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Development of A Forecasting Model for Investment in Tehran Stock Exchange Based on Seasonal Coefficient

Reza Darvishinia[1,], Hossein Ebrahimzadeh shermeh[2], Samira Barzkar[3]*

[1]*Department of Industrial Engineering, Productivity Management System, Industrial Management Institute (IMI), Tehran, Iran.*
[2]*Technology Enterprises Incubator Center, University of Mazandaran, Babolsar, Iran.*
[3]*Department of Economy and Political Science, Central Branch, Islamic Azad University, Tehran, Iran.*

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ABSTRACT

The present study aims at suggesting a model for intelligent investment, through enabling us to be Autoregressive Integrated Moving Average of ARIMA and seasonal coefficient. In this study, the researcher uses seasonal fluctuation Model. The previous trend of time series, related to the companies for a period of 11 years, from 2006 to 2017, was carried out based on seasonal data. Then the researcher predicted the final price based on moving average method. In the next stage, the proportion of real final price and predicted the final price is calculated regarding each period. Then, the seasonal coefficient average is calculated for similar seasons. In the final stage, the value of a prediction, for a given period, is calculated when moving average method is multiplied by a seasonal coefficient average. As a result, seasonal coefficient of a given stock is derived.

1. Introduction

The main purpose of nearly all companies is making a profit and increasing value for shareholders. Moreover, with regard to advanced technology, expansion of huge production corporations and their transformation into international companies as well as ever-increasing thrive of the stock market, are only a few of criterions for evaluating the commercial management, profit potentiality of profit and value of the share of a company. Investors and shareholders try to make decisions while having a vision of the companies' profit trend so that they can make the right decisions and meet their expectations. Thus, predicting the profit of the shares is of high importance regarding different aspects of the decision-making theory. This prediction helps the investors to improve their decision-making process and reduce the risk of their decisions. They are keen on meeting the future interests of their investment and evaluate their would-be received cash profits. Thus, investors seek to have access to the prediction of their shares' profits. The prediction assists the current shareholder with selling or keeping the shares. An investor, with the help of the prediction of the distribution of future cash trend of a share, makes up his mind, to purchase the share or invest somewhere else in advance. Therefore, observing the method of paying the share profit in the future is of high importance, with respect to investment decisions and decisions pertinent to paying the profit, which then depends on companies' profits.

* Corresponding author
E-mail address: r.darvishinia.tse@gmail.com
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The purpose of the present study is putting forth a model for intelligent investment applying; consequently, generating more confidence and knowledge for investment on the market exchange. About 500 years ago, in a city in Belgium, in front of the house belonging to Mr. Wonder Bourse, an assembly to exchange stock began. Since then, any place, where the stock was exchanged, was called Burse (Stock Exchange). The first stock market was established in the city of Anvers, Belgium. Now it is found almost everywhere in the world. Federation of world stock market, as an international planner, helps the interaction among stock markets, protects shareholders rights and develops their market. Some of the prominent stock markets are the New York stock market, London stock market, Montreal stock market, and Tokyo stock market.

There are different factors, such as monetary and financial, political, structural variables, which can have an impact on the investment process and, finally, on the economic progress of a country. Various researches, conducted regarding theories and models of investment, by economic experts and researchers, were largely pertinent to advanced countries, which are heavily dependent on the market economy; while underdeveloped countries' economies have differentiated in their economies from that of the developed countries' economy. Underdeveloped countries have paramount economic structural problems and, as a result, classic economic theories don't work there. Thus, underdeveloped countries' economists have to consider these differences when applying economic theories. As such, they should know the characteristics of their own economy and put forth theories and models based on situations within that context. Therefore, the present study takes the above points into consideration and suggests a better investment model for the stock market. To do so, first, classic theories of investment were studied, regarding particular situations of the country, through benefiting from other studies, and then the research puts forth an investment model for the stock market.

By investment, the researcher means spending a specific amount of money while accepting certain or uncertain risk (probability of risk) for future profit. The most important goal of investment is reducing chance-related charges, that is, a person might have extra money stashed somewhere, which can be used for investment and might lose the profitable opportunities. Intelligent investment means well-informed decision making for investment of certain amount of money, so that the investor can personally observe investment process and protect his/her money. So, he can reach the desired profit in a certain period of time.

Now we should find out why a vast majority of people is willing to enter the stock market. Here the researcher is going to point out a number of factors as advantages of investment in stock market.There is no restrictions when it comes to amount of money for investment; so anybody can enter this market. For instance, you can buy one million Rials of a prominent company's share easily. But if there is no stock market, it is almost impossible to invest that much money on something in order to earn profit.

Another factor is ability to cash your share within a few days, which makes you enter or leave the stock market in a short while. Actually, with the electronic advancement of the market, you can do it in less than a few hours. This hardly ever happens on other investments. Higher output of this market, compared to other markets, encourages people in Iran to enter this market by considering calculated risks. In addition, it has not reached its full potentiality and balance so there are big steps to be taken ahead of it. In spite of the lack of variety in Iran's exchange market, sources of gaining profits in this market are so vast that a purchased share can be beneficial for the buyer in different ways, like different kinds of increase in capital, the difference between the purchase price and selling price, cash profit, etc.

Although the market has developed in Iran, there are still untouched capacities here that can grow remarkably well. The Government's policy on privatization is one of the major economic goals for boosting this issue. Regarding the investment and transaction in stock market, the current data form a time series that can help us predict the progress or loss tendency of stock market transaction. A time series is a series of observations, which is arranged chronologically and its theoretical and practical analysis was conducted by Box et al. [8], and afterwards it spread quickly. It is mainly used to predict the variables tendency. Analysis of dynamic trend of a series compared to its components increases the prediction precision. In the past, a time series analysis was only applied as a prediction tool. However, gradually novel methods to analyze time series developed into seasonal, irregular, and cyclical procedure parts.

Procedural parts change the mean of data series over time and seasonal parts creates a cyclical pattern, in which for every 12 period of time, there is a peak and among these components only seasonal ones have the stationary characteristic. Therefore, one can predict stock market transaction tendencies based on it.

There are drawbacks to the investment model of stock market, having presented so far. To solve these problems, we need to develop the previous models to OPT for suitable share for investment in stock market, based on seasonal coefficient. One of the main tenets of the modern financial theories, during 50s, is Efficient-market theory. As it was pointed out, in most financial and investing literature, the most decisive factor of this theory is information. Thus, they call an efficient market a market, in which price of exchange, like a general share, reflects all the necessary information of the current market.

The father of the efficient market [20], is Eugene Fama, who first defined the term efficient market as: “a market whose prices always reflect all the current information [19]. Availability of enough information and communicating information on stock market fast is closely intertwined with the market efficiency. An efficient market should be watchful of new information so that, if there is new information communicated about a company to the public, it is share prices vary according to the communicated information. The focus of primary research is on random pricing and those prices that do not follow any specific trend.

The results of these studies brought about the economic debate and investment as a strong theory and ideology. Then theory of random behavior of price or school of random walk was shaped [29]. One might state that theory of efficient market is a theory that has been investigated much and drawn attention to many among social theories. 80's studies focused on compatibility of efficient market, with whole stock market utilizing economic assessment models that examine characteristics of time series, price, and cash profits [7].

The efficiency of the companies and their stock returns on the stock market have been considered. Several studies have been conducted to evaluation the efficiency of companies that operate on stock exchanges. Continuous review of companies’ performance can help increase their stock returns [3, 18, 28, 36]. Brown et ai. [11] demonstrated that majority of unusual profit of small business share takes place in the first two weeks of January, which signifies the beginning of the year. These findings along with end of the month effect, yearend effect, January and weekend effect, and primary introduction of the share as “Anomalies of market,” cast serious doubts on efficient market [2, 15, 24, 25, 37].

One of the discussions and tests conducted at low level of efficient market is examining the presence or absence of seasonal patterns, which is identified based on historical information and then used to predict the future via analysis. Seasonal patterns, besides output historical examination of stock market or volume of transaction in a certain period of time, are identified and if they are significant, historical information would be the basis of shareholders' future decision-making [10]. Fama pointed out that those who chose some certain shares in a long run and could earn unusual and above the mean profit, questioned the efficiency of the market and this is a reason against efficient market theory [21].

The anomalies mentioned in efficient market theories falls into two groups: calendar anomalies and non - calendar anomalies patterns. There are documents related to calendar anomalies of financial markets like stock market and stock exchange, which date back to 50 years ago. Among scholarly circles and experimental scientists, lots of discussion and debate focused on these patterns, identification, confirming or rejecting those patterns. Based on efficient market theory, share price in an efficient market always randomly changes which stems from response of share price to information communicated over time. Now, if time itself is a factor, which changes share price in a way that in a specific period of time, besides the communicated information (randomly), then it has an effect on changing the share price and the random nature of the market, while these patterns create pitfalls to efficient market and form a kind of anomaly. These effects are called calendar effects or calendar anomalies [5, 12, 26, 31, 34].

Some examples of these calendar anomalies are mentioned below that some of Marcus Davidson's studies on them are given. Thaler [37] suggested the term "effect of political spin". He maintained that due to the effect of political spin that usually happens in the first year and the last year of a president's term (administration), financial markets experience unusually higher output compared with other years. Therefore, the investors make a timely decision and arrange their purchase and selling time. When a government cannot stabilize its economic policies in the first year and doubts the next government's term, the last year of current government increases, financial market fluctuations and mitigated output will be earned at higher risk, compared with other years.

One of the first calendar effects, which drew researchers' attention, is summer effect. Wachtel [38] found some documents in stock market that showed prices in the summer experienced an increase compared to other seasons. Various studies were carried out in different countries, by which documents indicated higher unusual outputs take place days before national holidays. Liano [27], suggested holidays effect or pre-holidays effect notion and presented documents related to markets outside stock market OTC. Most of these studies were conducted in the U.S stock market and nearly all of them confirmed such an effect that is unusual outputs days before national holidays.

Another effect, playing an important role in share price fluctuations, is weekend effect that refers to pattern in share output in the past, relating to special days of the week. These relations were mainly confirmed in the U.S. in a way that the last days of transactions in a week were followed by an unusual and positive outputs while Monday, which is the first day of transaction week, experiences lower output and even negative one, compared to other days.

Presence of such an effect indicates that output on different days of the week is not independent and it is against the random walk theory. If the effects of days of week do not exist, the output should be the same at the end of each day of the week, yet studies showed that utilizing some daily patterns can lead to extra outputs [12].

Ariel [4] for the first time examined monthly effect pattern for share index of the U.S. between 1963 and 1981. He used regression model having virtual variables in his test of the theory. He divided the share transaction months into two halves that the first half of each month begins with the last workday of the previous month. After examining the New York share index, he found out that the average output data of the share is positively significant for the first half of the calendar month and negative for the second half [22]. The effect of special month of the year or, in other words, effects of the end of the year, drew researchers' attention much and became the main area of research in applied studies of market anomalies. Over the past few years, a large body of research indicated that share output, specially, small companies' output was significantly higher in first month compared with other months. Thus, this phenomenon, which was examined in most financial markets in the world, is known as January effect. In addition, what was witnessed and examined in the last month of the year, in financial markets, in most countries, has shown a reverse phenomenal against January effect, which is known as the December effect. This effect indicates that the average output of the share is lower in last month of the year [2, 41]. Some factors that has been contributing to the mentioned effects in stock market drew attention. They are explained below:

One of the ubiquitous factors in all studies regarded as a main factor in December and January effect is tax-loss selling hypothesis. Wachtel was the first person to justify this as January effect in the U.S stock market in 1942 [38]. He suggested that when the end of the year is approaching, investors tend to sell the shares, which experienced lower value over the year, in order to reduce their tax. That is why the share price goes down due to the increase in demand. Toward the end of the year and in January, the pressure of sale falls gradually and prices return to their balanced levels, which result in greater output in January.

A noteworthy point regarding January effect factors is that information hypothesis and circulated information can be considered another factor. Rozef and Keini [33] while confirming the January effect, suggested that January is a month that companies should submit their important financial reports, like financial statements and yearly accounting reports to the public and stock market. Therefore, in this month, uncertainty and probability, emanating from financial reports and good or bad news, are seen alongside one another. Another factor of share fluctuation is cash increase hypothesis. Expansion of commercial and business activities near the end of fiscal year would result in higher profits in December for the owner of such businesses. So, a great amount of cash goes to January and due to receiving bonuses, salary and pension, households have greater cash compared with other months. Another identified factor playing a role in share fluctuations is the particular effect of lunar month of Ramadan in Islamic countries. During Ramadan, due to the Muslims' downward tendency of economic activities, number of transactions in financial markets fall. One of the reasons for this decrease might be what Mohsen Alhaji attributed to in 2005 [35], gambling is regarded Haram in Islam. In 2004, Fazel Saeed et al. carried out a study in Saudi Arabia's market, which is the greatest stock market among Islamic countries, worth approximately 237 billion dollars. GARCH model, which belongs to time series model, was used to test effects of Ramadan on changing share output. The findings of their study indicated that the mean of share output in this month is not much different from other lunar months, while significantly decreased in this month [35]. Anomalies that questioned efficient market hypothesis and cannot be categorized in seasonal anomalies, are known as non-calendar anomalies. In non-calendar anomalies, factor of time doesn't hurt efficient market hypothesis, indeed content factors of the market shape these incompatible phenomena. Some of these anomalies are:

- Stock split effect.
- Divided yield effect.

- Low prices stock effect.
- Inside transaction effect.
- Effect of market over reaction.
- Initial public offering effect.
- Index effect.
- Day of Week Effects [5].

Regarding the volume of investment of companies on stock exchange and wrong choice on the part of the employees and managers, which result in failure in stock market, the model chosen in the present project leads to saving financial resource and time, while increasing the profits in this process. Prediction in stock exchange investment is a significant parameter, so some researchers over world have been tried to improve old methods [1, 32, 39].

2. Research Method

The research method of the present study is a time series and prediction based on quantitative method, which is the combination of moving average method, seasonal fluctuation method and regression. In the present study, the researcher utilizes following notation:

Table 1. *Notation.*

F_{t+1}	*Linear regression equation to predict the closing prices of the next period.*
F_t	*Linear regression equation to predict the closing prices of the previous period.*
A_t	*The closing price of the t week for the month in question.*
n	*The number of period.*
y_i	*The actual closing price of the stock in question in the month (week or day).*
y_i'	*The forecasted closing price of the stock in question in the month (week or day).*
R_i	*The ratio of the actual closing price to the forecasted stock price (seasonal factor of the target. stock).*
$\overline{R_i}$	*Average seasonal factor.*
a	*Parameter of linear regression equation.*
b	*Parameter of linear regression equation.*
x_i	*Seasonal coefficient of the intended month (week or day) in year i.*
$\bar{X}$	*The average of Seasonal coefficient of the intended month (week or day) in year i.*
$\bar{Y}$	*The average actual closing price of the intended month (week or day) in year i.*
r	*Constant.*
t_i	*Time periods in month (week or day) i.*
$\hat{y}$	*Simple linear regression equation.*

2.1. Time Series

Time series are data, which have been collected over time. Frequency of such data has made analysis of time series one of the most functional fields of statistics. Now the question is what is the main purpose of time series analysis? Although describing a time series behavior from a local and long-term changes' perspective or study of current dependence between series elements is examined frequently on time series, one can state that the most important purpose of a time series analysis is predicting its future figures. If there is such a relation, it can assist us in more precise predictions. It is also applied in discussion of a series behavior control with the control of a pertinent series, which we have to do with [9, 17].

In following parts, the researcher will present time series and applied models for calculating the coefficient and prediction.

Different types of time series:

- Least squares method.
- Seasonal fluctuation method.
- Simple average method.
- The method of forecast based on the last period.
- Moving Average (MA).
- Weighed Moving Average (WMA).
- Simple exponential smoothing.
- Double exponential smoothing.
- Seasonal exponential smoothing.
- Simple regression method.

The author of the present study used the model, which is the combination of seasonal fluctuations, simple average and moving average. Now the author presents the definition of each method applied in the present study [9, 30].

2.1.1. Moving average (MA)

In this method the average of n for former period is used for the current period and likewise new information is used and updated on a daily basis.

$$F_{t+1} = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-n+1}}{n} \tag{1}$$

This formula is applicable when demand has a trend if n=1 moving average method turns into prediction method based on last period and if n=t it changes into simple average method [17, 22, 30].

Seasonal Fluctuation Method.

This method is used as following: first, demand is predicted based on moving average method.

Then, the proportion of real demand to the predicted demand is calculated.

$$R_i = \frac{y_i}{y'_i} \tag{2}$$

Seasonal coefficient average $\overline{R_1}$ is calculated for similar seasons.

Prediction value of the given period is multiplied by $\overline{R_1}$ using moving average method [22, 26].

Simple Regression Method.

Simple regression enables the predictors to predict the value of given variable (dependent variable). For example, suppose a producer applies simple regression to predict future demand of his/her products according to demand date data, in this case independent variable is time and dependent variable is product demand. Now refer to regression formula

$$\hat{y} = \alpha + \beta x_i + r \tag{3}$$

In which α and β are calculated as following

$$\beta = \frac{n\sum_{i=1}^{n} X_i Y_i - \sum_{i=1}^{n} X_i \sum_{i=1}^{n} Y_i}{n\sum_{i=1}^{n} X_i^2 - \left(\sum_{i=1}^{n} X_i\right)^2} \tag{4}$$

$$\alpha = \bar{y} - \beta\bar{x}$$

In which:

$$\overline{X} = \frac{\sum_{i=1}^{n} X}{n} \qquad \overline{Y} = \frac{\sum_{i=1}^{n} y}{n} \tag{5}$$

2.1.2. Moving average method regarding seasonal changes

If there are seasonal changes in real demand of the former periods, first seasonal coefficient should be calculated based on previous years' data. To calculate seasonal coefficient, it is better to consider data over the past 10 or 12 years. In order to do so, we should follow:

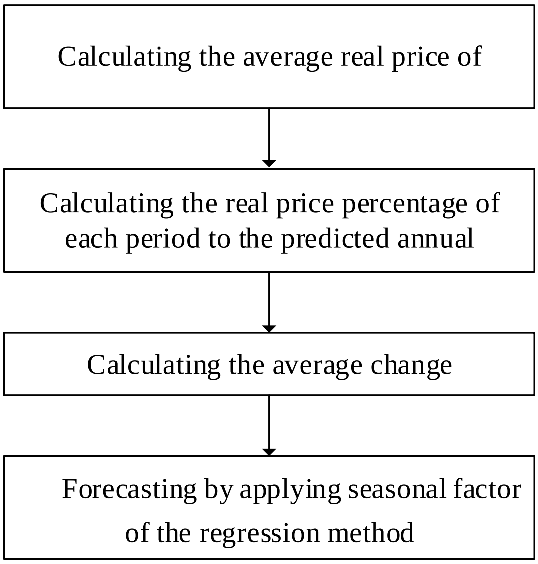

Fig. 1. *Algorithm model.*

Regarding the algorithm mentioned earlier, general trend of each company is like:

First, we obtain the final price of a company on last days of week; then we calculate the average of real final price in each year. After that, percentage of real final price for each period is calculated against final price average of the given year. Finally, Percentage average of change related to each season is obtained and it is called seasonal coefficient of the given season. Since some companies are not participating in stock market on some days due to low production, yearly meeting, etc., those days are omitted from the population or are the price of the day, before it is considered for the next day. Thus, to reach the precise result of the prediction, all data were derived from stock market as real data.

2.2. Forecasting

Forecasting means estimate something that will be happen in future. It is a link between an organization and its environment, which plays an important role in planning and decision making; as the period increases, prediction precision decreases [30].

Effective factors in chasing a suitable model for forecasting:

- Time limit.
- Previous data and figures trend.
- The link between the present information and the given variable.
- Charges.
- Desired precision.
- Simplicity.
- Different types of demand fluctuations over time.
- Trend.
- Seasonal coefficient.
- Irregular variables.
- Random variables.

Random variables Forecasting is a deduction from past to future. Forecasting is different from prediction in that it involves a management's estimation of changes. It is an objective and real calculation based on data [8, 16, 40].

Forecasting techniques fall into three groups: quantitative, qualitative, and causal. Forecasting divides into two types: forecasting in a short run and forecasting in a long run. Now we turn to these two terms: Forecasting in a short run is usually depends on people's experiences. Accuracy of the forecast varies according to the person's experience and amount of information of the subject he/she has. The more the information is, the more precise the forecast is. Therefore, it is advised to apply experience of various people. Accordingly, Delphi method is commonly used to forecast the future according to experience. This notion will be dealt with here in more detail.

Forecasting is picturing a situation in the future according to previous information. In other words, the forecasting is done based on quantitative data from the past to estimate the future. These data are called time series. So, forecasting based on quantitative data is part of time series discussion.

Qualitative techniques are mostly used for long term and strategic issues. These evaluations are usually related to a specific time or irregular decision making, which integrate variations, vague patterns and reciprocal relations. Decisions on investment, new products or markets should naturally be made on the part of a management using qualitative techniques. Market research Delphi method, forecasting techniques for new markets, products and estimation management, are considered. One aspect of market research is data sources, which are regarded as one of the vital factors in mind. Market research technique can be a base for good theories and a background for information evaluation. To make decisions regarding market, one of the most common ways of qualitative forecasting is Delphi method [6, 13, 14].

The most important component of deciding the given share coefficient, is predicting the final price for future months. Utilizing the following formulas, known as regression equation, one can predict the demand value for next month, so:

$$F_t = a + b.t_i \tag{6}$$

$$a = \frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} t_i}{n}, \quad b = \frac{n\sum_{i=1}^{n}(ty)_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} t_i{}^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \tag{7}$$

That:

F_t: Linear regression equation to predict final prices.
t: Time periods.
y: Closing prices.
a , b: Linear regression parameters.

And in the end, applying the mentioned forecasting formula to companies' trends for future months will be examined and explained in more detail within the next section.

Regarding the previously discussed issues, one can come to the conclusion that, with the help from former models, a suitable and comprehensible way to forecast stock data can be set forth and based on these models behavior of data is predicted and observed.

In this section, the author explains the model fully. In previous section moving average was described completely. Now in this section a model is suggested to predict profits of companies interred in stock market and discus how to invest in this market. In this chapter, moving average method, regarding seasonal changes, is suggested and then the method is explained fully. In the present study, first stock information, related to companies were obtained from stock market organization from 2006 to 2017 and final prices of each company, over that period, were listed on a daily basis and inserted in the table.

Now we turn to the calculation method for seasonal coefficient of accepted companies in stock market. This project includes 48 industrial groups and 668 companies. As a sample for calculation, Abidi pharmaceutical group was chosen from Iran's stock market and the model was used for this company. The author examined the information about Abidi pharmaceutical company in 2006. The items of table 2 included; period, real price, moving average of price. Real price average of each month and the percentage of price fluctuations, all items will be described later.

Period.

It refers to the time; in the present study it is decided to be weeks of every month. For instance, in April there exist four weeks; first, second, third, and fourth week.

Real price.

Since workdays of Tehran's stock market is from Saturday to Wednesday and working hours is from 9:00 A.M to 12:30 p.m., real price means the final price or closing price of a given share on Wednesday, which is the last day of workdays in Tehran's stock market.

Moving average of price.

The formula for moving average of price was mentioned previously.

Real price average of each month.

It refers to final price average of each month obtained through adding closing prices of each week and then divided it by 4.

Percentage of final price fluctuation.

After calculating Real price average, percentage of final price fluctuation is obtained when real price of each week is divided by real price average of each month.

2.3. ARIMA

The ARIMA procedure analyzes and forecasts equally spaced variable time series data, transfer function data, and intervention data using the Auto Regressive Integrated Moving-Average (ARIMA) or Autoregressive Moving-Average (ARMA) model. An ARIMA model predicts a value in a response time series as a linear combination of its own past values, past errors (also called shocks or innovations), and current and past values of other time series. The ARIMA approach was first popularized by Box and Jenkins, and ARIMA models are often referred to as Box-Jenkins models. The general transfer function model employed by the ARIMA procedure was discussed by Ledolter et al. [42]. When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model. Pankratz [30] refers to the ARIMAX model as dynamic regression. The ARIMA procedure provides a comprehensive set of tools for variable time series model identification, parameter estimation, and forecasting, and it offers great flexibility in the kinds of ARIMA or ARIMAX models that can be analyzed. The ARIMA procedure supports seasonal, subset, and factored ARIMA models; intervention or interrupted time series models; multiple regression analysis with ARMA errors; and rational transfer function models of any complexity. The design of PROC ARIMA closely follows the Box-Jenkins strategy for time series modeling with features for the identification, estimation and diagnostic checking, and forecasting steps of the Box-Jenkins method. Before using PROC ARIMA, you should be familiar with Box-Jenkins methods, and you should exercise care and judgment when using the ARIMA procedure. The ARIMA class of time series models is complex and powerful, and some degree of expertise is needed to use them correctly. If you are unfamiliar with the principles of ARIMA modeling, refer to textbooks on time series analysis. Also refer to SAS/ETS Software: Applications Guide 1, Version 6, and First Edition. You might consider attending the SAS Training Course "Forecasting Techniques Using SAS/ETS Software." This course provides in-depth training on ARIMA modeling using PROC ARIMA, as well as training on the use of other forecasting tools available in SAS/ETS software.

The analysis performed by PROC ARIMA is divided into three stages, corresponding to the stages described by Box and Jenkins [8]. The IDENTIFY, ESTIMATE, and FORECAST statements perform these three stages, which are summarized below.

- In the identification stage, you use the IDENTIFY statement to specify the response series and identify candidate ARIMA models for it. The IDENTIFY statement reads time series that are to be used in later statements, possibly differencing them, and computes autocorrelations, inverse autocorrelations, partial autocorrelations, and cross correlations. Stationary tests can be performed to determine if differencing is necessary. The analysis of the IDENTIFY statement output usually suggests one or more ARIMA models that could be fit. Options allow you to test for stationary and tentative ARMA order identification.
- In the estimation and diagnostic checking stage, you use the ESTIMATE statement to specify the ARIMA model to fit to the variable specified in the previous IDENTIFY statement, and to estimate the parameters of that model. The ESTIMATE statement also produces diagnostic statistics to help you judge the adequacy of the model. Significance tests for parameter estimates indicate whether some terms in the model may be unnecessary. Goodness of fit statistics aid in comparing this model to others. Tests for white noise residuals indicate whether the residual series contains additional information that might be utilized by a more complex model. If the diagnostic tests indicate problems with the model, you try another model, and then repeat the estimation and diagnostic checking stage.
- In the forecasting stage you use the FORECAST statement to forecast future values of the time series and to generate confidence intervals for these forecasts from the ARIMA model produced by the preceding ESTIMATE statement.

3. Empirical Results

As a sample 2017's values of Abidi pharmaceutical are chosen and calculations are done for a desired month. Other calculations of different months of the year are similar and this process is repeated until the last month of the year.

To calculate, the author chose May, which consists of four weeks. In this project the final price of Wednesday, the last day of workdays in Tehran’s stock market, is considered for the desired share and similar one. In the first week of May the final price of Abidi pharmaceutical company was 6728 Rials, and 6725, and 6751 Rials for the second, third, and fourth week respectively. Now we calculate

Moving average of the price for May based on:

$$F_{t+1} = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-n+1}}{n} \tag{8}$$

For the first week of May:

That here we have n=4 & t=4, therefore

$$\mathrm{F}_{4+1} = \mathrm{F}_5 = \frac{\mathrm{A}_4 + \mathrm{A}_3 + \mathrm{A}_2 + \mathrm{A}_1}{4} \tag{9}$$

Table 2. *Calculations of seasonal change percentage of Abidi pharmaceutical company in 2017*.

		2017			
Period		**Closing price**	**Average moving price**	**Average closing price per month**	**Percentage of fluctuations closing price**
April	*Week 1*	*7,089*		*6925.75*	*102.36%*
	Week 2	*6,847*			*98.86%*
	Week 3	*6,894*			*99.54%*
	Week 4	*6,873*			*99.24%*
May	*Week 1*	*6,728*	*6925.75*	*6736.5*	*99.87%*
	Week 2	*6,725*	*6835.5*		*99.83%*
	Week 3	*6,742*	*6805*		*100.08%*
	Week 4	*6,751*	*6767*		*100.22%*
June	*Week 1*	*6,491*	*6736.5*	*6555.5*	*99.02%*
	Week 2	*6,490*	*6677.25*		*99.00%*
	Week 3	*6,608*	*6618.5*		*100.80%*
	Week 4	*6,633*	*6585*		*101.18%*
July	*Week 1*	*6,629*	*6555.5*	*6652.75*	*99.64%*
	Week 2	*6,637*	*6590*		*99.76%*
	Week 3	*6,674*	*6626.75*		*100.32%*
	Week 4	*6,671*	*6643.25*		*100.27%*
August	*Week 1*	*6,892*	*6652.75*	*6925*	*99.52%*
	Week 2	*6,934*	*6718.5*		*100.13%*
	Week 3	*6,936*	*6792.75*		*100.16%*
	Week 4	*6,938*	*6858.25*		*100.19%*
September	*Week 1*	*7,132*	*6925*	*7475*	*95.41%*
	Week 2	*7,456*	*6985*		*99.75%*
	Week 3	*7,614*	*7115.5*		*101.86%*
	Week 4	*7,698*	*7285*		*102.98%*
October	*Week 1*	*7,723*	*7475*	*7946.25*	*97.19%*
	Week 2	*7,969*	*7622.75*		*100.29%*
	Week 3	*8,029*	*7751*		*101.04%*
	Week 4	*8,064*	*7854.75*		*101.48%*
November	*Week 1*	*8,080*	*7946.25*	*8765.5*	*92.18%*
	Week 2	*8,513*	*8035.5*		*97.12%*
	Week 3	*9,194*	*8171.5*		*104.89%*
	Week 4	*9,275*	*8462.75*		*105.81%*

Table 3. *Average moving price for the first week of May*.

Average moving price for the first week of May		
A_1	*The closing price of the first week of April*	$F_{4+1} = F_5 = \frac{A_4 + A_3 + A_2 + A_1}{4}$
A_2	*The closing price of the second week of April*	
A_3	*The closing price of the third week of April*	$F_5 = \frac{A_4+A_3+A_2+A_1}{4} = \frac{6{,}873 + 6{,}894 + 6{,}847 + 7{,}089}{4}$
A_4	*The closing price of the fourth week of April*	$= 6{,}926$

For the second week, n=4 & t=5

So:

$$F_{5+1} = F_6 = \frac{A_5 + A_4 + A_3 + A_2}{4} \tag{10}$$

Table 4. *Average moving price for the second week of May.*

Average moving price for the second week of May		
A_2	*The closing price of the second week of April*	$F_{5+1} = F_6 = \frac{A_5 + A_4 + A_3 + A_2}{4}$
A_3	*The closing price of the third week of April*	$F_6 = \frac{A_5+A_4+A_3+A_2}{4}$
A_4	*The closing price of the fourth week of April*	$= \frac{6{,}728 + 6{,}873 + 6{,}894 + 6{,}847}{4}$
A_5	*The closing price of the first week of May*	$= 6{,}836$

For the third week, n=4 & t=6

So:

$$F_{6+1} = F_7 = \frac{A_6 + A_5 + A_4 + A_3}{4} \tag{11}$$

Table 5. *Average moving price for the third week of May.*

Average moving price for the fourth week of May		
A_4	*The closing price of the fourth week of April*	$F_{7+1} = F_8 = \frac{A_7 + A_6 + A_5 + A_4}{4}$
A_5	*The closing price of the first week of May*	$F_8 = \frac{A_7+A_6+A_5+A_4}{4}$
A_6	*The closing price of the second week of May*	$= \frac{6{,}742+6{,}725+6{,}728+6{,}873}{4}$
A_7	*The closing price of the third week of May*	$= 6{,}778$

For the fourth week, n=4 & t=7

So:

$$F_{7+1} = F_8 = \frac{A_7 + A_6 + A_5 + A_4}{4} \tag{12}$$

Likewise, these calculations are made for all months of different years. It is noteworthy that the calculated values are used as moving average of price in final price prediction section, which will be dealt with later.

Calculation of percentage of real price changing fluctuation:

As an example, for the first week of May changing percentage equals final price of first week of May divided by average of real price demand in May:

$$\frac{\text{The real price of the first week of May}}{\text{The average of real price}} * 100 \tag{13}$$

$$\frac{33.152}{34.524} * 100 = 96.03\ \%$$

And the calculations continue accordingly. Now, after calculating the percentage of closing price fluctuations for all the examined years, the author specifies a table for first, second, third, and fourth week separately in which all values are inserted like the Table 7.

Table 6. *Percentage of actual fluctuations for the first week.*

	Average moving price for the third week of May	
A_3	*The closing price of the third week of April*	$F_{6+1} = F_7 = \frac{A_6 + A_5 + A_4 + A_3}{4}$
A_4	*The closing price of the fourth week of April*	$F_7 = \frac{A_6 + A_5 + A_4 + A_3}{4}$
A_5	*The closing price of the first week of May*	$= (6{,}725 + 6{,}728 + 6{,}873 + 6{,}894)/4 \quad = 6{,}805$
A_6	*The closing price of the second week of May*	

Table 7. *Average moving price for the fourth week of May*.

Month / Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
April	99.25%	106.52%	117.46%	98.61%	97.69%	97.45%	100.00%	92.25%	97.11%	100.00%	99.73%	102.36%
May	96.03%	100.20%	97.79%	92.74%	99.59%	97.19%	100.77%	97.76%	104.36%	98.96%	90.15%	99.87%
June	90.92%	107.82%	100.09%	100.11%	97.12%	106.37%	103.41%	105.20%	99.80%	98.82%	102.89%	99.02%
July	125.43%	103.89%	111.95%	99.50%	96.97%	100.82%	102.20%	94.28%	101.51%	100.46%	94.58%	99.64%
August	99.99%	100.00%	100.11%	97.27%	96.98%	100.89%	99.75%	105.06%	100.24%	101.47%	90.93%	99.52%
September	100.00%	113.66%	104.77%	98.61%	93.15%	100.16%	99.06%	102.87%	97.95%	100.77%	110.25%	95.41%
October	100.12%	100.00%	105.74%	100.64%	99.81%	100.13%	93.00%	102.59%	100.49%	95.45%	97.14%	97.19%
November	100.76%	123.24%	102.07%	99.69%	101.89%	100.15%	100.82%	100.66%	101.56%	100.99%	98.02%	92.18%
December	100.27%	83.13%	94.29%	96.88%	99.59%	100.06%	99.24%	99.62%	94.65%	104.00%	99.67%	101.83%
January	100.38%	100.40%	103.43%	102.11%	96.05%	100.00%	96.47%	92.21%	106.48%	92.23%	106.57%	100.56%
February	101.92%	100.07%	100.99%	101.50%	101.71%	100.04%	98.82%	101.07%	100.12%	102.16%	90.95%	99.18%
March	100.00%	100.00%	100.42%	99.15%	100.95%	100.00%	99.77%	100.92%	100.00%	98.22%	100.98%	100.27%

Table 8. *Percentage of actual fluctuations for the second week.*

Month / Year	April	May	June	July	August	September	October	November	December	January	February	March
2006	99.25%	96.99%	100.41%	131.70%	99.99%	100.00%	100.12%	100.58%	100.10%	100.10%	99.46%	100.00%
2007	101.20%	100.15%	102.43%	98.70%	100.00%	95.45%	100.00%	105.69%	89.96%	100.30%	100.07%	100.00%
2008	100.72%	100.94%	99.97%	111.95%	100.02%	100.27%	104.32%	101.91%	96.51%	102.90%	100.71%	100.05%
2009	98.68%	104.57%	100.08%	99.45%	99.01%	99.40%	100.59%	99.69%	97.55%	100.79%	99.50%	99.15%
2010	101.57%	98.35%	103.03%	99.28%	98.91%	97.80%	100.13%	99.85%	99.43%	97.05%	99.74%	100.75%
2011	98.87%	100.75%	97.93%	100.82%	100.30%	100.16%	100.00%	99.95%	100.06%	100.00%	100.04%	100.00%
2012	100.00%	100.76%	99.58%	102.25%	99.81%	99.22%	95.79%	100.81%	96.53%	101.45%	98.82%	100.26%
2013	98.07%	97.02%	100.98%	97.07%	100.26%	100.30%	101.57%	100.28%	99.68%	101.04%	100.80%	100.75%
2014	99.56%	97.18%	99.84%	101.89%	100.29%	95.96%	100.43%	101.46%	97.07%	101.16%	100.11%	100.00%
2015	100.00%	101.22%	99.93%	99.88%	99.53%	99.97%	98.33%	100.44%	99.17%	99.41%	101.66%	98.99%
2016	99.90%	97.48%	98.75%	97.75%	96.26%	103.79%	99.01%	96.97%	97.07%	104.24%	99.33%	99.92%
2017	99.54%	99.83%	99.00%	99.76%	100.13%	99.75%	100.29%	97.12%	101.52%	104.89%	99.80%	100.58%

Table 9. *Percentage of actual fluctuations for the third week.*

Month / **Year**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
April	*100.25%*	*96.14%*	*90.91%*	*100.91%*	*101.51%*	*99.18%*	*100.00%*	*102.41%*	*102.42%*	*100.00%*	*99.98%*	*99.54%*
May	*100.91%*	*99.88%*	*100.63%*	*101.80%*	*99.18%*	*101.29%*	*100.74%*	*101.43%*	*99.14%*	*100.63%*	*104.27%*	*100.08%*
June	*103.20%*	*97.31%*	*99.97%*	*100.06%*	*101.10%*	*98.00%*	*98.53%*	*96.33%*	*100.10%*	*101.86%*	*97.97%*	*100.80%*
July	*71.44%*	*98.70%*	*111.95%*	*98.15%*	*100.26%*	*99.25%*	*99.26%*	*100.90%*	*97.95%*	*99.85%*	*100.17%*	*100.32%*
August	*96.28%*	*100.00%*	*99.93%*	*101.21%*	*100.44%*	*99.40%*	*100.14%*	*96.56%*	*99.91%*	*99.51%*	*100.24%*	*100.16%*
September	*100.00%*	*95.45%*	*100.05%*	*100.01%*	*104.53%*	*99.91%*	*99.38%*	*98.53%*	*99.71%*	*99.70%*	*94.28%*	*101.86%*
October	*99.97%*	*100.00%*	*103.76%*	*100.39%*	*100.07%*	*99.96%*	*98.66%*	*98.15%*	*99.57%*	*101.20%*	*101.73%*	*101.04%*
November	*99.37%*	*81.82%*	*98.13%*	*99.71%*	*99.24%*	*99.95%*	*96.98%*	*99.71%*	*99.47%*	*99.95%*	*100.24%*	*104.89%*
December	*99.85%*	*107.49%*	*105.84%*	*100.18%*	*100.16%*	*99.94%*	*100.72%*	*100.02%*	*102.75%*	*98.96%*	*96.71%*	*101.00%*
January	*99.85%*	*99.70%*	*96.93%*	*99.57%*	*100.98%*	*100.00%*	*100.14%*	*102.64%*	*96.63%*	*104.39%*	*96.50%*	*98.00%*
February	*99.43%*	*99.93%*	*100.09%*	*99.50%*	*100.09%*	*99.96%*	*99.94%*	*100.53%*	*100.00%*	*98.02%*	*104.95%*	*100.22%*
March	*100.00%*	*100.00%*	*99.77%*	*100.84%*	*98.42%*	*100.00%*	*100.48%*	*99.43%*	*100.00%*	*100.71%*	*99.55%*	*100.58%*

Table 10. *Percentage of actual fluctuations for the fourth week.*

Month / Year	April	May	June	July	August	September	October	November	December	January	February	March
2006	*101.25%*	*106.07%*	*105.47%*	*71.43%*	*103.74%*	*100.00%*	*99.78%*	*99.29%*	*99.78%*	*99.66%*	*99.19%*	*99.99%*
2007	*96.14%*	*99.76%*	*92.44%*	*98.70%*	*100.00%*	*95.45%*	*100.00%*	*89.26%*	*119.42%*	*99.60%*	*99.93%*	*100.00%*
2008	*90.91%*	*100.63%*	*99.97%*	*64.14%*	*99.93%*	*94.90%*	*86.18%*	*97.90%*	*103.36%*	*96.73%*	*98.21%*	*99.77%*
2009	*101.80%*	*100.88%*	*99.75%*	*102.91%*	*102.51%*	*101.98%*	*98.38%*	*100.91%*	*105.38%*	*97.53%*	*99.50%*	*100.86%*
2010	*99.23%*	*102.87%*	*98.74%*	*103.50%*	*103.67%*	*104.53%*	*99.98%*	*99.02%*	*100.82%*	*105.91%*	*98.46%*	*99.87%*
2011	*104.50%*	*100.78%*	*97.70%*	*99.10%*	*99.40%*	*99.77%*	*99.90%*	*99.95%*	*99.94%*	*100.00%*	*99.96%*	*100.00%*
2012	*100.00%*	*97.73%*	*98.48%*	*96.29%*	*100.30%*	*102.35%*	*112.55%*	*101.39%*	*103.50%*	*101.93%*	*102.41%*	*99.50%*
2013	*107.27%*	*103.78%*	*97.49%*	*107.76%*	*98.13%*	*98.30%*	*97.69%*	*99.35%*	*100.68%*	*104.11%*	*97.59%*	*98.90%*
2014	*100.91%*	*99.31%*	*100.26%*	*98.65%*	*99.55%*	*106.39%*	*99.51%*	*97.52%*	*105.54%*	*95.73%*	*99.77%*	*100.00%*
2015	*100.00%*	*99.19%*	*99.39%*	*99.82%*	*99.50%*	*99.56%*	*105.01%*	*98.63%*	*97.86%*	*103.97%*	*98.16%*	*102.08%*
2016	*100.40%*	*108.11%*	*100.39%*	*107.51%*	*112.58%*	*91.68%*	*102.12%*	*104.77%*	*106.55%*	*92.69%*	*104.77%*	*99.55%*
2017	*99.24%*	*100.22%*	*101.18%*	*100.27%*	*100.19%*	*102.98%*	*101.48%*	*105.81%*	*95.65%*	*96.55%*	*100.80%*	*98.56%*

Now seasonal coefficients in May as a sample is calculated, according to table 7, for the first week of May from 2006 to 2017 calculation are made:

$$\frac{\sum_{i=2006}^{i=2017} x_i}{12} = \frac{96.03+100.20+97.79+92.74+99.59+97.19+100.77+97.76+104.36+98.96+90.15+99.87}{12}$$
$$= \frac{1175.42}{12}$$
$$= 97.95\%$$

x_i is the values of the percentage of fluctuations between 2006 to 2017, 97/95% is the seasonal coefficient for the first week of May, After that table of seasonal coefficient is presented for that period of time.

Table 11. *Seasonal coefficients of Abidi pharmaceutical company from 2006 to 2017.*

Month	**1**	**2**	**3**	**4**
Week				
April	*100.70%*	*99.78%*	*99.44%*	*100.14%*
May	*97.95%*	*99.60%*	*100.83%*	*101.61%*
June	*100.96%*	*100.16%*	*99.60%*	*99.27%*
July	*102.60%*	*103.37%*	*98.18%*	*95.84%*
August	*99.35%*	*99.54%*	*99.48%*	*101.62%*
September	*101.39%*	*99.34%*	*99.45%*	*99.82%*
October	*99.36%*	*100.05%*	*100.37%*	*100.22%*
November	*101.84%*	*100.39%*	*98.29%*	*99.48%*
December	*97.77%*	*97.89%*	*101.14%*	*103.21%*
January	*99.74%*	*101.11%*	*99.61%*	*99.53%*
February	*99.88%*	*100.00%*	*100.22%*	*99.90%*
March	*100.06%*	*100.04%*	*99.98%*	*99.92%*

Table 12. *Seasonal coefficients for the 48-weeks in 2017, shares of Abidi pharmaceutical company.*

Week 1	**Week 2**	**Week 3**	**Week 4**	**Week 5**	**Week 6**	**Week 7**	**Week 8**
100.70%	*99.78%*	*99.44%*	*100.14%*	*97.95%*	*99.60%*	*100.83%*	*101.61%*
Week 9	*Week 10*	*Week 11*	*Week 12*	*Week 13*	*Week 14*	*Week 15*	*Week 16*
100.96%	*100.16%*	*99.60%*	*99.27%*	*102.60%*	*103.37%*	*98.18%*	*95.84%*
Week 17	*Week 18*	*Week 19*	*Week 20*	*Week 21*	*Week 22*	*Week 23*	*Week 24*
99.35%	*99.54%*	*99.48%*	*101.62%*	*101.39%*	*99.34%*	*99.45%*	*99.82%*
Week 25	*Week 26*	*Week 27*	*Week 28*	*Week 29*	*Week 30*	*Week 31*	*Week 32*
99.36%	*100.05%*	*100.37%*	*100.22%*	*101.84%*	*100.39%*	*98.29%*	*99.48%*
Week 33	*Week 34*	*Week 35*	*Week 36*	*Week 37*	*Week 38*	*Week 39*	*Week 40*
97.77%	*97.89%*	*101.14%*	*103.21%*	*99.74%*	*101.11%*	*99.61%*	*99.53%*
Week 41	*Week 42*	*Week 43*	*Week 44*	*Week 45*	*Week 46*	*Week 47*	*Week 48*
99.88%	*100.00%*	*100.22%*	*99.90%*	*100.06%*	*100.04%*	*99.98%*	*99.92%*

The findings of this table show that period of time.

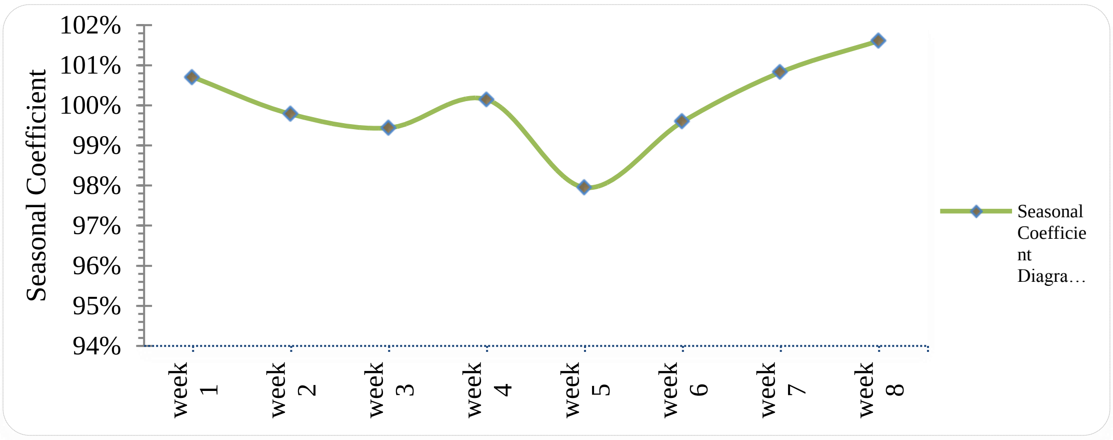

Fig. 1. *Seasonal coefficients diagram for April & May.*

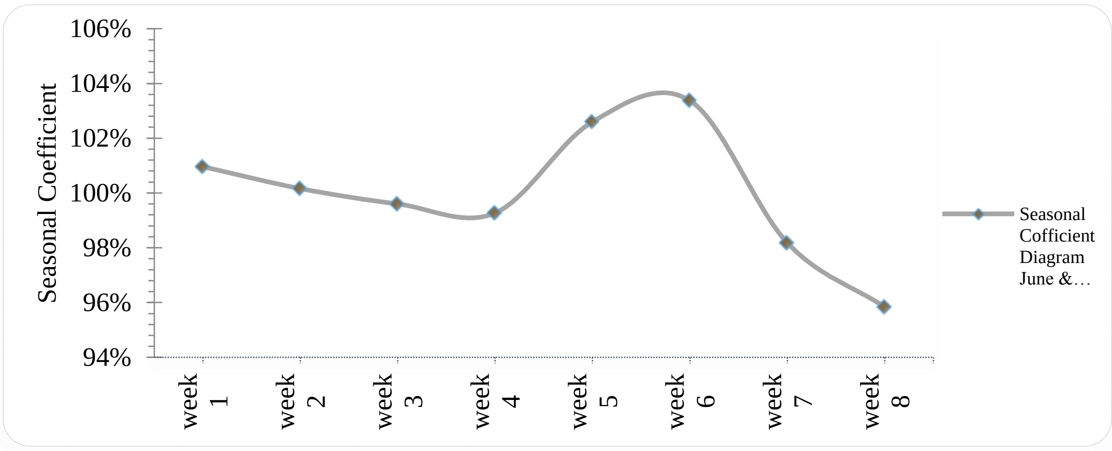

Fig. 2. *Seasonal coefficients diagram for June & July.*

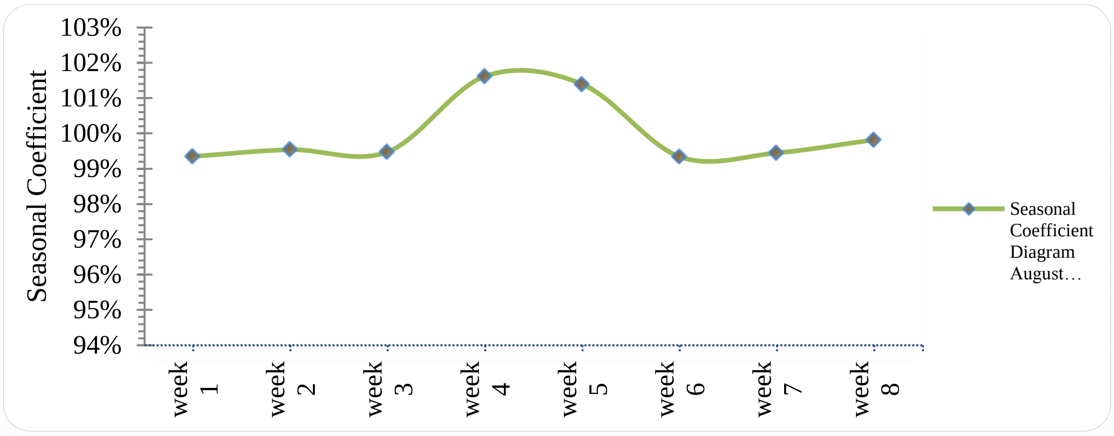

Fig. 3. *Seasonal coefficients diagram August & September.*

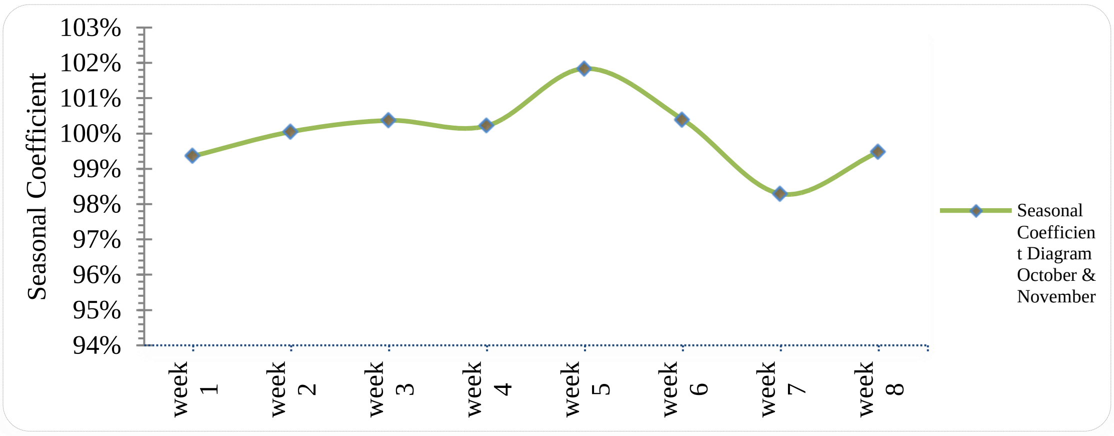

Fig. 4. *Seasonal coefficients diagram October & November.*

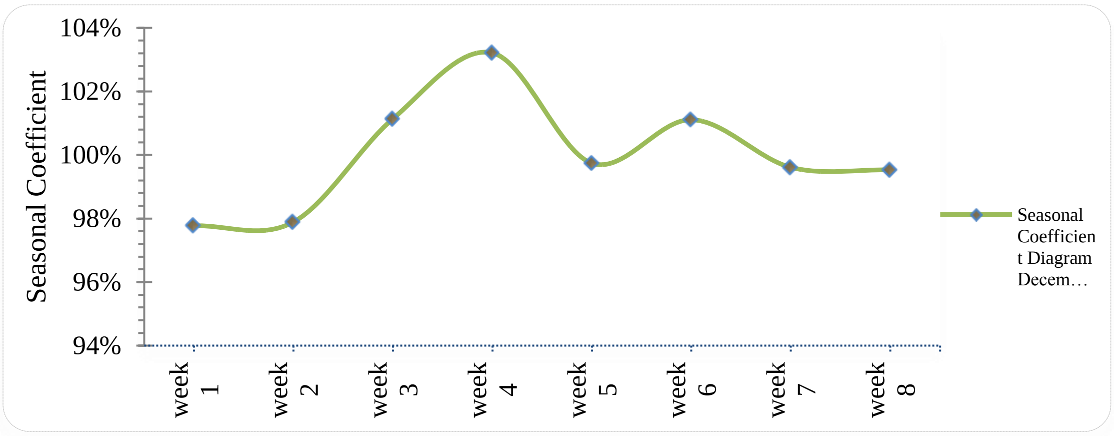

Fig. 5. *Seasonal coefficients diagram December & January.*

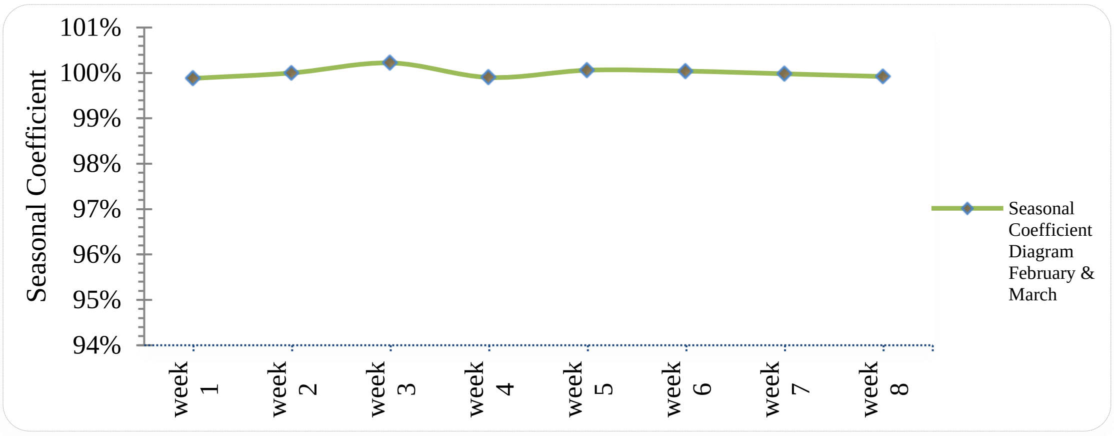

Fig. 6. *Seasonal coefficients diagram February & March.*

The findings of this table show that Abidi pharmaceutical company's seasonal coefficient values are 100/70% in the first week of April to 100/14% in fourth week of April. These figures mean that if someone wishes to buy Abidi pharmaceutical company's share, he or she can buy the share in the third week since it is cheaper compared to other weeks. If a person wants to sell its share, he/she should sell it in the fourth week, because the seasonal coefficient of the share reaches its peak. Accordingly, in the first week of May the seasonal coefficient value is the lowest one, so it is advised to purchase the given share then and in the fourth week of May, the coefficient value reaches its peak. Therefore, this is the best time to sell that share. This trend continues till March. The results of the calculations for all nonfinancial industrial groups, accepted in stock market, are that the first one should obtain the seasonal coefficient for all groups and examine the financial fluctuation of each company based on that. Relying on this model, one can calculate acceptance value of each share for selling or buying. Now, we focus on predicting closing prices of the given share in new months. Thus, in this section, only calculations of closing prices in first, second, third, and fourth week of April 2017 are considered. Using the regression equation, which is the basis of prediction for April of 2017 values of closing price prediction are calculated with regarding for seasonal coefficient. Applying the following formulas, known regression equation values of closing price for the next months are predicted, so:

$$F_t = a + b.t_i \tag{14}$$

$$a = \frac{\sum_{i=1}^{n} y_i - b\sum_{i=1}^{n} t_i}{n} \quad , \quad b = \frac{n\sum_{i=1}^{n}(ty)_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} {t_i}^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \tag{15}$$

Now the author decided to calculate prediction values of seasonal coefficient for first, second, third, and fourth week of April 2017.

Table 13. *Regression variables.*

t	y	t^2	t*y
1	7,089	1	7,089
2	6,847	4	13,694
3	6,894	9	20,682
4	6,873	16	27,492
5	6,728	25	33,640
6	6,725	36	40,350
7	6,742	49	47,194
8	6,751	64	54,008
9	6,491	81	58,419
10	6,490	100	64,900
11	6,608	121	72,688
12	6,633	144	79,596
13	6,629	169	86,177
14	6,637	196	92,918
15	6,674	225	100,110
16	6,671	256	106,736
17	6,892	289	117,164
18	6,934	324	124,812
19	6,936	361	131,784
20	6,938	400	138,760
21	7,132	441	149,772
22	7,456	484	164,032
23	7,614	529	175,122
24	7,698	576	184,752
25	7,723	625	193,075
26	7,969	676	207,194
27	8,029	729	216,783
28	8,064	784	225,792
29	8,080	841	234,320
30	8,513	900	255,390
31	9,194	961	285,014
32	9,275	1024	296,800
33	12,822	1089	423,126
34	12,782	1156	434,588
35	12,717	1225	445,095
36	12,043	1296	433,548
37	12,037	1369	445,369
38	12,555	1444	477,090
39	11,730	1521	457,470
40	11,556	1600	462,240
41	5,256	1681	215,496
42	5,289	1764	222,138
43	5,311	1849	228,373
44	5,342	1936	235,048
45	6,564	2025	295,380
46	6,584	2116	302,864
47	6,584	2209	309,448
48	6,452	2304	309,696
$\sum_{i=1}^{n} t_i$	$\sum_{i=1}^{n} y_i$	$\sum_{i=1}^{n} {t_i}^2$	$\sum_{i=1}^{n} t_i * y_i$
1,176	377,553	38,024	9,703,228

According to values of regression variables, mentioned in Table 13, seasonal coefficients for first, second, third, fourth week of April 2017 are calculated.

For example, for the first week:

According to formulas 6, 7, 8, 13:

$\overline{X} = 24.5$, $\overline{Y} = 7{,}865$, $\overline{XY} = 24.5$, $\overline{X}^2 = 800.25$, $\overline{X^2} = 792.17$

And

$$t = 49 \ , \ a = 49.19 \ , \ b = 6{,}660$$

So, equation:

$$\begin{aligned} F &= a.t + b \\ &= 49.19 * 49 + 6660 \\ &= 9{,}071. \end{aligned}$$

Therefore, the closing price for 49th week or the first week of April is 9,071. Now, accordingly and using these equations, results are as follow:

Table 14. *Closing price of April in 2017.*

The closing price of April	Values calculated as Rials
Week 1	*9,071*
Week 2	*9,120*
Week 3	*9,169*
Week 4	*9,219*

Table 15. *Seasonal coefficient for April 2017.*

Seasonal coefficient for April	Values calculated as percentage
Week 1	*99.19%*
Week 2	*99.73%*
Week 3	*100.27%*
Week 4	*100.81%*

Now applying the predicted values and moving average formula seasonal coefficient is calculated as following, then Tables 7, 8, 9, 10 are updated and the final results are following:

Table 16. *Seasonal coefficient forecast for the first week of April 2017.*

Year \ Month	April	May	June	July	August	September	October	November	December	January	February	March
2005	*99.25%*	*96.03%*	*90.92%*	*125.43%*	*99.99%*	*100.00%*	*100.12%*	*100.76%*	*100.27%*	*100.38%*	*101.92%*	*100.00%*
2006	*106.52%*	*100.20%*	*107.82%*	*103.89%*	*100.00%*	*113.66%*	*100.00%*	*123.24%*	*83.13%*	*100.40%*	*100.07%*	*100.00%*
2007	*117.46%*	*97.79%*	*100.09%*	*111.95%*	*100.11%*	*104.77%*	*105.74%*	*102.07%*	*94.29%*	*103.43%*	*100.99%*	*100.42%*
2008	*98.61%*	*92.74%*	*100.11%*	*99.50%*	*97.27%*	*98.61%*	*100.64%*	*99.69%*	*96.88%*	*102.11%*	*101.50%*	*99.15%*
2009	*97.69%*	*99.59%*	*97.12%*	*96.97%*	*96.98%*	*93.15%*	*99.81%*	*101.89%*	*99.59%*	*96.05%*	*101.71%*	*100.95%*
2010	*97.45%*	*97.19%*	*106.37%*	*100.82%*	*100.89%*	*100.16%*	*100.13%*	*100.15%*	*100.06%*	*100.00%*	*100.04%*	*100.00%*
2011	*100.00%*	*100.77%*	*103.41%*	*102.20%*	*99.75%*	*99.06%*	*93.00%*	*100.82%*	*99.24%*	*96.47%*	*98.82%*	*99.77%*
2012	*92.25%*	*97.76%*	*105.20%*	*94.28%*	*105.06%*	*102.87%*	*102.59%*	*100.66%*	*99.62%*	*92.21%*	*101.07%*	*100.92%*
2013	*97.11%*	*104.36%*	*99.80%*	*101.51%*	*100.24%*	*97.95%*	*100.49%*	*101.56%*	*94.65%*	*106.48%*	*100.12%*	*100.00%*
2014	*100.00%*	*98.96%*	*98.82%*	*100.46%*	*101.47%*	*100.77%*	*95.45%*	*100.99%*	*104.00%*	*92.23%*	*102.16%*	*98.22%*
2015	*99.73%*	*90.15%*	*102.89%*	*94.58%*	*90.93%*	*110.25%*	*97.14%*	*98.02%*	*99.67%*	*106.57%*	*90.95%*	*100.98%*
2016	*102.36%*	*99.87%*	*99.02%*	*99.64%*	*99.52%*	*95.41%*	*97.19%*	*92.18%*	*101.83%*	*100.56%*	*99.18%*	*100.27%*
2017	*99.19%*	-	-	-	-	-	-	-	-	-	-	-

Table 17. *Seasonal coefficient forecast for the second week of April 2017.*

Month / Year	April	May	June	July	August	September	October	November	December	January	February	March
2005	99.25%	96.99%	100.41%	131.70%	99.99%	100.00%	100.12%	100.58%	100.10%	100.10%	99.46%	100.00%
2006	101.20%	100.15%	102.43%	98.70%	100.00%	95.45%	100.00%	105.69%	89.96%	100.30%	100.07%	100.00%
2007	100.72%	100.94%	99.97%	111.95%	100.02%	100.27%	104.32%	101.91%	96.51%	102.90%	100.71%	100.05%
2008	98.68%	104.57%	100.08%	99.45%	99.01%	99.40%	100.59%	99.69%	97.55%	100.79%	99.50%	99.15%
2009	101.57%	98.35%	103.03%	99.28%	98.91%	97.80%	100.13%	99.85%	99.43%	97.05%	99.74%	100.75%
2010	98.87%	100.75%	97.93%	100.82%	100.30%	100.16%	100.00%	99.95%	100.06%	100.00%	100.04%	100.00%
2011	100.00%	100.76%	99.58%	102.25%	99.81%	99.22%	95.79%	100.81%	96.53%	101.45%	98.82%	100.26%
2012	98.07%	97.02%	100.98%	97.07%	100.26%	100.30%	101.57%	100.28%	99.68%	101.04%	100.80%	100.75%
2013	99.56%	97.18%	99.84%	101.89%	100.29%	95.96%	100.43%	101.46%	97.07%	101.16%	100.11%	100.00%
2014	100.00%	101.22%	99.93%	99.88%	99.53%	99.97%	98.33%	100.44%	99.17%	99.41%	101.66%	98.99%
2015	99.90%	97.48%	98.75%	97.75%	96.26%	103.79%	99.01%	96.97%	97.07%	104.24%	99.33%	99.92%
2016	99.54%	99.83%	99.00%	99.76%	100.13%	99.75%	100.29%	97.12%	101.52%	104.89%	99.80%	100.58%
2017	99.73%	-	-	-	-	-	-	-	-	-	-	-

Table 18. *Seasonal coefficient forecast for the third week of April 2017.*

Month Year	April	May	June	July	August	September	October	November	December	January	February	March
2005	*100.25%*	*100.91%*	*103.20%*	*71.44%*	*96.28%*	*100.00%*	*99.97%*	*99.37%*	*99.85%*	*99.85%*	*99.43%*	*100.00%*
2006	*96.14%*	*99.88%*	*97.31%*	*98.70%*	*100.00%*	*95.45%*	*100.00%*	*81.82%*	*107.49%*	*99.70%*	*99.93%*	*100.00%*
2007	*90.91%*	*100.63%*	*99.97%*	*111.95%*	*99.93%*	*100.05%*	*103.76%*	*98.13%*	*105.84%*	*96.93%*	*100.09%*	*99.77%*
2008	*100.91%*	*101.80%*	*100.06%*	*98.15%*	*101.21%*	*100.01%*	*100.39%*	*99.71%*	*100.18%*	*99.57%*	*99.50%*	*100.84%*
2009	*101.51%*	*99.18%*	*101.10%*	*100.26%*	*100.44%*	*104.53%*	*100.07%*	*99.24%*	*100.16%*	*100.98%*	*100.09%*	*98.42%*
2010	*99.18%*	*101.29%*	*98.00%*	*99.25%*	*99.40%*	*99.91%*	*99.96%*	*99.95%*	*99.94%*	*100.00%*	*99.96%*	*100.00%*
2011	*100.00%*	*100.74%*	*98.53%*	*99.26%*	*100.14%*	*99.38%*	*98.66%*	*96.98%*	*100.72%*	*100.14%*	*99.94%*	*100.48%*
2012	*102.41%*	*101.43%*	*96.33%*	*100.90%*	*96.56%*	*98.53%*	*98.15%*	*99.71%*	*100.02%*	*102.64%*	*100.53%*	*99.43%*
2013	*102.42%*	*99.14%*	*100.10%*	*97.95%*	*99.91%*	*99.71%*	*99.57%*	*99.47%*	*102.75%*	*96.63%*	*100.00%*	*100.00%*
2014	*100.00%*	*100.63%*	*101.86%*	*99.85%*	*99.51%*	*99.70%*	*101.20%*	*99.95%*	*98.96%*	*104.39%*	*98.02%*	*100.71%*
2015	*99.98%*	*104.27%*	*97.97%*	*100.17%*	*100.24%*	*94.28%*	*101.73%*	*100.24%*	*96.71%*	*96.50%*	*104.95%*	*99.55%*
2016	*99.54%*	*100.08%*	*100.80%*	*100.32%*	*100.16%*	*101.86%*	*101.04%*	*104.89%*	*101.00%*	*98.00%*	*100.22%*	*100.58%*
2017	*100.27%*	-	-	-	-	-	-	-	-	-	-	-

Table 19. *Seasonal coefficient forecast for the fourth week of April 2017*.

Month / Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
April	101.25%	96.14%	90.91%	101.80%	99.23%	104.50%	100.00%	107.27%	100.91%	100.00%	100.40%	99.24%	100.81%
May	106.07%	99.76%	100.63%	100.88%	102.87%	100.78%	97.73%	103.78%	99.31%	99.19%	108.11%	100.22%	-
June	105.47%	92.44%	99.97%	99.75%	98.74%	97.70%	98.48%	97.49%	100.26%	99.39%	100.39%	101.18%	-
July	71.43%	98.70%	64.14%	102.91%	103.50%	99.10%	96.29%	107.76%	98.65%	99.82%	107.51%	100.27%	-
August	103.74%	100.00%	99.93%	102.51%	103.67%	99.40%	100.30%	98.13%	99.55%	99.50%	112.58%	100.19%	-
September	100.00%	95.45%	94.90%	101.98%	104.53%	99.77%	102.35%	98.30%	106.39%	99.56%	91.68%	102.98%	-
October	99.78%	100.00%	86.18%	98.38%	99.98%	99.90%	112.55%	97.69%	99.51%	105.01%	102.12%	101.48%	-
November	99.29%	89.26%	97.90%	100.91%	99.02%	99.95%	101.39%	99.35%	97.52%	98.63%	104.77%	105.81%	-
December	99.78%	119.42%	103.36%	105.38%	100.82%	99.94%	103.50%	100.68%	105.54%	97.86%	106.55%	95.65%	-
January	99.66%	99.60%	96.73%	97.53%	105.91%	100.00%	101.93%	104.11%	95.73%	103.97%	92.69%	96.55%	-
February	99.19%	99.93%	98.21%	99.50%	98.46%	99.96%	102.41%	97.59%	99.77%	98.16%	104.77%	100.80%	-
March	99.99%	100.00%	99.77%	100.86%	99.87%	100.00%	99.50%	98.90%	100.00%	102.08%	99.55%	98.56%	-

Finally, after calculating seasonal coefficient of each week the table related to seasonal coefficient would be like:

Table 20. *The table of seasonal coefficient changes in 2016.*

Month / Week	1	2	3	4
April	*100.70%*	*99.78%*	*99.44%*	*100.14%*
May	*97.95%*	*99.60%*	*100.83%*	*101.61%*
June	*100.96%*	*100.16%*	*99.60%*	*99.27%*
July	*102.60%*	*103.37%*	*98.18%*	*95.84%*
August	*99.35%*	*99.54%*	*99.48%*	*101.62%*
September	*101.39%*	*99.34%*	*99.45%*	*99.82%*
October	*99.36%*	*100.05%*	*100.37%*	*100.22%*
November	*101.84%*	*100.39%*	*98.29%*	*99.48%*
December	*97.77%*	*97.89%*	*101.14%*	*103.21%*
January	*99.74%*	*101.11%*	*99.61%*	*99.53%*
February	*99.88%*	*100.00%*	*100.22%*	*99.90%*
March	*100.06%*	*100.04%*	*99.98%*	*99.92%*

Table 21. *The table of seasonal coefficient changes 2016 with the forecasted closing prices of April 2017*

Month / Week	1	2	3	4
April	*100.59%*	*99.98%*	*99.50%*	*100.19%*
May	*97.95%*	*99.60%*	*100.83%*	*101.61%*
June	*100.96%*	*100.16%*	*99.60%*	*99.27%*
July	*102.60%*	*103.37%*	*98.18%*	*95.84%*
August	*99.35%*	*99.54%*	*99.48%*	*101.62%*
September	*101.39%*	*99.34%*	*99.45%*	*99.82%*
October	*99.36%*	*100.05%*	*100.37%*	*100.22%*
November	*101.84%*	*100.39%*	*98.29%*	*99.48%*
December	*97.77%*	*97.89%*	*101.14%*	*103.21%*
January	*99.74%*	*101.11%*	*99.61%*	*99.53%*
February	*99.88%*	*100.00%*	*100.22%*	*99.90%*
March	*100.06%*	*100.04%*	*99.98%*	*99.92%*

Seasonal coefficients for April was as predicted. Now seasonal for April are seen as real value of final price obtained from stock market of Tehran:

Table 22. *The table of seasonal coefficient changes 2016 with the real closing prices of April 2017*.

Month / **Week**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**	**January**	**February**	**March**
1	*100.35%*	*97.95%*	*100.96%*	*102.60%*	*99.35%*	*101.39%*	*99.36%*	*101.84%*	*97.77%*	*99.74%*	*99.88%*	*100.06%*
2	*99.78%*	*99.60%*	*100.16%*	*103.37%*	*99.54%*	*99.34%*	*100.05%*	*100.39%*	*97.89%*	*101.11%*	*100.00%*	*100.04%*
3	*99.62%*	*100.83%*	*99.60%*	*98.18%*	*99.48%*	*99.45%*	*100.37%*	*98.29%*	*101.14%*	*99.61%*	*100.22%*	*99.98%*
4	*100.30%*	*101.61%*	*99.27%*	*95.84%*	*101.62%*	*99.82%*	*100.22%*	*99.48%*	*103.21%*	*99.53%*	*99.90%*	*99.92%*

After the calculations regarding seasonal coefficients, changes in them in 2015 are in table 10 and seasonal coefficients for April are as below:

Table 23. *Forecast Abidi pharmaceutical company's seasonal coefficient in April 2017*.

Week	**April**
1	*100.70%*
2	*99.78%*
3	*99.44%*
4	*100.14%*

Now the seasonal coefficients predicted April of 2017 according to table:

Table 24. *The seasonal coefficient share of Abidi pharmaceutical company in April 2017*.

Week	**April**
1	*100.59%*
2	*99.98%*
3	*99.50%*
4	*100.19%*

Then we compare tables and witness that seasonal coefficient, for the first week of April in 2017, was going down. In second week, it experienced upward trend that was same for the third week and fourth. These values were in line with real values of weeks in April of 2017 and it is confirmed that the diagram shows the change trend below:

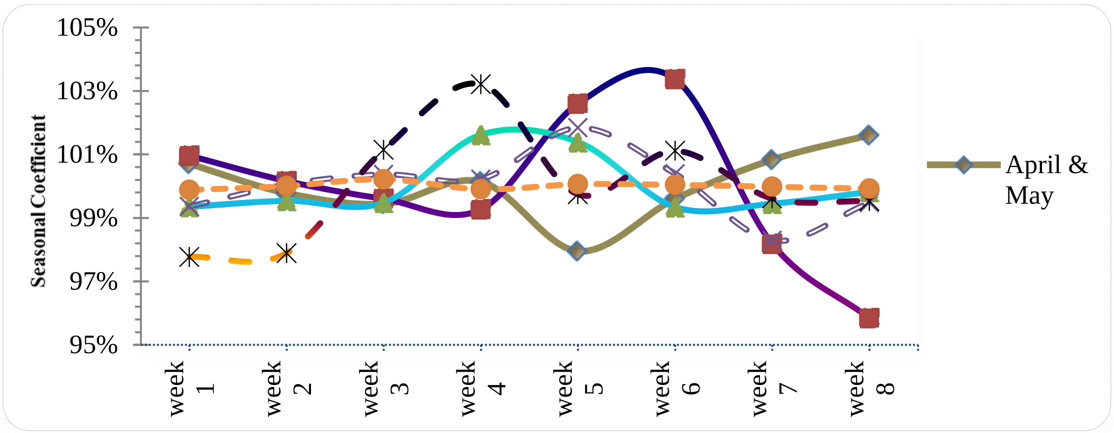

Fig. 8. *Seasonal coefficient diagram April to March in 2017.*

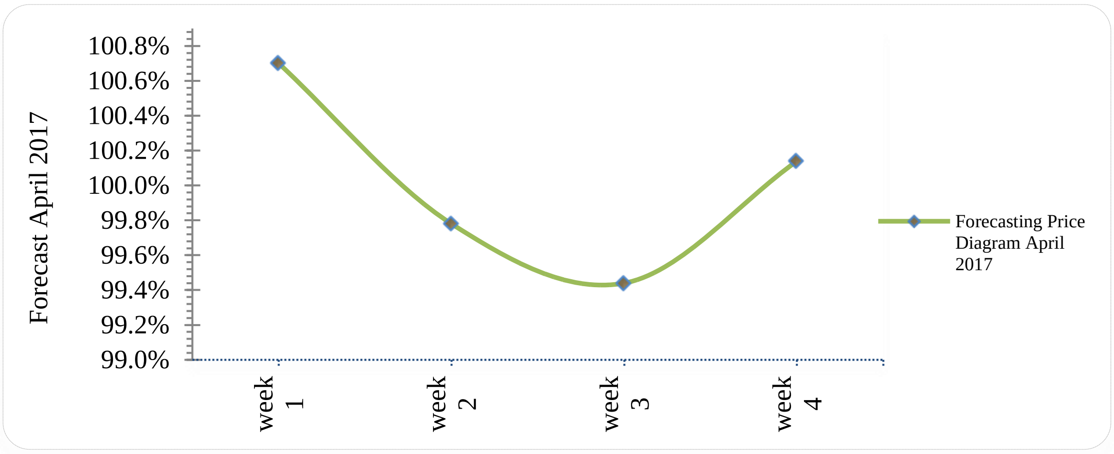

Fig. 9. *Diagram of seasonal coefficient forecast in April 2017.*

It is obvious that the seasonal coefficient of both diagrams are similar are, so the prediction of seasonal coefficient Of The Given Share Was In Line With The Presented Model.

4. Conclusion

Stock investment model is one of the most optimal ways for forecasting when seasonal coefficient is used. This model can help us predict shares in Tehran's stock markets and around the world with precision. It can also help share purchase or when selling of the given weeks take place, depending on upward trend or downward trend, which leads to intelligent investment with high profit margin. Moreover, it prevents us from listening to rumors that spread by inexperienced individual, who express their own ideas about what share brings profit or loss. Relying on this model, one can invest realistically in the shares of Tehran's stock market or the stock exchange of other stock markets around the globe. In the present study, the author suggested a new model of investment on stock market applying seasonal coefficient and combination of number of models.

The suggested model was used to invest on companies accepted in Tehran's stock market. As it was mentioned earlier the model designed for investment on stock market applied seasonal coefficient. In addition, future uses of this model can expand it and, therefore, use cluster ways to choose industrial groups.

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