-on-year growth rate and ring-to-ring growth rate have been relatively fluctuating. And at different times, the reasons for price fluctuations are different. During the Spring Festival, China's CPI generally has a peak during the year. In the nearly half year of 2018, China's CPI growth rate has fluctuated greatly. In addition to the impact of holidays, it may also be related to the impact of Sino-US trade friction on the economy. This paper chooses to use the X-12-ARIMA model to conduct an empirical study on China's CPI monthly sequence.

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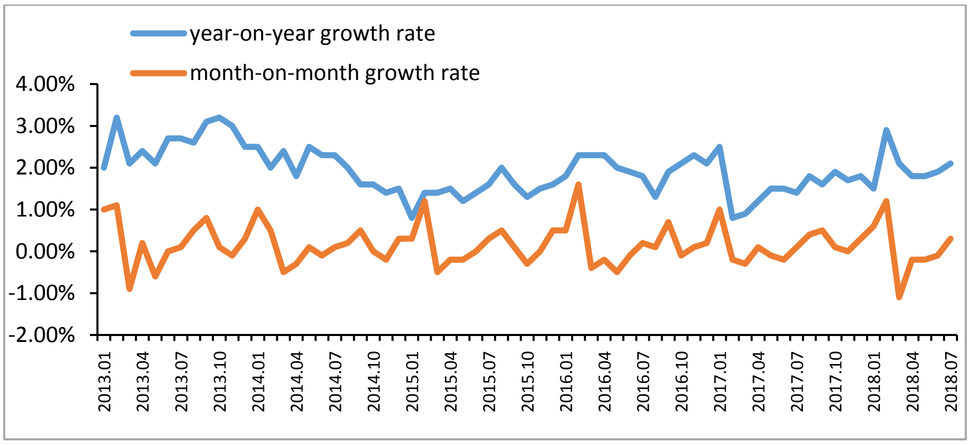


**Figure 1.** China's CPI monthly sequence data Jan. 2013-Jul.2018

## 2. THEORETICAL UNDERPINNINGS

### 2.1. The Related Studies

In 1998, the US. Census Bureau launched the first version of X-12-ARIMA [1]. X-12-ARIMA includes all the capabilities of the X-11 [2] and X-11-ARIMA [3]. Also, it offers new capabilities beyond the X-11 and X-11-ARIMA. The X-12-ARIMA program can be divided into two sub-modules, regARIMA and X-11, regARIMA is used to build the ARIMA model, and X-11 is used for seasonal adjustment [4-7]. Compared with the previous version, X-12-ARIMA version 0.3 has added the Spring Festival effect adjustment function module, which is more suitable for studying China's economic data [8]. Based on the SARIMA model and the X-12-ARIMA model, the trend and seasonality of China's CPI data are verified. The results show that the X-12 seasonal adjustment model is more effective than the SARIMA model, and the estimation error of the predicted and actual values is better [9]. On the basis of the X-12-ARIMA model, He Fengyang and Liu Jianping introduced the unequal rights and the equal rights of the GENHOL program in the process of adjusting the CPI [10].

### 2.2. The ARIMA Model

In order to obtain a stationary series, the first difference is first performed on the sequence, and then the seasonal analysis is performed. In this paper, we first calculate the D seasonal difference and the d non-seasonal difference, and then perform the original sequence of ARIMA(p, d, q)×(P, D, Q)s on the regression function, where p, q, P, Q is the maximum lag order of non-seasonal and seasonal autoregressive and moving average operators, and d and D respectively represent non-seasonal and seasonal difference times.

Seasonal time series intervals have a strong correlation with random variables at two time points of cycle length s. For monthly data, s=12, $X_t$ and $X_{t-12}$ are related. Therefore, this cycle correlation can be used to fit between $X_t$ and $X_{t-12}$.

The form of the ARIMA model is:

$$\begin{cases} \Phi(B)\nabla^d X_t = \Theta(B)E(\varepsilon_t\varepsilon_s) \\ E(\varepsilon_t) = 0,\ Var(\varepsilon_t) = \sigma^2, E(\varepsilon_t\varepsilon_s) = 0,\ s \neq t \\ E(X_s\varepsilon_t) = 0, \forall_s < t \end{cases} \tag{1}$$

Where $\nabla^d = (1 - B)^d$.

Equation (2) is an autoregressive coefficient polynomial of the stationary and reversible ARIMA (p,q) model.

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$$\Phi(B) = 1 - \emptyset_1 B - \cdots - \emptyset_p B^p \tag{2}$$

Equation (3) is the moving smoothing coefficient polynomial of the ARIMA (p,q) model.

$$\Theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q \tag{3}$$

## 3. EMPIRICAL DATA

The raw data used in this paper is the year-on-year sequence and the month-on-month sequence.

The year-on-year data indicators ignore the effects of seasonal factors. But such data metrics rely on data from the past 12 months, and implicitly assume that the annual seasonal pattern remains the same, easily masking trend changes. Therefore, using this data to observe the turning point of economic trends is not accurate. The solution to this deficiency is to use month-on-month or quarter-on-quarter indicators to reflect economic activity. However, due to the seasonality of economic and production activities, the chain index is affected by seasonal fluctuations. For example, the consumption before the Spring Festival is strong, and the month-on-month price may fall or rise, which does not reflect the price trend of the whole year. In addition, holidays, such as the Chinese New Year, also lead to seasonal fluctuations in economic operations. Therefore, the use of these indicators often requires the influence of seasonal factors.

In addition to this seasonal factor, these raw data also include trends, periodicity, irregularities, including outliers, and other parts. Direct adjustment of the original data may result in problems that may cause large data changes due to different data base periods.

In this paper, the time series adjustment is based on a fixed base index. The data sequence of fixed base ratio comes from the data sequence of month-on-month ratio, and the base period is January 2008. Fig.2 shows the calculated data.

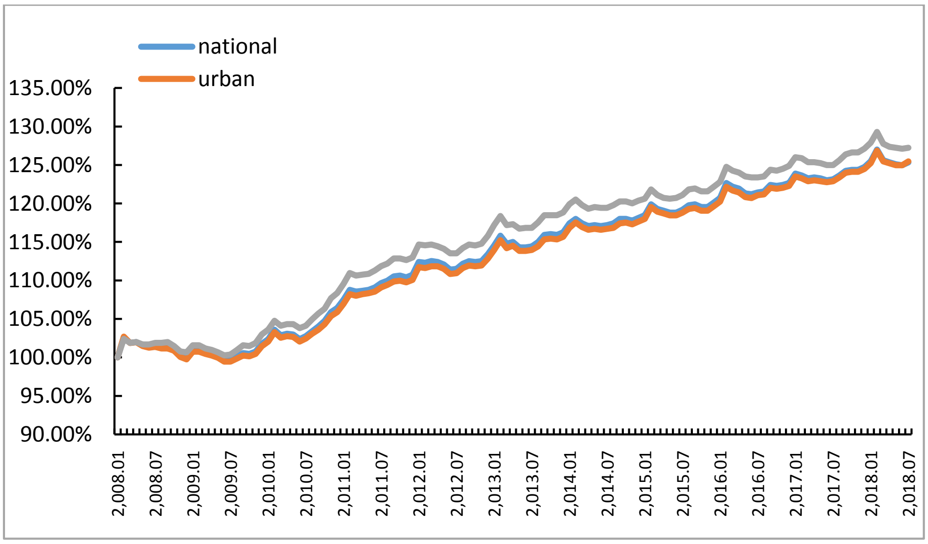


**Figure 2.** The fixed base ratio growth rate of China's CPI

Fig.2 shows the trend of CPI monthly series in urban and rural areas in China is in sync with the trend of national CPI monthly series. They all present a seemingly linear uprising trend with

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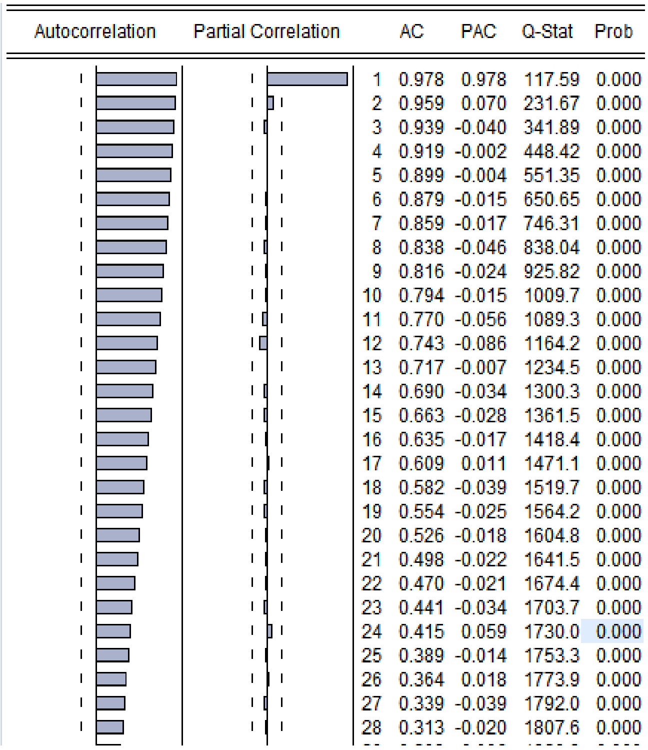
short term fluctuations. In addition, the entire sequence almost has the same cyclical trend change every year, indicating the obvious seasonal changes in the trend of China's CPI. In this paper, national CPI data sequence is the main objects.

# 4. EMPIRICAL ANALYSIS

Prior to seasonal adjustment, the regARIMA part will use ARIMA models to adjust outliers, trading day impacts, and holiday effects.

## 4.1. Model Identification

Fig.3 shows that the residual sequence is not stable. In other words, after removing the seasonality, the results present the data correlation. Fig.4 shows the seasonality after first difference. However, Fig.5 shows the seasonal tailings in both autocorrelation and partial correlation after the second differential processing. Therefore, the above results suggest that the model specification of ARIMA process is $(0,1,0) \times (1,1,1)_{12}$.



| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | 0.978 | 0.978 | 117.59 | 0.000 |
| 2 | 0.959 | 0.070 | 231.67 | 0.000 |
| 3 | 0.939 | -0.040 | 341.89 | 0.000 |
| 4 | 0.919 | -0.002 | 448.42 | 0.000 |
| 5 | 0.899 | -0.004 | 551.35 | 0.000 |
| 6 | 0.879 | -0.015 | 650.65 | 0.000 |
| 7 | 0.859 | -0.017 | 746.31 | 0.000 |
| 8 | 0.838 | -0.046 | 838.04 | 0.000 |
| 9 | 0.816 | -0.024 | 925.82 | 0.000 |
| 10 | 0.794 | -0.015 | 1009.7 | 0.000 |
| 11 | 0.770 | -0.056 | 1089.3 | 0.000 |
| 12 | 0.743 | -0.086 | 1164.2 | 0.000 |
| 13 | 0.717 | -0.007 | 1234.5 | 0.000 |
| 14 | 0.690 | -0.034 | 1300.3 | 0.000 |
| 15 | 0.663 | -0.028 | 1361.5 | 0.000 |
| 16 | 0.635 | -0.017 | 1418.4 | 0.000 |
| 17 | 0.609 | 0.011 | 1471.1 | 0.000 |
| 18 | 0.582 | -0.039 | 1519.7 | 0.000 |
| 19 | 0.554 | -0.025 | 1564.2 | 0.000 |
| 20 | 0.526 | -0.018 | 1604.8 | 0.000 |
| 21 | 0.498 | -0.022 | 1641.5 | 0.000 |
| 22 | 0.470 | -0.021 | 1674.4 | 0.000 |
| 23 | 0.441 | -0.034 | 1703.7 | 0.000 |
| 24 | 0.415 | 0.059 | 1730.0 | 0.000 |
| 25 | 0.389 | -0.014 | 1753.3 | 0.000 |
| 26 | 0.364 | 0.018 | 1773.9 | 0.000 |
| 27 | 0.339 | -0.039 | 1792.0 | 0.000 |
| 28 | 0.313 | -0.020 | 1807.6 | 0.000 |



**Figure 3.** Residual sequence

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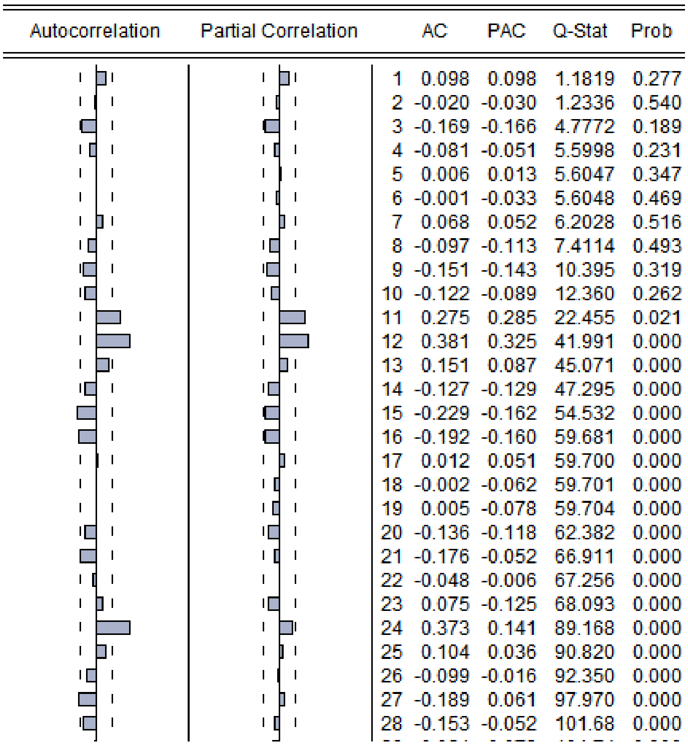
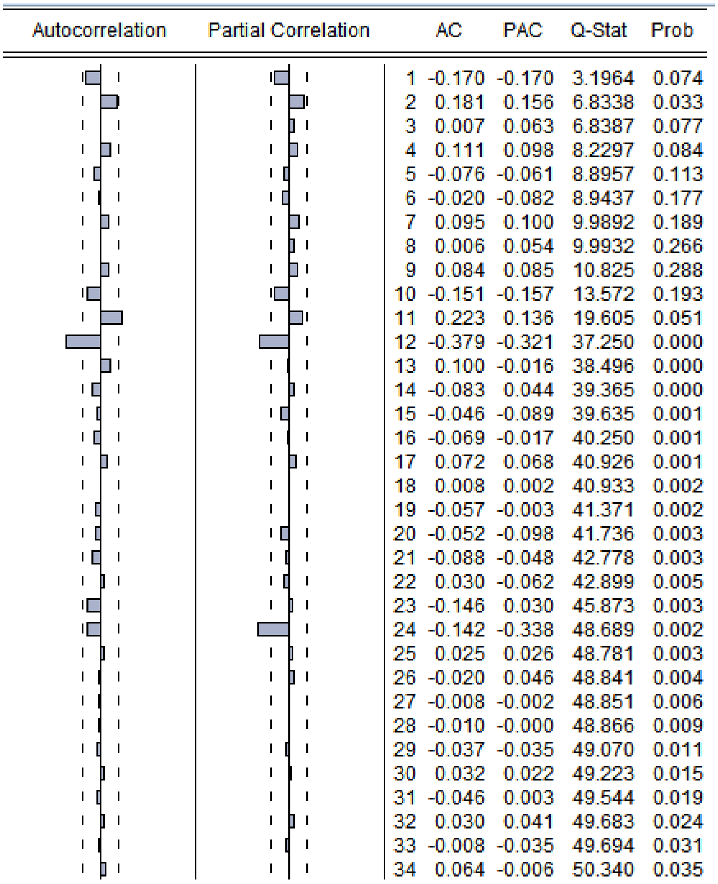


| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | 0.098 | 0.098 | 1.1819 | 0.277 |
| 2 | -0.020 | -0.030 | 1.2336 | 0.540 |
| 3 | -0.169 | -0.166 | 4.7772 | 0.189 |
| 4 | -0.081 | -0.051 | 5.5998 | 0.231 |
| 5 | 0.006 | 0.013 | 5.6047 | 0.347 |
| 6 | -0.001 | -0.033 | 5.6048 | 0.469 |
| 7 | 0.068 | 0.052 | 6.2028 | 0.516 |
| 8 | -0.097 | -0.113 | 7.4114 | 0.493 |
| 9 | -0.151 | -0.143 | 10.395 | 0.319 |
| 10 | -0.122 | -0.089 | 12.360 | 0.262 |
| 11 | 0.275 | 0.285 | 22.455 | 0.021 |
| 12 | 0.381 | 0.325 | 41.991 | 0.000 |
| 13 | 0.151 | 0.087 | 45.071 | 0.000 |
| 14 | -0.127 | -0.129 | 47.295 | 0.000 |
| 15 | -0.229 | -0.162 | 54.532 | 0.000 |
| 16 | -0.192 | -0.160 | 59.681 | 0.000 |
| 17 | 0.012 | 0.051 | 59.700 | 0.000 |
| 18 | -0.002 | -0.062 | 59.701 | 0.000 |
| 19 | 0.005 | -0.078 | 59.704 | 0.000 |
| 20 | -0.136 | -0.118 | 62.382 | 0.000 |
| 21 | -0.176 | -0.052 | 66.911 | 0.000 |
| 22 | -0.048 | -0.006 | 67.256 | 0.000 |
| 23 | 0.075 | -0.125 | 68.093 | 0.000 |
| 24 | 0.373 | 0.141 | 89.168 | 0.000 |
| 25 | 0.104 | 0.036 | 90.820 | 0.000 |
| 26 | -0.099 | -0.016 | 92.350 | 0.000 |
| 27 | -0.189 | 0.061 | 97.970 | 0.000 |
| 28 | -0.153 | -0.052 | 101.68 | 0.000 |

**Figure 4.** 1st difference of residual sequence



| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | -0.170 | -0.170 | 3.1964 | 0.074 |
| 2 | 0.181 | 0.156 | 6.8338 | 0.033 |
| 3 | 0.007 | 0.063 | 6.8387 | 0.077 |
| 4 | 0.111 | 0.098 | 8.2297 | 0.084 |
| 5 | -0.076 | -0.061 | 8.8957 | 0.113 |
| 6 | -0.020 | -0.082 | 8.9437 | 0.177 |
| 7 | 0.095 | 0.100 | 9.9892 | 0.189 |
| 8 | 0.006 | 0.054 | 9.9932 | 0.266 |
| 9 | 0.084 | 0.085 | 10.825 | 0.288 |
| 10 | -0.151 | -0.157 | 13.572 | 0.193 |
| 11 | 0.223 | 0.136 | 19.605 | 0.051 |
| 12 | -0.379 | -0.321 | 37.250 | 0.000 |
| 13 | 0.100 | -0.016 | 38.496 | 0.000 |
| 14 | -0.083 | 0.044 | 39.365 | 0.000 |
| 15 | -0.046 | -0.089 | 39.635 | 0.001 |
| 16 | -0.069 | -0.017 | 40.250 | 0.001 |
| 17 | 0.072 | 0.068 | 40.926 | 0.001 |
| 18 | 0.008 | 0.002 | 40.933 | 0.002 |
| 19 | -0.057 | -0.003 | 41.371 | 0.002 |
| 20 | -0.052 | -0.098 | 41.736 | 0.003 |
| 21 | -0.088 | -0.048 | 42.778 | 0.003 |
| 22 | 0.030 | -0.062 | 42.899 | 0.005 |
| 23 | -0.146 | 0.030 | 45.873 | 0.003 |
| 24 | -0.142 | -0.338 | 48.689 | 0.002 |
| 25 | 0.025 | 0.026 | 48.781 | 0.003 |
| 26 | -0.020 | 0.046 | 48.841 | 0.004 |
| 27 | -0.008 | -0.002 | 48.851 | 0.006 |
| 28 | -0.010 | -0.000 | 48.866 | 0.009 |
| 29 | -0.037 | -0.035 | 49.070 | 0.011 |
| 30 | 0.032 | 0.022 | 49.223 | 0.015 |
| 31 | -0.046 | 0.003 | 49.544 | 0.019 |
| 32 | 0.030 | 0.041 | 49.683 | 0.024 |
| 33 | -0.008 | -0.035 | 49.694 | 0.031 |
| 34 | 0.064 | -0.006 | 50.340 | 0.035 |

**Figure 5.** 2nd difference of residual sequence

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## 4.2. The Prior Adjustment

Table 1 shows the regression result. The t value of AO is -5.45 (February 2012), and the t value of LS is -4.69 (February 2009), indicating that AO and LS outliers are monitored. That is, February 2009 and February 2012 are regarded as outliers. Second, the t-values of the weekend regression factor and the leap year regression factor were 0.72 and 3.36, respectively, indicating that at the 1% significance level, the weekend effect was in significant and the leap year effect was significant. Third, the chi-square test shows that the trading day effect is not significant at the 1% significance level and can be ignored; the joint trading day and the leap year effect have a chi-square value of 17.47>9.21 at the 1% significance level (critical chi-square value) and therefore cannot be ignored.

**Table 1.** Regression results

| Regression Model | | | |
|---|---|---|---|
| Variable | Parameter Estimate | Standard Error | t-value |
| Trading Day | | | |
| Mon | 0.0001 | 0.00048 | 0.12 |
| Tue | 0.0002 | 0.00046 | 0.36 |
| Wed | -0.0003 | 0.00047 | -0.57 |
| Thu | 0.0007 | 0.00045 | 1.54 |
| Fri | -0.0008 | 0.00047 | -1.63 |
| Sat | -0.0002 | 0.00049 | -0.5 |
| Sun | 0.0004 | 0.0005 | 0.72 |
| Leap Year | 0.007 | 0.00208 | 3.36 |
| Automatically Identified Outliers | | | |
| LS2009.Feb | -0.0163 | 0.00348 | -4.69 |
| AO2012.Feb | -0.018 | 0.0033 | -5.45 |
| Chi-squared Tests for Groups of Regressors | | | |
| Regression Effect | df | Chi-Square | P-Value |
| Trading Day | 6 | 5.33 | 0.5 |
| Combined Trading Day and Leap Year Regressors | 7 | 17.47 | 0.01 |

## 4.3. The Seasonal Adjustments and the Test

Fig.6 shows the comparison before and after seasonal adjustment of the CPI time series by the X-12-ARIMA program and Fig.7 shows the seasonal factor separated from the sequence. The time series of CPI fixed base index does have obvious seasonality, and the line of adjusted CPI time series is smoother than the line of original sequence, indicating that the seasonal adjustment is effective.

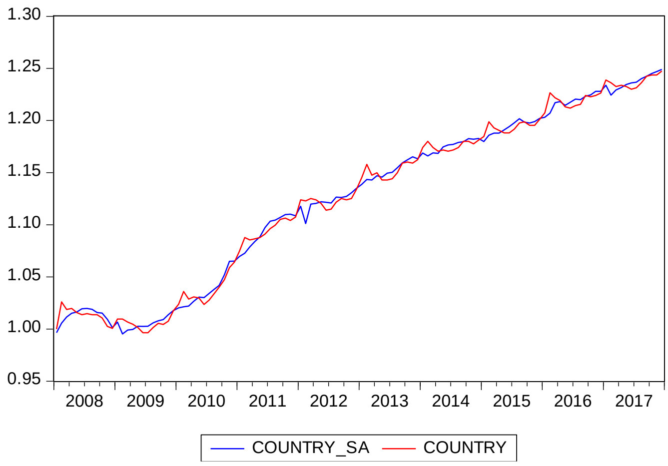


**Figure 6.** Comparison before and after seasonal adjustment

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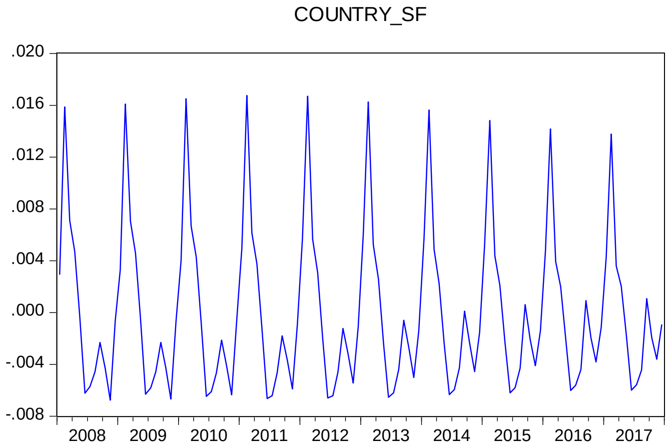


**Figure 7.** Seasonal factor

Q statistic is the indicator for the test of the seasonal adjustment. Table 2 shows the 11 statistics are given to judge the quality of seasonal adjustment. The values of these statistics are in the interval [0, 3]. Only their value less than 1 is acceptable, and the smaller the value, the better. Using the linear combination of these statistic indicators, a composite indicator -- Q statistic, is calculated by weighting, which is used as an indicator to measure the seasonal adjustment, and whether it is accepted or rejected. Table 2 shows the calculated statistical data are all less than 1, and the Q value is small, indicating that the X-12-ARIMA program is effective for seasonal adjustment.

**Table 2.** Q-statistic

| Measure | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| value | 0.134 | 0.056 | 0 | 0.564 | 0 | 0.064 | 0.309 |
| Measure | M8 | M9 | M10 | M11 | Q | Q without M2 | |
| value | 0.463 | 0.333 | 0.543 | 0.509 | 0.22 | 0.25 | |

From the data diagnosed by the model in Table 3, for the CPI monthly sequence, the stable seasonal test F statistic and the Kruskal-Wallis statistic are all rejecting the null hypothesis, indicating that the seasonal effect is clearly present. The statistic accepts the null hypothesis, indicating that there has been no significant fluctuation in seasonality between years, which means that seasonality is relatively stable and identifiable. Both the combined seasonal test and the Q statistic pass the test and therefore accept the seasonality of the CPI monthly sequence. The seasonally adjusted time series and residual sequence did not have seasonality, and the above results were verified again.

**Table 3.** The seasonality tests

| | F-Test for stable seasonality | F-Test for Moving Seasonality | Kruskal-Wallis statistics | combined seasonality test | Q-statistic |
|---|---|---|---|---|---|
| Original series | present at 0.1% | no at 5% | Present at 0.1% | identifiable | 0.96 |

## 5. CONCLUSION

In this paper, the seasonal adjustment of China's CPI monthly sequence is carried out by using X-12-ARIMA program. The seasonality of CPI monthly sequence is significant and stationary, but the seasonality of movement is not significant, seasonally identifiable, Q statistic accepts

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season. Sexuality, which indicates that the seasonal sequence of CPI in China is seasonally stable and identifiable. The prediction results show that the predicted values in the short-term are close to the true values, and the better prediction results are obtained.

The seasonal adjustment results are based on the X-12-ARIMA model, although the seasonal components are eliminated to some extent. However, the rejection effect still exists, and there will still be seasonality in the residual sequence. In addition, in terms of order determination and model identification, it is still based on subjective experience to judge, there is no objective standard.

## REFERENCES

[1] Zhong-bing Zhou, Xiu-cheng Dong. Analysis about the seasonality of China's crude oil import based on X-12-ARIMA.Energy, 2012, Vol. 42(1), p281-288.

[2] Shiskin J, Young AH, Musgrave JC. The X-11 variant of the census method II seasonal adjustment program. Technical paper No.15. US Department of Commerce, Bureau of Economic Analysis, 1967.

[3] Dagum EB. The X11ARIMA/88 seasonal adjustment method-foundations and user’s manual Time Series Research and Analysis Division, Statistics Canada technical report,1988.

[4] ChangI, TiaoGC. Estimation of time series parameters in the presence of outliers. Technical report 8. Statistics Research Center, University of Chicago, 1983.

[5] Bell WR, Hillmer SC. Modeling time series with calendar variation. Journal of the American Statistical Association, 1983, Vol. 78(383), p526-534.

[6] Box, Jenkins. Time series analysis; forecasting and control. Revised ed. San Francisco: Holden Day, 1976.

[7] Findley DF, Monsell BC, Bell WR, Otto MC, Chen Bor-Chung. New capabilities and methods of the X-12-ARIMA seasonal-adjustment program. Journal of Business & Economic Statistics, 1998, Vol. 16(2), p169-177.

[8] Time-series X-12-ARIMA seasonal adjustment: principles and methods. 1st ed. Statistics and Analysis Department, the People’s Bank of China. Beijing: China Financial Publishing House, 2006.

[9] Zhang Ting. Comparative and predictive analysis of CPI's SARIMA model and X-12 seasonal adjustment model. Economic Issues, 2014, Vol. 0 (12), p37-41. (In Chinese)

[10] He Feng-yang, Liu Jian-ping. How to adjust the seasonal adjustment of China's CPI——Based on the improvement of X-12-ARIMA method [J]. Quantitative Economics & Economics Research, 2011, Vol.28(05), p110-124. (In Chinese)