

# Autoregression and Decision Making under Uncertainty

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## Abstract

There are innumerable social and economic situations in which we are influenced in our decision making by what others are doing. Under uncertainty it's general tendency of an individual to get inspired by decisions of others or mass opinion. However, such herd behavior many times leads to autoregressive affect i.e. output at some moment is weighted average of past few observation. Hence can autoregressive models be used to predict the outcomes in the situations exhibiting such behavior? Studies have already been done on herd behavior in financial market. So, can models used to forecast financial markets be used to predict general decision making under uncertainty. To prove the validity of the point we conduct a small experiment of human decision making under uncertainty and try to forecast future responses using autoregressive models. A group of students were surveyed such that they can also look upon previous responses which would promote herding. A unique financial market type framework is used to quantify the responses and time series models of autoregression are used to forecast mass opinion.

**Keywords:** Herd mentality, Autoregressive process, Decision making

## 1. Introduction

There are innumerable social and economic situations in which we are influenced in our decision making by what others are doing. Perhaps the common example is from our everyday life we often patronize on what stores and restaurants to patronize and what school to attend based upon their popularity. But it has been suggested by Keynes [1936], for example that this is how investors in asset markets behave. Voters are known to be influenced by opinion polls to vote in the direction that poll predicts to win, this is another instance of going with the flow. The same kind of influence is also at work for example academic researchers choose to work on the topic which is currently hot.

In recent years, there has been much interest, both theoretical and empirical, on the extent to which trading in financial markets is characterized by herd behavior. Such an interest stems from the effects that herding may have on financial markets' stability and ability to achieve allocative and informational efficiency. The theoretical literature has tried to identify the mechanisms that lead traders to herd (for surveys, see, e.g., Gale, 1996; Hirshleifer and Teoh, 2003; Chamley, 2004; Vives, 2007). The theoretical contributions have emphasized that, in financial markets, the fact that prices adjust to the order flow makes it more difficult for herding to arise than in

other setups, such as those studied in the social learning literature, where there is no price mechanism. Nevertheless, it is possible that rational traders herd, e.g., because there are different sources of uncertainty in the market. To test herding models directly with data from actual financial markets is difficult. In order to test for herd behavior one needs to detect whether agents choose the same action independently of their private information. The problem for the empiricist is that there are no data on the private information available to the traders. So, it is difficult to determine whether traders make similar decisions because they disregard their own information and imitate or because they are reacting to the same piece of public information, for instance. To overcome this problem, some authors (Cipriani and Guarino, 2005; Drehman et al., 2005) have tested herd behavior in a laboratory financial market. In the laboratory, participants receive private information on the value of a security and observe the decisions of other subjects. Given these two pieces of information, they choose sequentially if they want to sell, to buy or not to trade a security with a market maker. In the laboratory one can observe the private information that subjects have when making their decisions, so it is possible to test models of herding directly.

This study proposes modeling of human decision making in such a way that option available on a certain issue can be visualized as companies and humans would behave as investors and they have to invest on one single company or a single opinion as trading is done in stock markets. Whole system would behave similar to stock market and it is expected that sudden rise in acceptance of a particular alternative would trigger a surge in its acceptance rate as under circumstances of uncertainty employees would consider the option accepted by most others. A real time survey is conducted to acknowledge the accuracy of the proposed visualization. As an empirical analysis, 58 students of MBA class were asked about their preferable employment location in North Central Region of India. They were giving four options which are similar in various contexts. In this scenario students are investors while options for employment are companies to choose from to invest. As other's responses are viewable so this may affect their decision as in financial market. So this paper tries to forecast capitalization of an option lets say New Delhi. Result will tell about percentage of population who want to be employed in New Delhi.

## 2. Previous Research

Herd behavior describes how individuals in a group can act together without planned direction. The term pertains to the behavior of animals in herds, flocks, and schools, and to human conduct during activities such as stock market bubbles and crashes, street demonstrations, sporting events, religious gatherings, episodes of mob violence and even everyday decision making, judgment and opinion forming.

Herd behavior is a term implying alignment to a mode of collective conduct and is expressed as a "similarity in behavior" following the "interactive observation" of actions and payoffs (arising from those actions) among individuals (Hirshleifer and Teoh, 2003). In the stock market context, herding involves the intentional sidelining of investors' private information in favor of the observable "consensus" (Bikhchandani and Sharma, 2001) irrespective of fundamentals (Hwang and Salmon, 2004) and the roots of such behavior can be traced to a series of factors be they of psychological or rational nature. From a psychological viewpoint, the impetus underlying imitation has often been assumed to stem from the human nature itself, in the sense that people may tend towards conformity (Hirshleifer, 2001) as a result of their interactive communication. The latter could be explicit (when people are conversing- Shiller, 1995) or tacit (when people observe others' choices).

However, herding could also be driven by more subtle considerations, if its practice is associated with the realization of informational payoffs (Devenow and Welch, 1996) by those imitating the decisions of others. This is the case when one:

- a) Possesses no private information,
- b) has private information yet is uncertain about it perhaps because it is of low quality,
- c) Considers his information-processing abilities to be inadequate or
- d) Perceives others as better-informed.

If a large number of investors decide to discard their private signals and free-ride on the informational content of others' actions, this is expected to bear an adverse effect over the public pool of information and may well pave the way towards the development of "informational cascades" (Banerjee, 1992; Bikhchandani, 1992).

A basic tenet of classical economic theory is that investment decisions reflect agents' rationally formed expectations; decisions are made using all available information in an efficient manner. A contrasting view is that investment is also driven by group psychology, which weakens the link between information and market outcomes. In *The General Theory*, Keynes (1936) expresses skepticism about the ability and inclination of

"long-term investors' to buck market trends to ensure full efficiency. In his view, investors may be reluctant to act according to their own information and beliefs, fearing that their contrarian behavior will damage their reputations as sensible decision-makers.

Thus Keynes suggests that professional managers will follow the herd' if they are concerned about how others will assess their ability to make sound judgements. There are a number of settings in which this kind of herd behavior might have important implications. One example is the stock market, for which the following explanation of the pre-October 1987 bull market is often repeated: The consensus among professional money managers was that price levels were too high--the market was, in their opinion, more likely to go down rather than up. However, few money managers were eager to sell their equity holdings. If the market did continue to go up, they were afraid of being perceived as lone fools for missing out on the ride. On the other hand, in the more likely event of a market decline, there would be comfort in numbers--how bad could they look if everybody else had suffered the same fate?

The same principle can apply to corporate investment, when a number of companies are investing in similar assets. In *Selling Money*, Gwynne (1986) documents problems of herd behavior in banks' lending policies towards LDC's.

### 2.1 Econometric Modeling

A time series is defined as a set of quantitative observations arranged in chronological order. It is generally assumed that time is a discrete variable. Time series have always been used in the field of econometrics. Tiberger (1939) constructed the first econometric model for the United States and thus started the scientific research programme of empirical econometrics. At that time, however, it was hardly taken into account that chronologically ordered observations might depend on each other. Durbin and Watson (1950/51) developed a test procedure which made it possible to identify first order autocorrelation. Box and Jenkins (1970) introduced univariate models for time series which simply made systematic use of the information included in the observed values of time series. This offered an easy way to predict the future development of this variable. Granger and Newbold (1975) showed that simple forecasts which only considered information given by one single time series often outperformed the forecasts based on large econometric models which sometimes consisted of many hundreds of equations.

Over recent years rigorous treatments of the time series concepts are presented by Fuller (1996) and Hamilton (1994). Applications of these concepts to financial time series are provided by Campbell, Lo, and MacKinlay (1997), Mills (1999), Gouriéroux and Jasiak (2001), Tsay (2001), Alexander (2001), and Chan (2002). The problem we are having in this research is of quantifying each observation as the survey is being filled by each student such after each observation a value represents population with that particular option. In this way a time series will be generated and econometric modeling can be done over it to forecast it

### 2.2 Auto Regressive Process

ARIMA (Auto Regressive Integrated Moving Average) processes are mathematical models used for forecasting. In ARIMA terms, a time series is a linear function of past actual values and random shocks, that is:

$$Y_t = f(Y_{t-k}, e_{t-k}) + e_t, \text{ where } k > 0 \quad (1)$$

The ARIMA approach to forecasting is based on the following ideas:

- The forecasts are based on linear functions of the sample observations.
- The aim is to find the simplest models that provide an adequate description of the observed data. This is sometimes known as the principle of parsimony.

Each ARIMA process has three parts: the autoregressive (or AR) part; the integrated (or I) part; and the moving average (or MA) part. However, this paper concentrates mainly on autoregressive process as model is mainly concerned with dependence of future responses on past little observation. Integrated part refers to number of times a time series is differenced to make it stationary.

Auto-regressive Process ARIMA (1,0,0) is given by :

$$Y_t = \theta + \Phi Y_{t-1} + e_t \quad (2)$$

The absolute value of  $\Phi < 1$ , ( $-1 < \Phi < 1$ ) and  $e_t$  pure random process with zero mean and variance  $\sigma^2$  and  $\theta$  is a constant.  $Y_t$  is the time series which is being analyzed in our case its New Delhi share first 30 observation. If  $\Phi > 1$ , the past values of  $Y_{t-k}$  and  $e_{t-k}$  have greater and greater influence on  $Y_t$ , it implies the series is non-stationary with an ever increasing mean. If Bound of Stationary does not hold, the series is not autoregressive; it is either

drifting or trending, and first-difference should be used to model the series with stationary. So, NDS time series will have to be first analyzed for the stationarity then only autoregressive models can be applied on it. Autoregressive Process ARIMA (p, 0,0) is:

$$Y_t = \theta + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p} + e_t \quad (3)$$

Many economic and financial time series are well characterized by an ARIMA(1,0,0) process. Leading examples in finance are valuation ratios (dividend price ratio, price-earning ratio etc), real exchange rates, interest rates, and interest rate differentials (spreads). The partial autocorrelation function (PACF) is a useful tool to help identify AR(p) models. The PACF is based on estimating the sequence of AR. The last coefficient of ARIMA (p,0,0) is called partial autocorrelation coefficient,  $\Phi_p$  (eq-4) in this case. For an AR(q) all of the first q partial Autocorrelation coefficients are non-zero, and the rest are zero. This will help us to determine value of p for ARIMA (p,d,0) models. Many economic and financial time series exhibit trending behavior or non-stationarity in the mean. Unit root tests can be used to determine if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary. The stationarity tests of Kwiatkowski, Phillips, Schmidt and Shinn (KPSS) (1992) is used to check the stationarity of NDS time series and Phillips-Perron Unit Root Tests (1988) will be used to determine if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary

### 3. Methodology and Concept

The starting point is a sample survey which includes sample of population having major specific characteristics. A questionnaire is designed in such a way that its options cover major decisional alternatives and are close to each other i.e. similar to each other in various aspects to reduce biasing. Options represent a company and students investors, so if a student goes for a particular option means he buys that company's share and its share price will increase. Taking share price analogues to percentage of people those have chosen that option a time series is obtained which varies each time an student fills the questionnaire. After having collected the questionnaire data comes the analysis part. Principle behind this concept is autoregressive nature of time series models which takes into account only few previous observations before forecasting data but not whole past data. Hence, while taking survey it is expected that before making any decision a student would take a look into decisions taken by few others before him which may influence his decision and lead to autoregressive affect in data collected. An individual may be tempted to believe that others are having a secret information which he is not sure about, hence majority are following that particular option. Generally financial time series are non stationary and have unit roots data collected in the survey will be checked for unit roots and stationary

Question asked to students is which job location they will prefer for employment. This question has four options: - (a) Chandigarh (b) Gurgaon (c) New Delhi (d) Noida. As these four locations are very close to each other in North Central region (NCR) of India, hence climatic conditions and distance from far location is nearly same. These cities offer equally attractive job opportunities for the individuals and comprises major part of NCR region of the country, unless a student doesn't live nearby any place or have a bias related to it, is expected to answer the option answered by his most other friends just before him. This would in coordination with our principle.

After collecting the data or choices of students' share of each option is calculated by using this formula

$$NDS [n] = \frac{\text{Number of Students opted for New Delh (after n responses)}}{n} \quad (4)$$

n = number of responses and varies from 1-58 as this survey has 58 students

NDS [n] (New Delhi Share) = % of students that have opted for New Delhi after n students have filled the responses from the sample.

As our sample size is 58 a time series with 58 observations will be obtained. First 30 observations will be used to train model parameters while forecast for next 28 observations will be made. This series is expected to behave similar to price of a stock in stock market and show characteristics similar to financial time series, tests will confirm this test later. Further statistical test will confirm about its stationarity and unit root characteristics. Similarly for options b,c and d their share will be calculated. Initially, all options are given 1 value each as base, so at 0<sup>th</sup> count share of each option is .25 or 25%. Now suppose as first student fills the questionnaire and opts for New Delhi then resulting share figures would be .4 ( 2/5 ) for New Delhi and .2 for remaining options. Similarly, with each student filling the questionnaire this share would change. After getting this questionnaire filled by 58 student's four time series with 58 rows each containing share value changes of respective option is obtained. These series will be analyzed in the same way as a financial time series is analyzed.

#### 4. Observation Analysis

As New Delhi has been opted by most of the students until 30 observations, so we will try to forecast next 28 observations and check of its series follows some autoregressive process. Consider New Delhi share (NDS) over 30 entries (Fig (1), below). ACF (Fig (2)) and PAF (Fig (3)) of NDS for first 30 responses is very high and decays slowly which indicates presence of some trend, so NDS will have to be differenced. NDS' and NDS'' represents first and second differenced series. KPSS and Philips Perron test (Table 1 and 2 below) confirms that NDS has unit roots and is non stationary while NDS' and NDS'' are stationary as well as doesn't have unit roots. Fig (4) and Fig (5) shows that PAF becomes zero after 2nd and 3ed lag for NDS' and NDS'' respectively. Hence, it can be said that NDS' and NDS'' follows AR (2) and AR (3) processes and are first and second differenced series of NDS. Finally, Fig (6) and Fig (7) compares next 28 observed and forecasted values of NDS using ARIMA(2,1,0) and ARIMA(3,2,0). According to forecast 52% of total students will finally opt for New Delhi while the observed results show that 49% have gone for Delhi.

#### Conclusion

Analysis shows that variations in percentage of population going for a particular option follow similar behavior as a financial time series. Options presented for decision making were kept as unbiased as possible still some biasing may arise due some personal preferences of population; still forecast results are highly motivating under given environment. Results of KPSS and Philips Perron test confirms that time series generated has trending behavior and non-stationary of mean as any other financial time series. ARIMA (3,2,0) forecast greatly follows the trend observed in students responses. Final results differ only by 3%. Autoregressive models to some extent have successfully forecasted group decision making under uncertainty.

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Table 1. Phillips-Perron Test Statistics for NDS, NDS', NDS''

Series	Test	Statistic	P-Value	Null Hypothesis	DOF	Residuals	Residual Std.	Outcome
NDS	Phillips-Perron	-0.5895	0.8582	there is a unit root	29	27	0.03642	Acceptance of null hypothesis
NDS'	Phillips-Perron	-7.007	2.66e-6	there is a unit root	28	26	0.02747	Rejection of null Hypothesis
NDS''	Phillips-Perron	-15.15	4.922e-6	there is a unit root	27	25	0.03067	Rejection of null Hypothesis

Table 2. KPSS test Statistics for NDS, NDS', NDS''

Series	Test	Type of Test	Statistics	Significance Level	Bandwidth	Outcome
NDS	KPSS	Stationarity test	0.8473	1%	2	Not Stationary
NDS'	KPSS	Stationarity test	0.1221	5%	2	Stationary
NDS''	KPSS	Stationarity test	0.1657	5%	2	Stationary

\*NDS: New Delhi share in survey (first 30 responses)

NDS': 1<sup>st</sup> differencing of NDS

NDS'': 2<sup>nd</sup> differencing of NDS

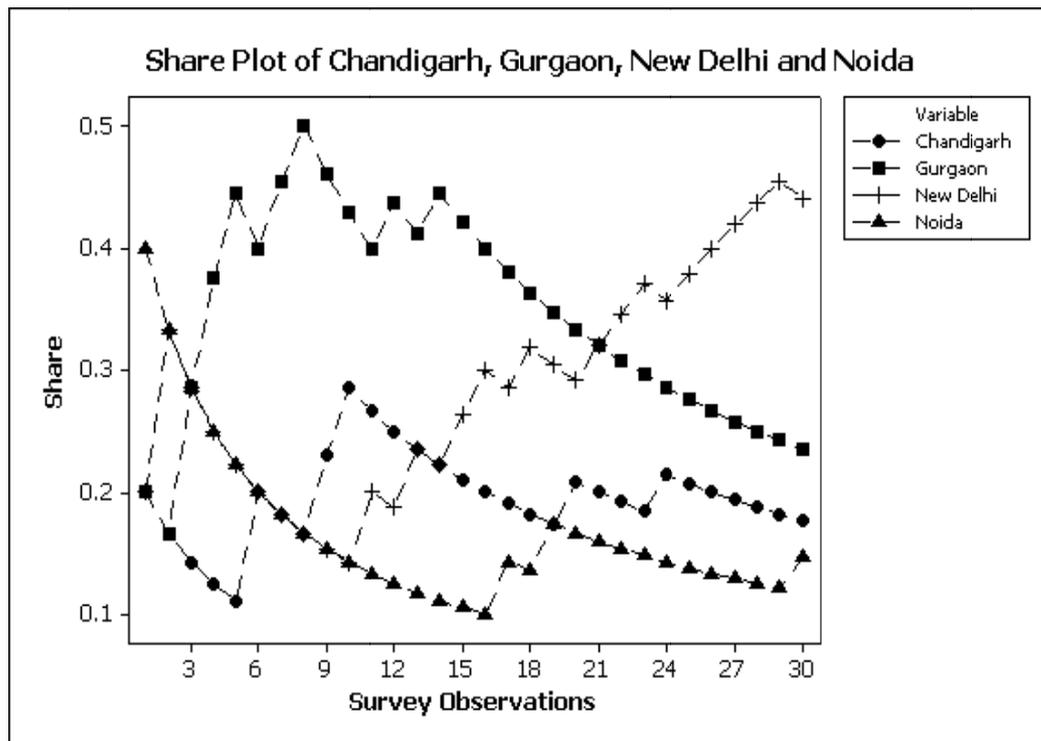


Figure 1. Variations in share of various options during survey

eg. Symbol (+) depicts percentage of students who have opted for New Delhi as the survey is being filled by the students.

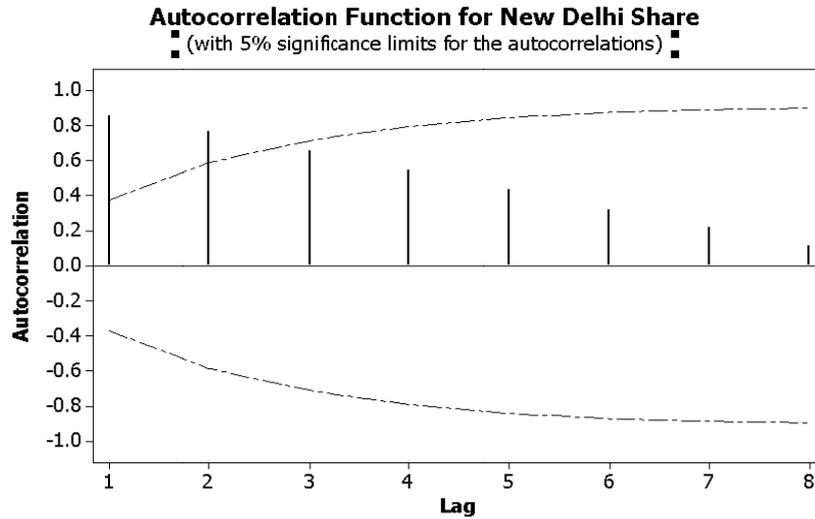


Figure 2. ACF (Auto Correlation Function) New Delhi Share (NDS)

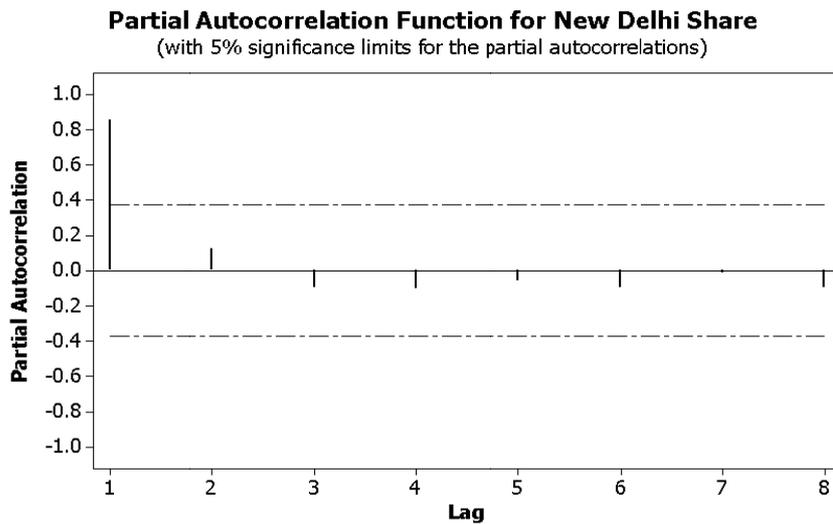


Figure 3. PACF (Partial Auto correlation Function) New Delhi Share (NDS)

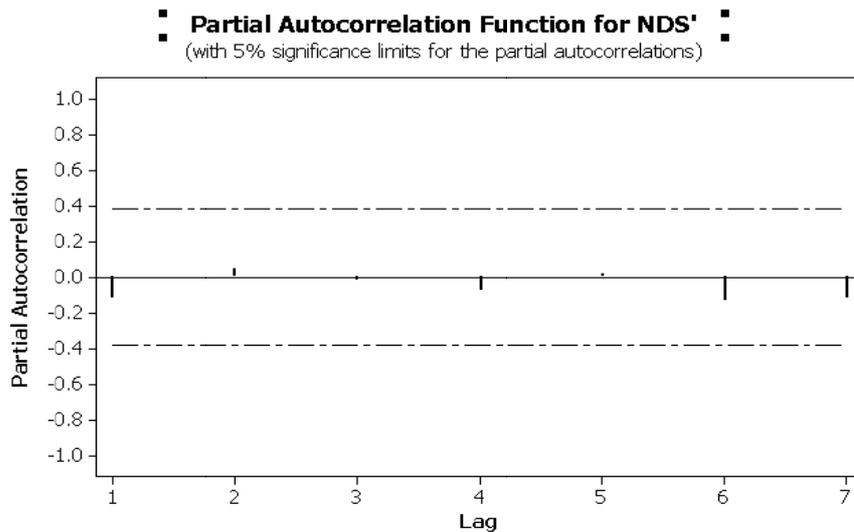


Figure 4. PACF for NDS' (first difference of NDS)

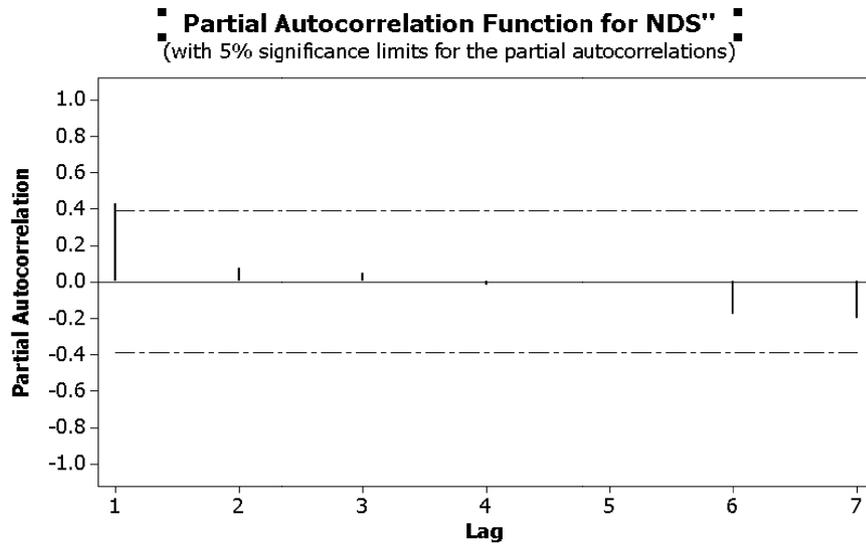


Figure 5. PACF for NDS” (Second difference of NDS)

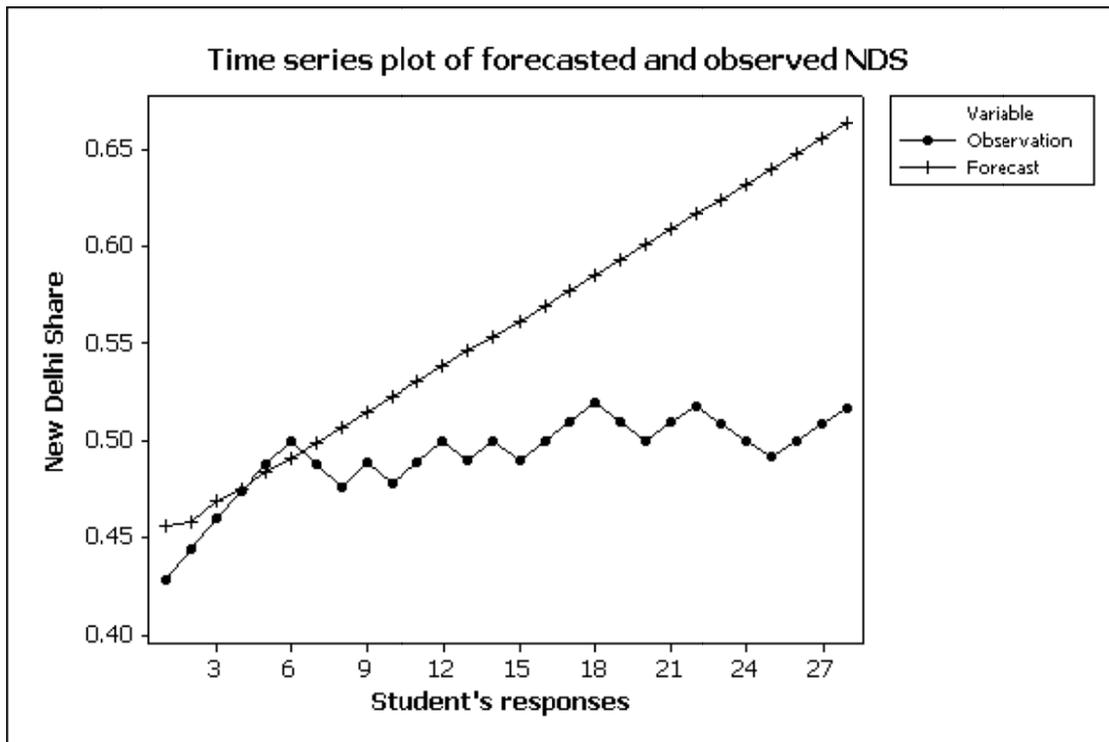


Figure 6. Comparison of New Delhi’s share in students responses and forecast using ARIMA (2,1,0)

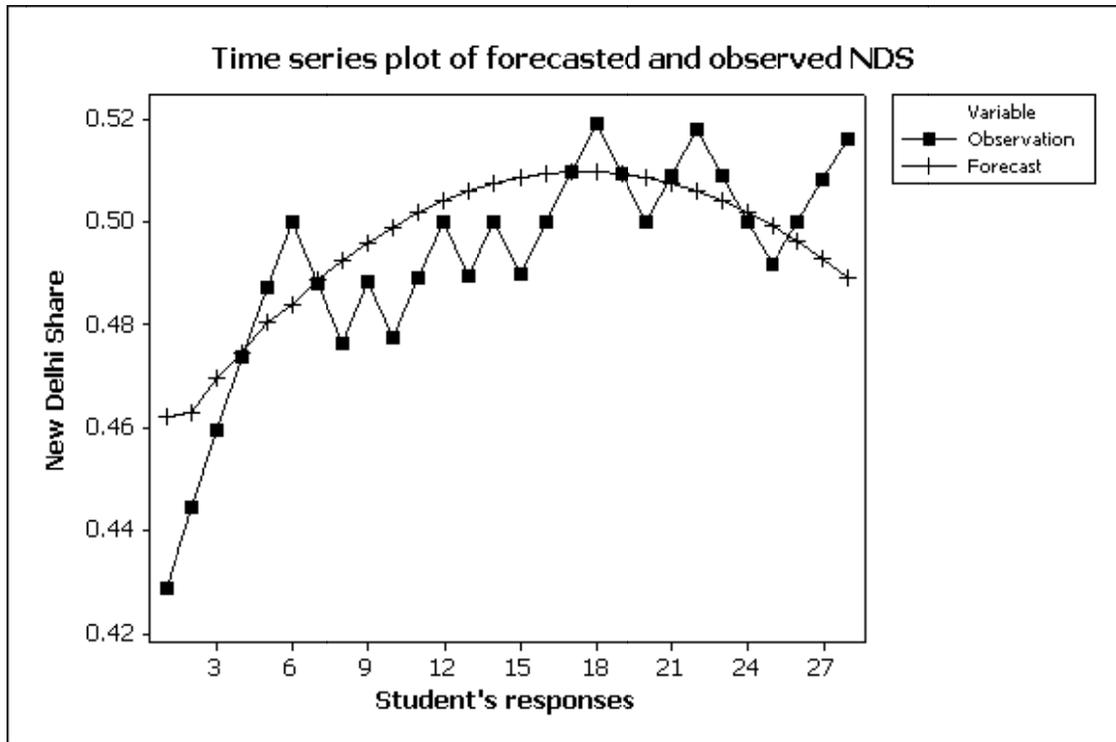


Figure 7. Comparison of New Delhi's share in students responses and its forecast using ARIMA (3,2,0). Forecast (+) and Observation (■)